Master's Thesis

The Anatomy of a Stock Market Winner Revisited

An Empirical Analysis

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Abstract

The purpose of this thesis is to assess if the trading strategies created by Reinganum (1988) still outperform the S&P 500, and to test whether the same methodology of investigating shared characteristics among winner stocks is effective for creating a trading strategy in the time period 2000-2019 on the U.S. stock market. This thesis singles out stocks with a rapid price appreciation and analyses their shared fundamental and technical attributes. The analysis identifies several distinct features among the stock market winners, which are utilized to form the basis of an investment strategy. Previous research of stock market winners has mainly focused on how to identify stocks expected to rise significantly over longer time periods, while research addressing shorter term price acceleration is limited.

Reinganum (1988) presented two strategies, consisting of nine and four investment screens. This thesis finds that the four-screen strategy still outperforms the S&P 500 in terms of average excess cumulative holding period return over two years, while the limited number of stocks meeting all nine filter rules makes the nine-screen strategy essentially impossible to implement. Following the same methodology as Reinganum (1988), this thesis identifies six new investment screens through analyzing common attributes among a random sample of stocks that at least doubled in price within one calendar year.

Based on Reinganum's (1988) four-screen strategy and this thesis' constructed six-screen strategy, equal-weighted and value-weighted portfolios are created to examine how the strategies would have performed when backtested on historical data from 2000-2019. This thesis finds that Reinganum's (1988) four-screen strategy outperforms the market in terms of both cumulative holding period and risk adjusted returns, where the equal-weighted portfolio is the better investment. The constructed six-screen strategy outperforms Reinganum's (1988) four-screen strategy when equal-weighted but underperforms when value-weighted. The results are consistent before and after adjusting for transaction costs.

Neither of the portfolios generate consistent abnormal returns when taking into consideration the exposure to well-known risk factors. However, the equal-weighted six-screen portfolio produces statistically significant alphas in both the overall period and the sub-period from 2000-2009. This might indicate that the strategy captures more stocks that outperform in 2000-2009 compared to 2010-2019, suggesting that the attributes of what is considered a stock market winner is changing with the dynamics of the stock market.

Contents

1. Introduction

Nobel prize winner Sharpe (1991) claims in "The Arithmetic of Active Management", that for any time period, the return on the average actively managed dollar will be less than the return on the average passively managed dollar after costs. However, this does not mean that all active managers must underperform, and some are able to beat their passive brethren even after costs. The ultimate goal of active managers is therefore to be one of those that beat their passive counterparts, that seeks to follow the market. The development of finance as an academic field has highlighted the difficulty for active managers to consistently outperform their passive benchmarks (AQR Capital Management, 2018). Even though the empirical evidence of active management is discouraging, investors and researchers are nonetheless seeking to identify systematic strategies to achieve alpha.

Marc Reinganum published an article named "The Anatomy of a Stock Market Winner" in 1988, analyzing U.S. firms whose stocks had at least doubled in price during one year in the time period from 1970-1983 (Reinganum, 1988). Based on the common characteristics among these winner stocks, Reinganum (1988) created two different strategies using nine and four investment screens, that both produced economically significant excess returns above the S&P 500. These strategies were combining factors that are heavily researched today, like size, value and momentum. Hence, a natural expectation is that a portfolio constructed using publicly available information based on these factors no longer outperforms the overall market.

Other research has tried to isolate single attributes like value or size and investigated its associated return, but the literature discussing the method of singling out and analyzing shared attributes of high-performing stocks is limited. Reinganum's (1988) sample of winners exhibited a high degree of consistency in the shared characteristics, which might indicate that a majority of the sample consisted of similar types of companies. Stock markets are continuously evolving and so could the attributes of what is considered a stock market winner. This makes it relevant to investigate whether Reinganum's (1988) methodology is effective in creating an investment strategy that consistently produces abnormal returns over a different time period.

1.2 Research question

The purpose of this thesis is to revisit Reinganum's (1988) investment strategy and subsequently create a new investment strategy based on common characteristics among U.S. stock market winners between 2000-2019. Thus, the scope of this thesis is anchored in Reinganum's (1988) research but extended to create and backtest portfolios based on his four-screen strategy and the shared characteristics among the winner stocks in this thesis' time period. An analysis of these winner stocks will decide whether it is possible to utilize his methods in today's stock market and create a strategy that produces consistent abnormal returns. The performance of Reinganum's (1988) four-screen strategy and the thesis' created six-screen strategy will be evaluated as portfolios based on holding period returns, performance measures and benchmark analyses. In accordance with the abovementioned outline, the following research question will be answered:

Does Reinganum's (1988) four-screen strategy yield excess returns above the S&P 500 in the period from 2000-2019 and is it possible to create an alpha-generating investment strategy based on analyzing common characteristics among today's stock market winners?

In order to gain insights into the research area and provide a comprehensive answer to the research question, four sub-questions are specified:

- How does the excess returns over S&P 500 for Reinganum's (1988) four-screen strategy from 2000-2019 compare to his original findings, and this thesis' six-screen strategy?
- Is it possible to construct an investment strategy on the basis of shared characteristics among stock market winners between 2000-2019?
- How do the portfolios formed by the four-screen strategy of Reinganum (1988) and this thesis' sample of winner stocks perform relative to each other, the S&P 500 and the market portfolio?
- Do these portfolios generate statistically significant abnormal returns, and are they consistent over the complete period and individual sub-periods?

1.3 Delimitations

Before embarking on the empirical analysis of the research topic, it is necessary to make delimitations of the thesis' scope. The delimitations are presented below.

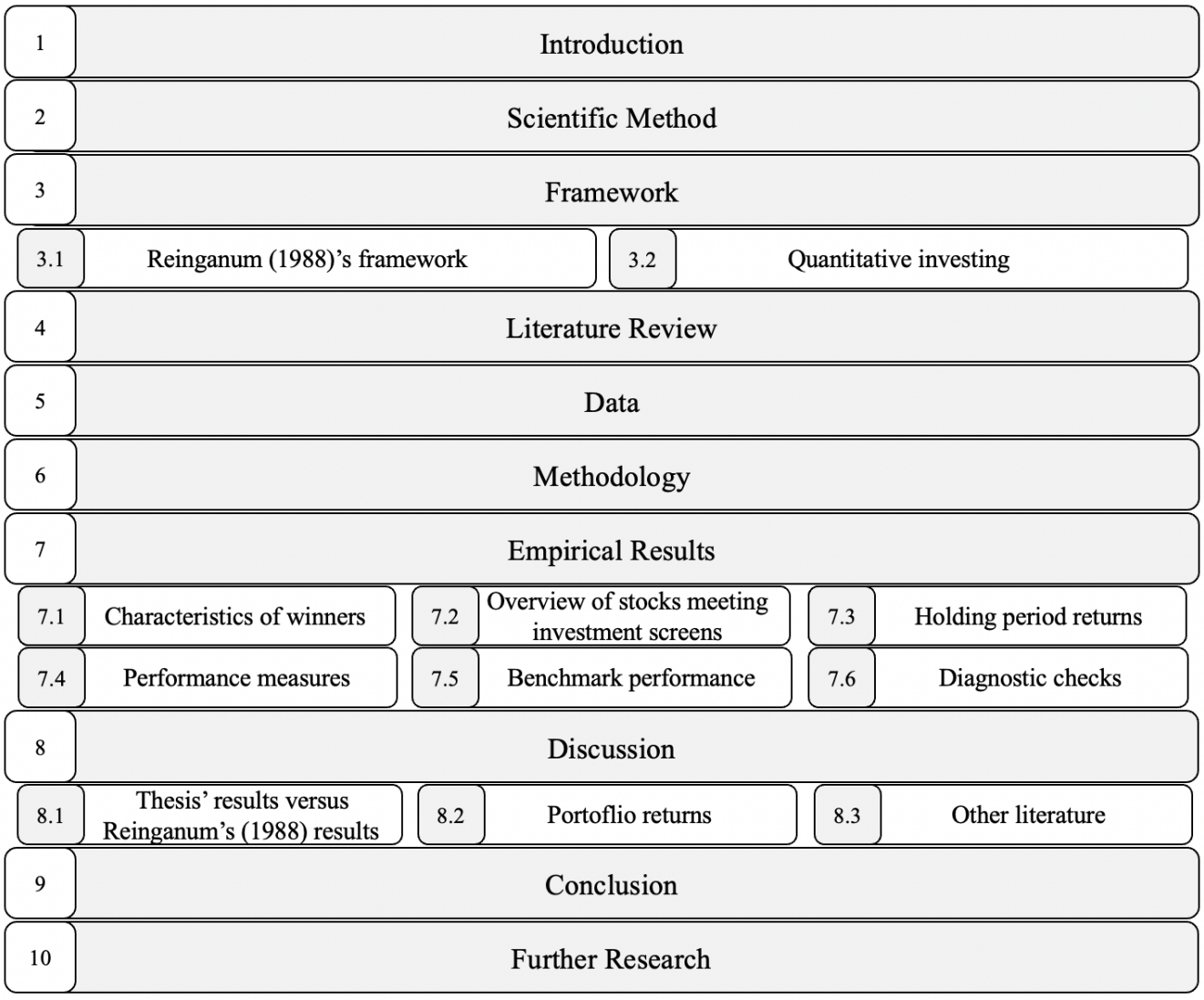
Scope	The empirical analysis will be conducted on the time period between January 2000 and December 2019.
Investor	The thesis is constructed from the point of view of a professional investor trading in USD.
Equity universe	The equity universe is limited to ordinary common shares of companies in the U.S., listed on the NYSE, AMEX and Nasdaq stock exchanges.
Data	The sample of potential winners is limited to companies with fundamental, price and return data available at the CRSP and Compustat databases.
Fractions	It is assumed that investors can hold fractions of stocks.
Transaction costs	Transaction costs are assumed to be constant across the investment period.
Liquidity	All stocks are assumed to be liquid at the closing price at all times.
Shorting	The thesis is limited to long-only investment strategies.
Source of information	The thesis relies solely on publicly available information.

1.4 Contribution

The majority of papers that research the characteristics of stock market winners have focused on stocks appreciating in price over longer periods of time, while little attention has been aimed towards researching the characteristics of shorter-term price appreciation. Reinganum (1988) researched this field of rapid price appreciation and documented impressive results, however, what seemed to produce excess returns in the 1970's and 1980's might no longer do so. Reinganum's (1988) strategy is tilted towards well-known risk factors like size, value and momentum, but he does not test whether the excess returns are statistically significant after controlling for the exposure to these risk factors. Therefore, the thesis will investigate whether Reinganum's (1988) methodology is able to identify and create an investment

strategy producing consistent abnormal returns. The findings will contribute to the ongoing debate between active and passive investing and the degree of efficiency in financial markets.

1.5 Structure



2. Scientific Method

In the following section, a thorough overview of this thesis' research structure will be presented. The structure will build on the stages of understanding and approaching research presented by Saunders, Lewis and Thornhill (2016), where the purpose is to enhance the readers interpretation and perception of the presented research. Section 2.1 will elaborate on considerations of research philosophy, research approach and methodology. Section 2.2 outlines the types of research used in the design of the thesis, while Section 2.3 clarifies the time horizon. Section 2.4 explains the data techniques and procedures applied in the process of data collection and data analysis. Finally, the quality of the research design is established through an assessment of the research reliability and validity in Section 2.5.

2.1 Research philosophy and design

The research philosophy of the thesis serves a fundamental role in how the empirical results will be analyzed and acknowledged. It is a system of beliefs and assumptions about methods of which data will be collected and used, which put in simpler terms implies how knowledge about the research questions is created and developed (Saunders et al., 2016). This is relevant because it addresses the results interpretability and credibility. The section will also help to outline the philosophical choices made along the research process and justify them in relation to the alternatives. The goal is to explain the methodological choices, research strategy and data collection approaches. The connection between research decisions and explanations is important to establish coherence between the research question and philosophy.

The thesis aims to develop an investment strategy which likely will feature one or several prominent trading strategies within the field of portfolio theory such as momentum, size and value. Furthermore, abnormal returns by constructing portfolios based on the strategy will be examined. This can be viewed as a critical empirical test of previously established theory. In a scenario of positive abnormal returns, hence falsifying the efficient market hypothesis, one would potentially get closer to the truth of abnormal returns. Thus, by exposing theory for critical testing of possible limitations, the theory will advance, and new knowledge is found. Hence, the design is customed to principles of critical rationalism, where science and experience-driven methods based on logical and mathematical tools are applied (Holm, 2018).

Critical rationalism believes in a deductive approach to research, which for the thesis implies that previously established theories of market anomalies, such as size, value, momentum can produce abnormal returns. The thesis' approach can arguably also be identified as inductive research, since analyses of general data observations are performed to generalize a theory based on the observed data. Put in simple terms, if the majority of the winner stocks trade at low P/B, all stocks trading at low P/B will be winner stocks. Given that the thesis studies quantitative observable data, with research objectivity at the center, the principles of interpretivism also have similarities to the research approach. Interpretivism focuses on understanding the process rather than explaining it, which is appropriate when interpreting prevailing market behavior and sentiment (Saunders et al., 2016). This means that the interpretivism promotes an understanding that the world is too complex to follow generalized rules, as opposed to positivism. Rather, the research philosophy should try to make sense and understand the fundamental meanings of the study.

Ultimately, the adopted design is to some extent polarized into deductive and inductive reasoning. Both designs have their strengths and weaknesses. The deductive approach is criticized for being stationary, meaning that the focus on testing known theory limits the extent of which new knowledge is procured. The inductive approach is, on the other hand, criticized for being tunneled towards verifying theories where researchers only look for evidence supporting the theories. The aim of the thesis is to obtain research objectivity, something both positivism epistemology and critical rationalism epistemology advocate (Saunders et al., 2016). However, while positivism believes in perfectly objective research, critical rationalism says that observing data with full objectivity is impossible. The researcher should rather be selective based on preparation and knowledge. This is related to the thesis' approach of observing previous winner stocks, when trying to predict future winners.

2.2 Methodical choice and research purpose

According to Saunders et al. (2016), quantitative research is based on various statistical and graphical techniques to analyze numerical relationships between variables. Quantitative research can also use several data collection techniques, although this study relies on a single technique of pulling data from accredited databases. Most data are pulled from the Center for Research in Security Prices (CRSP), Compustat and Kenneth French Data Library. Also, to ensure the validity of the data, random samples have been compared with data from Refinitiv and companies' SEC filings.

The research project is designed to fulfil a combination of descriptive, evaluative and explanatory purposes (Saunders et al., 2016). Considering the objective of the thesis, the descriptive purpose serves as a forerunner to the explanatory. It is essential to obtain accurate knowledge of already established portfolio investment strategies, including how, when and where they were introduced and their yielded results. This is presented in the literature review and in the framework section. Furthermore, evaluative research is performed in relation to both Reinganum's (1988) results and the thesis' findings. The focus is to evaluate to what extent the strategies are efficient based on the entire process from gathering data to evaluating the performance. Lastly, explanatory research seeks to answer what lies behind the presented results. Thus, explaining the relationship between returns and data attributes and providing color to why potential abnormal returns occur.

2.3 Time horizon

The next important clarification is related to the time horizon of the research, which can be divided into either cross-sectional or longitudinal (Saunders et al., 2016). In this case, the time horizon is longitudinal as data stretching from 1993 until 2019 is included in the thesis. The strength of this approach lies in the abilities to study change and development over longer periods of time, abating the significance of outliers and strengthening generalization (Saunders et al., 2016).

2.4 Data collection

The last step in presenting the research philosophy, approaches and theory development is an outline of data collection and data analyses. This process serves as a vital part of the thesis, thus an additional section is devoted to this area. A comprehensive overview of the data is presented in Section 5.

2.5 Reliability and validity

The final step in formulating the research design is to establish the quality of the research design through an assessment of the research's reliability and validity (Saunders et al., 2016). The reliability of the research refers to the consistency of the research and whether it can be replicated. The research will be seen as being reliable if other researchers are able to replicate the applied research design and achieve the same results. The concept of reliability is divided into internal and external reliability (Saunders et al., 2016). Hence, a lack of reliability will affect the quality of the research.

The internal reliability refers to whether the research is consistent and free of errors (Saunders et al., 2016). The thesis' authors have cooperated during the entire research process to secure that calculations, presentation of results and analyses are performed thoroughly and precisely. The frameworks and methodology applied in the thesis are presented in detail, providing insights into the research process and ensuring that the research is consistent. Thus, the research is considered internally reliable.

The external reliability is concerned with the data collection techniques, and whether other researchers will be able to reproduce the same results applying the same methodology (Saunders et al., 2016). The data downloaded and applied in this thesis consists to a large degree of secondary and quantitative data, downloaded from reputable databases such as CRSP and Compustat. Thus, the quality of the data collection techniques and the downloaded data depends on the quality of the aforementioned databases. Returns data ar downloaded from the CRSP database. CRSP is the main source in almost all studies of the U.S. stock market and is maintained by the University of Chicago's Booth School of Business (Bali, Engle, & Murray, 2016). This is also the same source that Reinganum (1988) applied when writing the original article, as well as Yu (2009) when revisiting his strategy.

The Compustat database is prepared and marketed by Standard & Poor's Capital IQ division using information from firms' financial disclosures (Casey, Gao, Kirschenheiter, Li, & Pandit, 2016). Compustat rely on Extensible Business Reporting Language (hereafter XBRL) data, which is an international business and financial reporting disclosure standard implemented to enhance internal and external reporting, electronic filing and sharing of information. Other distributors of XBRL data include Bloomberg, Refinitiv and Yahoo! Finance. Although company filings are a key source of data distributed by all of the data suppliers, the methods for obtaining, processing, storing and distributing the data vary by the distributors, where Compustat rely on manual data entry directly from the firm's SEC filings (Boritz & No, 2020). According to Casey et al. (2016), Compustat is the most widely used database of financial statement information for accounting and finance research. Both Reinganum (1988) and Yu (2009) apply Compustat in their analyses of stock market winners.

Based on the abovementioned, the internal reliability and the external reliability in terms of data sources and the data collection techniques are reflected upon and is considered to be reliable. However, to give readers and researchers deeper insights into the data collection and processing, all downloaded data items and calculations are provided in Appendix A and Appendix B. Reliability is a key characteristic of

research quality, but it is not sufficient by itself to secure high-quality research, which is why the validity is discussed. Validity refers to whether the research studies what it is intended to, and if the findings can be generalized to other situations (Saunders et al., 2016).

Internal validity is a concept associated with both positivist and quantitative research and is established when the research precisely displays a causal relationship between the investigated variables (Saunders et al., 2016). The data applied in the thesis is collected from secondary sources created by the different companies, collected and distributed through the CRSP and Compustat databases. The thesis applies companies fundamental and price data to identify potential winners, implicating a causal relationship between the data and future returns. According to Graham, Dodd and Klarman (2008), the market price of a company is a result of both general market factors and individual factors. Due to the many factors influencing the market price of a stock, other factors than the applied screens affect stock returns. However, the screens constructed are inspired by well-known market anomalies that have consistently created excess returns over longer periods of time. Thus, the degree of internal validity is somewhat questionable.

External validity is concerned with whether a study's findings can be generalized to other relevant situations (Saunders et al., 2016). This study is constructed on a sample of U.S. stocks, listed on the NYSE, AMEX and Nasdaq stock exchanges in the time period from 2000-2019. Thus, the external validity of the paper is concerned with whether the thesis' findings can be generalized to other markets and time periods. As investment returns and risk vary across regions and time, this research might not be generalizable to other markets in the U.S. or other regions. It is therefore necessary to conduct similar studies on other markets and time periods to assess whether the findings are generalizable to other samples. The external validity is considered to be limited.

To summarize, both the internal and external validity are considered to be limited and the research can therefore not be expected to be generalized to other markets and time periods, without conducting similar studies.

3. Framework

In this section, the thesis' frameworks are introduced. Section 3.1 introduces the framework in which Reinganum (1988) performs his analysis. In Section 3.2, the concept of quantitative investing is introduced.

3.1 The Anatomy of a Stock Market Winner – Reinganum (1988)

Reinganum (1988) examined 222 firms whose stock price at least doubled in price during one year in the 1970-83 period in his paper "The Anatomy of a Stock Market Winner". After analyzing these firms, he discovered several distinct characteristics shared by the majority of companies, which were used to form the basis of two trading strategies that were applied to 2,057 NYSE and AMEX firms over the 1970-83 period, making it an in-sample test. Reinganum (1988) found that both trading strategies significantly outperformed the S&P 500 index over the period.

Reinganum's (1988) methodology was to single out stocks with exceptionally high returns to see whether these firms shared any common attributes, hoping that these might suggest an investment strategy. The data in his paper was based on the *Datagraph* books (published by William O'Neil + CO. and sold primarily to institutional investors), which reported fundamental and technical information about firms traded on listed exchanges and the OTC markets (Reinganum, 1988). Reinganum's (1988) list of winners was gathered from another O'Neil publication, *The Greatest Stock Market Winners: 1970-1983*, which contained 272 episodes of explosive price appreciation for companies traded on the NYSE, AMEX and OTC markets.

Reinganum (1988) stated that to be considered a winner in the publication, a company typically had to at least double in price within a calendar year, with a few exceptions. Not all companies that doubled in price were considered as winners. He expressed that O'Neil personnel employed other criteria than just price appreciation to select firms, but these were not stated, and he did not know the criteria himself. Looking at CRSP tapes, he found 4,049 occurrences of a NYSE or AMEX firms doubling in price within a given calendar year in the time period, compared to the 272 winners in O'Neil's publication. Of the 272 winners, less than 5% sold at a price below USD 10, which indicated that O'Neil applied a price level screen when selecting winners. Reinganum (1988) pointed out that O'Neil's primary customers were institutional investors that might have been unable to invest in stocks below USD 10. Thus, it is

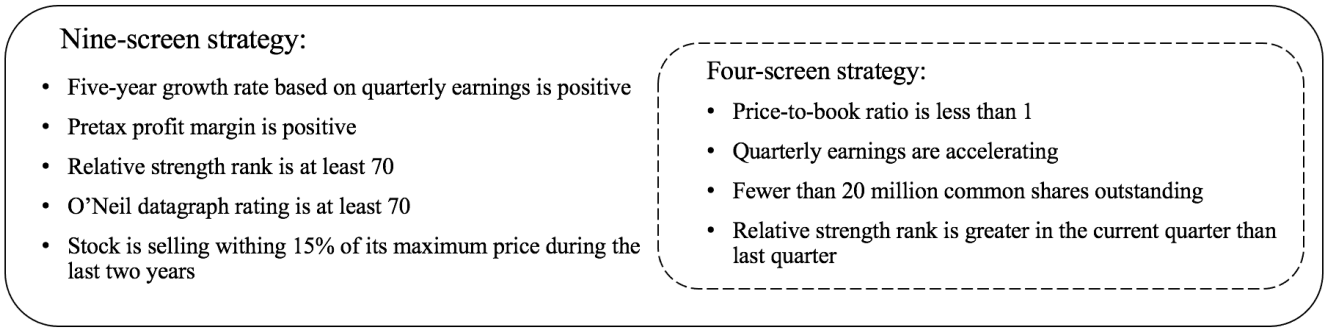
evident that O'Neil personnel had chosen companies not only based on explosive price appreciation but also on other metrics, which might have influenced Reinganum's (1988) findings. In other words, Reinganum (1988) did not cover the entire sample of firms doubling in price.

Looking at the winners, Reinganum (1988) classified each variable found in the *Datagraph* books into five different categories, including the behavior of professionally managed funds and corporate insiders, valuation measures, technical indicators, accounting earnings and profitability measures and miscellaneous variables that did not fit in the other groups. After comparing the different variables in these categories, Reinganum (1988) identified multiple potential investment strategies, where two of those were investigated further. He made no claim that the two presented strategies were the best possible strategies, but they revealed that what was common among winner stocks could be used to identify and implement investment strategies.

The first strategy included nine technical and fundamental variables that either saw a large change before the price appreciated or seemed to be widespread among the winners. Figure 3.1 lists the investment screens, where the four-screen strategy consisted of a subset of the nine-screen strategy (Reinganum, 1988, p. 25-26).

Figure 3.1

Screens for nine-screen and four-screen strategy, where all screens apply to the nine-screen strategy



The rules for the trading strategy stated that after a buy signal was generated, he waited 63 trading days before assuming a position in the stock, to ensure that the analyzed accounting information had actually been released (Reinganum, 1988). The stocks purchased were held for two years, with no other sell signal than the lapse of two years. 2,057 companies were possible investments, as the 222 winners were

excluded from the investment universe. The cumulative holding period return for each investment through each of the eight quarters were calculated and compared to the S&P 500 index over the same time period, where the difference was labeled an excess return. In cases where a buy signal for a particular company was generated at different times, he tracked the return for each buy signal separately. It is important to notice that the returns of the strategies were not tracked as portfolios, but as separate investments. Hence, the returns in Table 3.1 and 3.2 are returns on single investments from different time periods.

Table 3.1

Distribution of cumulative excess holding period returns from the nine-screen strategy (Reinganum, 1988, p. 25)

		Percentile								
Quarter	Average	1st	5th	10th	25th	50th	75th	90th	95th	99th
Buy+1	6%	-25%	-18%	-12%	-4%	5%	15%	26%	32%	46%
Buy+2	12%	-30%	-22%	-14%	-5%	10%	23%	37%	54%	90%
Buy+3	18%	-35%	-23%	-17%	-3%	15%	35%	56%	72%	133%
Buy+4	24%	-36%	-25%	-18%	-4%	17%	44%	74%	97%	158%
Buy+5	30%	-40%	-25%	-17%	-2%	21%	52%	91%	113%	183%
Buy+6	38%	-57%	-29%	-18%	0%	28%	63%	115%	144%	220%
Buy+7	44%	-53%	-34%	-19%	6%	35%	71%	126%	160%	242%
Buy+8	51%	-56%	-32%	-20%	5%	39%	83%	132%	170%	304%

The nine-screen strategy generated 453 buy signals for 319 different companies over the 1970-83 period. On average, the cumulative holding period returns of the selected securities exceeded the equivalent return for the S&P 500 index in each of the eight quarters. Over the two-year holding period, the selected firms outperformed the S&P 500 index by more than 50% on average. More than 79% of the investments outperformed the index, so the excess returns were spread across the sample. On an annual basis, the strategy earned average excess holding period returns of about 24% per year. Reinganum (1988) claimed that the results were not explained by higher risks, as the betas averaged only 1.03 in the two-year period preceding the buy date. Table 3.2 presents the results of the four-screen strategy.

Table 3.2

Distribution of cumulative excess holding period returns from the four-screen strategy (Reinganum, 1988, p. 27)

		Percentile								
Quarter	Average	1st	5th	10th	25th	50th	75th	90th	95th	99th
Buy+1	3%	-38%	-25%	-18%	-8%	1%	11%	25%	37%	68%
Buy+2	8%	-45%	-30%	-22%	-9%	4%	20%	40%	58%	108%
Buy+3	13%	-53%	-35%	-25%	-10%	7%	27%	54%	75%	149%
Buy+4	17%	-60%	-39%	-28%	-10%	10%	34%	65%	93%	180%
Buy+5	21%	-66%	-45%	-32%	-11%	13%	41%	79%	111%	216%
Buy+6	26%	-70%	-46%	-32%	-9%	16%	48%	93%	131%	244%
Buy+7	31%	-71%	-47%	-34%	-9%	19%	56%	106%	148%	268%
Buy+8	37%	-74%	-48%	-33%	-8%	22%	64%	119%	162%	319%

Table 3.2 shows that the less restrictive four-screen strategy generated 10,543 buy signals over the same time period and performed well relative to the S&P 500 index, with an average excess holding period return after two years of 37%, versus 51% for the nine-screen strategy. The four-screen strategy showed an impressive performance, but underperformed the nine-screen strategy, meaning that the five additional screens improved the performance.

3.2 Quantitative equity investing

Implementing a strategy based upon specific filters is a systematic way of investing, which makes it necessary to introduce the concept of quantitative equity investing (hereafter quant equity). Quant equity means investing in stocks using models where trading rules determined by humans are entered into and executed by computers, with humans keeping an eye on the process (Pedersen, 2015). There are both disadvantages and advantages of quant equity, that will be presented below.

One disadvantage of quant equity is that the machines carrying out the trades are not able to consider single cases, but simply executes trades based on the trading rules that are determined by the investors. This makes the quant equity strategies limited to quantitative measures that can be written out as trading rules, without paying attention to soft information from for example conference calls or annual reports (Pedersen, 2015). The thesis relies simply on fundamental, price and return data, which means that the aforementioned disadvantages are present when creating strategies and portfolios. Thus, the created strategies are unable to capture soft information such as positive or negative news regarding a particular company.

A major advantage of quant equity strategies is that they can be implemented on a large universe of stocks at the same time, constantly analyzing thousands of stocks before deciding what trades to execute. This leaves the investors holding a large portfolio of different companies, yielding significant diversification (Pedersen, 2015). Another advantage is that the quant equity models are less exposed to the biases known to affect human begins, for example the disposition effect. A final important advantage is that the quant equity strategies can be reliably backtested using historical data (Pedersen, 2015). Backtesting is applied in the thesis and is further described in Section 6.3.1.

Quant equity strategies can be subdivided into different types of trades, where fundamental quantitative investing (hereafter fundamental quant) is the one most similar to Reinganum's (1988) strategies. Pedersen (2015) explains that fundamental quant investors seeks to combine fundamental analysis with both economic and finance theory in a systematic way, along with statistical data analysis and computer systems. The portfolio turnover can range from days up to multiple months, and the large number of investments and affiliated diversification allows substantial capital to be invested in the strategies.

4. Literature Review

The literature review is structured around Reinganum's (1988) article which directly and indirectly relates to several widely discussed topics within the world of finance, such as the efficient market hypothesis, active versus passive investing and stock market anomalies. Hence, the literature review seeks to provide valuable insights into Reinganum's (1988) strategies and set the stage for parts of the thesis' methodology and discussion. The section will start off by introducing other studies of high performing stocks in Section 4.1. Thereafter, research on the efficient market hypothesis and to what extent the stock market is considered to be efficient is presented in Section 4.2, followed by an outline of the ongoing debate of passive versus active investing in Section 4.3. Finally, Section 4.4 will address some of the most known market anomalies.

4.1 High performers

Within the research area of high performing stocks, several techniques have been utilized to identify stock market winners. It is therefore interesting to dig deeper into other publications addressing stocks that have accelerated significantly in price and what the literature recognizes as promising features for

a potential winner. The section will, however, start off by presenting results from the only publication found that revisited Reinganum's (1988) strategy.

4.1.1 Reinganum's Trading Strategies Revisited (2009)

Yu (2009) published a paper with the purpose of reexamining the value, momentum and size factors employed in the trading strategy proposed by Reinganum (1988). The paper is divided into two parts. She started by showing why it was increasingly difficult to employ Reinganum's (1988) original strategy and tested his four-screen strategy on additional 23 years of data. The second part of the paper compared the four-screen strategy to similar strategies that incorporated modifications to his filters and was extended to a long/short trading strategy. Only the findings of the first part of the paper are presented below, as the second part deviates from the scope of this thesis.

The data analyzed consisted of all stocks that were in both the CRSP and Compustat database, with earnings data for at least five consecutive quarters and 15 months of return data in the period of 1970-2006. The data was winsorized at the top and bottom 0.5% to mitigate possible distortions due to extreme prices or fundamental data (Yu, 2009).

Yu (2009) found that the four-screen strategy was increasingly difficult to implement in the years up to 2006. The percentage of firms that passed the outstanding shares of fewer than 20 million filter dropped from the peak of 31.9% in 1975 to just 2.5% in 2006, which could be a result of corporate actions such as stock splits or seasoned equity issues. Another filter rule, P/B less than 1 also had a large decrease from 66.1% in 1975 to 12.4% in 2006, which indicated that it is increasingly difficult to find underpriced stocks. The percentage of stocks that met all four screens declined steadily from 5.8% (131 stocks) in 1975 to only 0.3% (16 stocks) in 2006. Yu (2009), therefore, claimed that it would be virtually impossible to implement Reinganum's (1988) original four-screen strategy in the early 2000's.

Yu's (2009) results showed that the strategy produced positive excess returns over the CRSP value-weighted index in the overall period. However, evaluating the portfolio return using Capital Asset Pricing Model (CAPM), Fama and French three-factor model (FF3) and Fama, French and Carhart's four-factor model (FFC4), the strategy failed to consistently produce positive and significant alphas in either of the time periods. The four-screen strategy did not generate significant alpha in either the original time period from 1970-1983, or in the complete period from 1970-2006 in any of the factor models. Performance in

the post-Reinganum (1988) period was somewhat stronger, and the four-screen strategy produced significant alpha from CAPM and FFC4 in the time period from 1984-2006.

Yu (2009) concluded that the four-factor strategy was profitable in the entire sample period (1970-2006) and in the two sub-periods (1970-1983 and 1984-2006), but that it was increasingly difficult to implement, especially because of the filter rule of number of outstanding common stock of less than 20 million.

4.1.2 Other articles presenting results from analyses of high performers

While Reinganum (1988) was one of the first to publish research on the characteristics of winner stocks, he is not the only one. One of the most renown publications is Peter Lynch's study addressing how to identify so-called 10-baggers, stocks that appreciates 10 times in value (Lynch, 1989). Lynch (1989) said that one should seek out firms exposed to mega-trends, with leading technology, new products and investor interest. Thus, some of his characteristics went beyond just the quantitative, however, there were similarities to Reinganum's (1988) strategies. To become a 10-bagger, stocks should typically trade at a price-to-earnings below the industry average and show a strong track-record of earnings-per-share growth. Additionally, he recommended investors to diversify investments across several small stocks with high potentials to increase the chances of hitting a 10-bagger (Lynch, 1989). This is similar to Reinganum's (1988) strategies which also ranged across several different stocks, opposed to singling out a few.

Martelli (2014) studied the performance of 21,000 global stocks and found that 3,800 became 10-baggers from the minimum share price over a 15-year period. From the 3,800 sample, he picked 100 that he considered to be the most obvious candidates for appreciating 10 times in value and presented several interesting findings. Firstly, one did not have to buy the stock at a low entry point, the most important thing was to identify cheap stocks relative to the growth potential. Thus, stocks that traded at a P/E above the industry average may still have had multi-bagger potential, if accompanied with strong growth. Further, small caps were most likely to become multi-baggers, as a vast majority of his sample had a market cap of less than USD 300 million before starting to accelerate in price.

Mayer (2014) made a similar study and considered all 100-baggers between 1962-2014. He also concluded that promising candidates should have consistently high earnings growth, and shared

Martelli's (2014) views on stock valuation. Mayer (2014) concluded that the median market cap from the low point among the 100-baggers was USD 500 million. These median market caps were higher than median of Reinganum's (1988) winners of USD 120 million, although Mayer's (2014) study considered stock price appreciation over a longer period. However, the findings were alike, a stock did not necessarily need to be the smallest small cap to become a winner.

4.2 Efficient Market Hypothesis

As the purpose of this paper is to investigate whether it is possible to construct an investment strategy that produces consistent abnormal returns based on analyzing common characteristics among previous stock market winners, an overview and understanding of the concept of efficient markets is needed. Since it is impossible to produce consistent abnormal returns according to the efficient market hypothesis (EMH), a deeper understanding of the concept is needed. There are several different definitions of the term, where one example was given by Fama (1970): "*A market in which prices always "fully reflect" available information is called "efficient."*" (p. 383). Fama (1970) further argued that this definition was too general to be tested empirically. Thus, the author introduced three categories of efficiency, dependent on the nature of the information: weak, semi-strong, and strong form of efficient markets, and revisited empirical content within each specific form.

According to Fama (1970), there were multiple models investigating whether markets were efficient in the weak form testing if prices reflected historical information, where the overall conclusions supported near-perfect efficiency. In other words, investment strategies based on historical data or share prices could not be utilized to earn long-run excess returns. This was, however, challenged by momentum strategies, which will be discussed further below. Fama (1970) also familiarized this topic, where he discussed previous statistically significant findings of interrelationships between share prices. Short term, such trades were found to be only marginal profitable, but the expected return would be absorbed by transaction costs (Fama & Blume, 1966)

The semi-strong form assumes that prices efficiently adjust to all publicly available information, and studies have also supported the semi-strong form of EMH. Both Fama et al. (1969) and Ball and Brown (1968) have tested this by looking at share price reactions on announcements of dividends, earnings, equity issuances and block trades, where all evidence was consistent with the semi-strong form of EMH. Although the consistency was robust, the quantity of empirical research testing the relationship between

share price reactions and company announcements was limited at the time of Fama's (1970) research. He addressed this issue but argued that the tests represented in literature covered the most important information-generating events and that future research probably would yield similar results.

While Fama (1970), among others, argued that share prices reflected all historical and public information, this was not a consensus among researchers. Grossman and Stiglitz (1970) claimed that because information was costly, investors would not rationally accept the cost of collecting information unless their benefits were higher than the alternative of investing to the market price. The authors went as far as stating that perfectly efficient markets were impossible, because markets would collapse without the incentive of gathering information. Pedersen (2015), on the other hand, had a more balanced view of the EMH and described the market as efficiently inefficient. Accordingly, Pedersen (2015) viewed markets as neither completely inefficient nor perfectly efficient, meaning that they were inefficient enough for money makers to be compensated for their cost of gathering information and efficient enough that profits after cost did not encourage additional active investing.

The strong form of EMH considers whether prices reflect all public and non-public information and has historically been tested by studying whether any individual generated excess returns due to monopolistic access to some information (Fama, 1970). Fama (1970) supported Jensen's (1964) view that market makers and corporate insiders (defined as institutions with inside information) inability to produce significant return excess of the market in the long run, induced strong form efficiency. However, strong form has not been tested to a large extent, because it ideally requires access to non-public information. Also, there was plenty of evidence against the strong form, compared to the weak and semi-form efficiency due to the conflict with insider trading restrictions and evidence of abnormal returns from insider trading over longer periods (Damodaran & Lio, 1993)

There are several market anomalies that challenge the EMH, where classical examples are behavioral biases, calendar effects and bubbles. Whether behavioral biases imply inefficiency have received substantial attention in the literature, where the focus is aimed at how psychological factors turn investors irrational and consequently impact market outcomes. De Bondt and Thaler (1985) presented comprehensive research on the topic and concluded that the stock market overreacted to current information and underweighted prior data. Still, if this was to make the markets inefficient, one must assume that the "mistakes" could not be corrected by arbitrary rational investors. De Bondt and Thaler

(1985) referred to Russel and Thaler's (1985) conclusion that the existence of some rational investors was not sufficient to guarantee rational equilibrium market outcomes.

De Bondt and Thaler (1985) also discussed calendar anomalies, arguing that their portfolios five-year straight January outperformance suggested a weak form of market inefficiency. This is known as the "January effect" and was set forth by Reinganum (1983). Another calendar strategy is known as "Sell in May and go away". Bouman and Jacobsen (2002) examined this effect by reporting stock returns from the period of May-October compared to the rest of the year between 1970-1998, across 37 countries. They found that the effect was present in 36 of 37 countries.

EMH is a cornerstone in financial theory, yet the literature is split between pioneers for passive and active investing, such as Fama (1970) and Shiller (1992), respectively. Shiller, known for predicting the dot-com bubble, was one of the first advocators of an inefficient market. Shiller (1992) argued that the volatility in the stock market was larger than what could be justified by fundamentals and that EMH ignores excess volatility anomalies such as the "January effect" discussed above. Fama (1970) stood by his view of efficient markets, and legitimized anomalies with unidentified risk factors. In addition, Fama (1970) described large pricing declines related to recessions as nothing unusual, as prices reflected the expectations of the state of the economy. Currently, it is difficult to find economists believing that the markets are perfectly efficient or inefficient. The views of EMH are much more nuanced and boils down to the degree of efficiency, whether markets are mostly efficient and whether inefficiencies are predictable.

4.3 Active versus passive investing

Sharpe's (1991) article "The Arithmetic of Active Management" was based on a simple equation, developed on his definitions of active and passive investors. A passive investor was one that always held every security from the market, weighted to its share of the total market. An active investor was simply defined as someone who was not passive, meaning that the investor held a portfolio that differed from the passive managers at some or all times. Within these definitions and before costs, the return on the average actively and passively managed dollar would always be equal. However, after costs, the return on the average actively managed dollar would be lower than the return on the average passively managed dollar, because active managers charge higher fees.

This theory was supported by Fama and French (2009), which stated that after costs, active investing is a negative sum game due to this arithmetic. French (2008) claimed that if a representative investor switched to a passive market portfolio, he would increase his average annual return by 67 basis points over the 1980-2006 period. Even though the total returns of active investors after costs would be lower than passive investors, it was still possible that individual investors could add value and beat the passive investors. If they did, it was at the expense of other active investors (Fama & French, 2009). This meant that "informed active managers" might have outperformed both the passive managers and the "non-informed active manager", but the average active manager would still perform worse than the passive manager, after costs.

Pedersen (2018) challenged Sharpe's (1991) arithmetic and claimed that active investors are able to earn positive returns in capital markets that are efficiently inefficient. Pedersen (2015) described the efficiently inefficient market:

> Prices are pushed away from their fundamental values of a variety of demand pressures and institutional frictions, and, although prices are kept in check by intense competition among money managers, this process leads the market to become *inefficient* to an *efficient* extent: just *inefficient* enough that money managers can be compensated for their costs and risks through superior performance and just *efficient* enough that the rewards to money management after all costs do not encourage entry of new managers or additional capital. (p 4)

Thus, Pedersen (2015) argued in favor of active management and claimed that active investors can be compensated for their costs and risks in making markets more efficient, moving prices closer to their fundamental values. Some active investors try to do this through fundamental quant, trading on factors such as value, momentum and size (Pedersen, 2015). These well-known factors will be elaborated upon in the following section.

4.4 Stock market anomalies

The shared attributes among Reinganum's (1988) 222 winners are characterized by several known and frequently discussed market anomalies such as momentum, value and size. Reinganum's (1988) strategies are therefore partly shaped by these factors, hence it is relevant to present what previous research of these anomalies have discovered.

4.4.1 Price momentum

Market inefficiencies such as a slow adjustment to news have paved the way for momentum trading strategies, which in part seeks to exploit errors in information processing. Reinganum's (1988) strategies partly selected stocks based on their relative strength rank (RSR), a tool for measuring price changes compared to changes in the overall market. Empirical studies on RSR strategies trace back to the 60's, where Levy (1967a) presented evidence that stocks with the 10% strongest RSR outperformed the benchmark over a six-month period. However, Levy's (1967a) methodology and results have been widely criticized. Among them are Jensen (1967) and Jensen and Benington (1970), stating that Levy (1967a) overstated the excess returns and that the results were inconclusive due to selection bias. According to Jensen and Benington (1970), Levy (1967b) corrected some of the errors, but the results were still mistaken. The two former authors tested Levy's (1967b) RSR trading strategy on 29 independent samples over five years from 1931 to 1965. They reported a risk-adjusted return below the benchmark and argued that Levy's (1967b) results still were subject to selection bias, due to the inability to replicate the trading rules on a different data sample.

Although Levy's (1967a) results were debatable, many researchers provided evidence indicating that RSR strategies may generate excess returns (Jegadeesh & Titman 1993). For example, the success of several mutual funds was partly due to RSR trading (Copeland & Mayers, 1982; Stickel, 1985). Grinblatt and Titman (1989) also found that a majority of the mutual funds in their study had a tendency to buy stocks with a positive price momentum. Further evidence in favor of RSR is presented by Jegadeesh and Titman (1993), as they showed that buying stocks that have overperformed and selling stocks that underperformed over the past 3-12 months and holding them for the next 3-12 months yielded excess returns. The authors applied the strategy between 1962-1989 and found that the profitability was not due to systematic risk or slow stock price reactions.

Another popular view among many researchers is that investors tend to overreact to information (Tversky & Kahneman, 1986; De Bondt & Thaler, 1985; Shiller, 1992). A natural extension to this view, is whether stock prices also overreact to information, implying that you should buy losers and sell winners. De Bondt and Thaler (1985) studied the results of such a strategy, known as a contrarian strategy, and achieved abnormal returns. The authors showed that stocks that performed poorly the previous 3-5 years outperformed stocks that performed better, over the next 3-5 years. Much research has also been

conducted on short-term contrarian strategies, providing evidence of stock price reversion over weekly time periods (Jegadeesh, 1990; Lehmann, 1990).

As discussed above, researchers have provided evidence of abnormal returns from RSR and contrarian strategies. These are two opposite trading strategies, so the fact that both generate abnormal returns, might be problematic to reconcile with. Jegadeesh and Titman (1993) shed some light on the situation suggesting: 1) that variables in either trading strategies were exposed to spurious relationships or 2) discrepancy due to different time horizons applied in the research. In other words, contrarian strategies focused on either short-term trading (weeks or months) or long-term reversals, while RSR strategies based their results on stock price movements over a 3–12-month horizon. This is interesting, as Reinganum (1988) used price momentum over the past 12 months as a filter in his strategies. However, he also held on to the stocks for two additional years. Thus, the total time period of three years has not been researched all that much, but after three years, Reinganum's (1988) strategy was approaching a time period for which contrarian strategies have been found to produce abnormal returns.

4.4.2 Earnings momentum

Reinganum's (1988) winner stocks showed margin expansions and accelerating quarterly earnings growth approaching the buy date, hence earnings momentum was also a cornerstone of his trading strategy. Similar to price momentum, researchers have been drawing attention to earnings momentum for several decades, exemplified by Darvas (1960) analysis of stock market winners. Darvas (1960) picked the winners based on promising price and earnings prospects, because he argued that it is anticipation of growth rather than the actual growth, that gives success in the stock market. In other words, Darvas (1960) argued that one must follow the flow of capital and the flow follows earnings improvement.

Several past research conclusions across different time periods supported the earnings momentum anomaly. Both Jaffe et al (1989) and Fama and French (2007), found positive correlations between previously reported earnings and future stock prices. To gain insights into this anomaly, Latane and Jones (1970) measured the informational content of financial reports and the effects on stock prices. The empirical evidence suggested that positive earnings surprises were related to excess returns, because the prices adjusted slowly to the unexpected earnings. Again, this contradicts the supporters of semi-strong efficient markets, stating that prices respond simultaneously with earnings releases.

Reinganum (1988) found that top performers saw earnings acceleration, accompanied with higher profit margins. This was in-line with Haugen and Baker's (1996) results from a study that analyzed the profitability of stock performance distributed across 10 deciles. As you moved from the low-end deciles towards the high-end, both margins and margin growth increased. However, as with price momentum, empirical findings on earnings momentum are not straight-forward.

The earnings yield effect is a known anomaly contradicting the positive earnings and stock price correlation. This was studied by Ettredge and Fuller (1991), who reported that firms with negative earnings on average generated excess returns, consistent with De Bondt and Thaler's (1985) view discussed above. However, Ettredge and Fuller (1994) revisited their documentation of negative earnings effect from 1991, using a substantially larger data sample. The authors altered their methodology slightly after receiving critiques from Ali and Klein (1994), but the most important new finding was not related to the issue of methodology, but rather the time period studied. Thus, Ettredge and Fuller (1994) still found evidence indicating that firms reporting substantial losses one year outperformed firms reporting substantial earnings the subsequent year. Possible explanations were overreactions from investors and too optimistic forecast for the high earnings stocks, according to Ettredge and Fuller (1994)

4.4.3 Value versus growth

Besides price and earnings momentum, Reinganum's (1988) investment strategies were tilted towards value stocks. Graham and Dodd (1934) and Graham (1949) laid the foundational work for a value investment strategy in the books Security Analysis and The Intelligent Investor. The authors argued that investors should analyze fundamental factors to derive stocks intrinsic value and compare it to its market value, because prices will converge in the long run, according to the EMH. Reese (2013) reported that Graham's investment firm generated annualized returns of above 20% from 1936-1956, beating the average market return of 12%. Warren Buffet's investment strategy is another example of value stocks consistently outperforming, and posted an average annual total return of 17% from 1985 to 2019, compared to the S&P 500's total return of 11% (Franck, 2019).

A great deal of literature has been published on the topic of value and growth investing. Much of the research, including Fama and French's (1993) study, trace back to Basu's (1977) empirical results of low P/E stocks outperformance. Basu (1977) argued that low P/E-stocks yielded a higher return than what was warranted by the stocks underlying risk. The value factor has also been found to be a significant

predictor of future returns, as given by Fama and French's (1993) HML factor. This did not necessarily contradict the EMH but indicated a failure of the CAPM, because CAPM did not capture the value premium reflected in market prices, according to the authors. Additionally, Fama and French (1993) claimed that the EMH holds because the excess returns of value stocks were attributed to risk, as opposed to Basu (1977).

Chan and Lakonishok (2004) discussed the various explanations behind why value stocks seemingly outperformed growth stocks. They provided evidence based on data from 1963 to 2001, hence the bear run for value stocks in the late 1990s was accounted for. The conclusion was that higher risk did not explain the value-growth spread. The key arguments comprised that growth stocks are associated with elevated levels of optimistic investor sentiment and that value stocks suffer less severely during market downturns. The authors highlighted behavioral patterns and investor sentiment when explaining the value premium, implying that investors got overexcited by new technology and owning "trendy" stocks regardless of the financials, and ultimately overpayed for growth stocks (Chan & Lakonishok, 2004).

Contrary to the abovementioned literature, O'Neil (1988) recommended that investors should buy growth stocks and derived the CANSLIM trading strategy to help investors pick stock market winners. O'Neil (1988) argued that one should not buy stocks when they have dropped, but rather buy them close to their all-time high, because one would prefer owning a quality stock trading to a premium opposed to a lower-quality stock trading at a discount.

Much of the evidence supporting the growth overpricing hypothesis defined growth as stocks trading at an inflated market-to-sales ratios and that a majority of these shares had negative earnings (Hsieh & Walkling, 2006). Thus, a key distinction between O'Neil's (1988) definition of growth stocks is earnings since O'Neil (1988) recommended investors to seek out stocks with high return on equity. O'Neil (1988) also believed in running tight stop-losses (7-8% below purchase price), meaning that the CANSLIM intended to limit the potential large downside of growth stocks, as Chan & Lakonishok (2014) pointed out.

"The bulk of empirical research documenting the superiority of value investing stops short of the late 1990s, which were not kind to value stocks" (Chan & Lakonishok, 2004, p. 84). Leading up to the dot-com bubble around year 2000, growth stocks significantly outperformed value stocks, something

Dowdee (2013) and Asness et al. (2000) quantified in their studies. Following the dot-com bubble, value stocks were again the center of attention for investors. According to an article published by Vanguard (2020), value gained momentum until 2009 when the pendulum swung in favor of growth stocks again, due to a low interest rate environment and a long period of economic growth. The takeaways from Vanguard's (2020) article were supported by Dowdee (2013), which concluded that risk-adjusted returns were not superior for one type of stock or the other, but that it ultimately depended on the studied time period.

Bearing in mind the extensive amount of research suggesting value outperformance for the majority of the period from the mid 20th century until the 1990s, another explanation for the recent shortfall of value stocks was whether the strategy stopped working simply because it was so well-known (The Economists, 2018). Lev and Srivastava (2019) provided evidence indicating that the value investing strategy has underperformed for over 30 years, except for a brief resurrection after the dot-com downturn. The authors stated that the construction of book values had changed due to accounting deficiencies and fundamental economic developments, and these changes were unfavorable to value stocks. There were, however, much literature suggesting otherwise, claiming that value stocks were poised to make a comeback in the 2020s (Romahi, Norman, & Turner, 2020; Asness, 2020).

4.4.4 Size premium

Reinganum (1988) discovered that nearly 90% of the winner stocks had fewer than 20 million shares outstanding, which supported O'Neil's (1988) opinion that investors should look for stocks with fewer than 25 million shares outstanding. O'Neil's (1988) argument was that small changes in demand could cause relatively large price increases for stocks with few shares outstanding. Accordingly, many of Reinganum's (1988) winning stocks were small caps, which is a widely discussed corner of the financial literature and relevant when analyzing stock market winners.

Size premium on stocks is the third factor in Fama and French's (1993) three-factor model, along with the market return and value factor. Fama and French (1993) reported that small cap companies consistently outperformed the market, hence the small-minus-big factor was one of the primary explanations behind stock returns. As previously mentioned, Fama and French (1993) concluded that the excess returns were due to risk premium in small cap stocks, in line with the EMH. Griffin and Lemmon (2002) on the other hand, found evidence against the risk-based explanation, based on studies of distress

risk and the excess returns given by value and size premium. Griffin and Lemmon (2002) mentioned other alternative explanations for the small cap premium and stated that these stocks were more likely to be mispriced due to large return reversals around earnings announcements and smaller analyst coverage.

During the 1980s, much research was published on the size anomaly and the strength of its performance compared to the market (Banz, 1981; Reinganum, 1983; Schwert, 1983). However, in a later paper published by Schwert (2003), one of the interesting findings was that the size effect disappeared after it was addressed by the abovementioned papers and others. The effect diminished shortly after this period, at the same time as several large professional institutions launched small cap funds, which may have priced away the strategy. Schwert's (2003) empirical work also addressed several other market anomalies, but it was particularly the size and value effect that had weakened over time.

Schwert's (2003) was just one of many academics who reported that the size premium disappeared after the early 1980s, which is noteworthy given that Reinganum's (1988) sample period stretched from 1970-1983. Extending a study by Vuolteenaho (2002), Hou and Dijk (2017) claimed that differences in profitability shocks (difference between realized profitability and expected profitability) between small and large firms were responsible for the shortfall of size premium in the early 1980s. Hou and Van Dijk (2017) found that after 1984, small firms experienced large negative profitability shocks, which were close to zero before 1984. The source of the large shocks after 1984 was a large amount of small cap IPO's with poor performance and increased competition due to industry deregulation. After adjusting for these factors, Hou and Dijk (2017) concluded that the size effect existed and that small firms outperformed large firms with almost 10% per year from 1984-2005.

In extension of whether the size effect has disappeared, Alquist et al. (2018) posted a paper arguing that the size effect had received disproportionally more attention compared to other anomalies with stronger empirical and theoretical foundation. For instance, they stated that papers specifically addressing the size effect had been cited close to 60,000 times by other literature. Alquist et al. (2018) further concluded that no size premium was prominent when investing generically in small caps. Conversely, the authors found evidence suggesting that the size effect accompanied with other factors such as value could enhance returns. The proposed strategy implied controlling small cap companies for quality, which made the size premium more robust across time periods. This approach was also familiar to Reinganum's (1988) strategy of controlling for quality through earnings and book value filters.

4.5 Section summary

Reinganum's (1988) method of investing is considered active, since he continuously made investment decisions identified through his screens. Thus, since he reported excess returns over the S&P 500 over 13 years, the results are interesting in the context on efficient markets, although this is not the scope of Reinganum's (1988) article. Yu (2009), on the other hand, tested the four-screen strategy over Reinganum's (1988) time period and found that the strategy did not generate alpha.

The efficient market hypothesis states that it is impossible to outperform the market in the long run, hence advocators of the EMH does not believe in active investing. To test the EMH, Fama (1970) split the term into weak, semi-strong and strong form of efficiency. The literature is divided both when it comes to whether the market is efficient in the weak and semi-strong form. The weak form is challenged by price momentum strategies and several hedge funds that have reported abnormal returns over longer periods utilizing the price momentum. Researchers who believe in the weak form have emphasized that momentum comes with higher risk and in most cases is not profitable after transaction cost. Calendar effects is also a much-used example of an inefficient market. The semi-strong efficiency is heavily disputed by behavioral finance studies, concluding that markets have overreacted to earnings announcement, opposed to prices adjusting immediately after information announcements. There is, however, a higher degree of consensus of a strong form of efficiency, but this is not tested to the extent as the two other forms of efficiency.

Researchers who defy the efficient markets hypothesis also look to value and small cap outperformance as examples of inefficient markets. Particularly early research concluded that investment strategies drawing on these anomalies delivered abnormal returns. Fama and French (1993), however, argued that these effects are in fact reflected in market prices and merely delivered higher returns due to higher risk. More recent literature on value and small cap premium have pointed towards fading premiums, although it varies with the time period studied.

5. Data

This section will present the data applied in the thesis. Section 5.1 outlines the different data sources applied to gather data, while Section 5.2 describes the data sample.

5.1 Data sources

All fundamental, price and returns data are downloaded from Wharton Research Data Services (WRDS). WRDS provides access to the Center for Research in Security Prices, LLC database (CRSP), the Compustat database and the CRSP/Compustat Merged database (hereafter CCM). CRSP data contains security-level historical descriptive information and market data for both inactive and active companies from the NYSE, AMEX and Nasdaq exchanges. Compustat data contains thousands of annual and quarterly income statements, balance sheet, cash flow, and other fundamental and descriptive data items for active and inactive companies. The CCM database combines market data from CRSP with fundamental data from Compustat within a single linked database (CRSP, 2021). Data variables for the risk-free rate, market and factor portfolios are downloaded from Kenneth R. French Data Library (French, 2021a).

5.2 Data descriptions

This section describes the data applied in this thesis, to increase the understanding of the properties of the sample. The data sample is described in terms of exchange and sector composition, before additional data variables used to evaluate and analyze the investment strategies are presented.

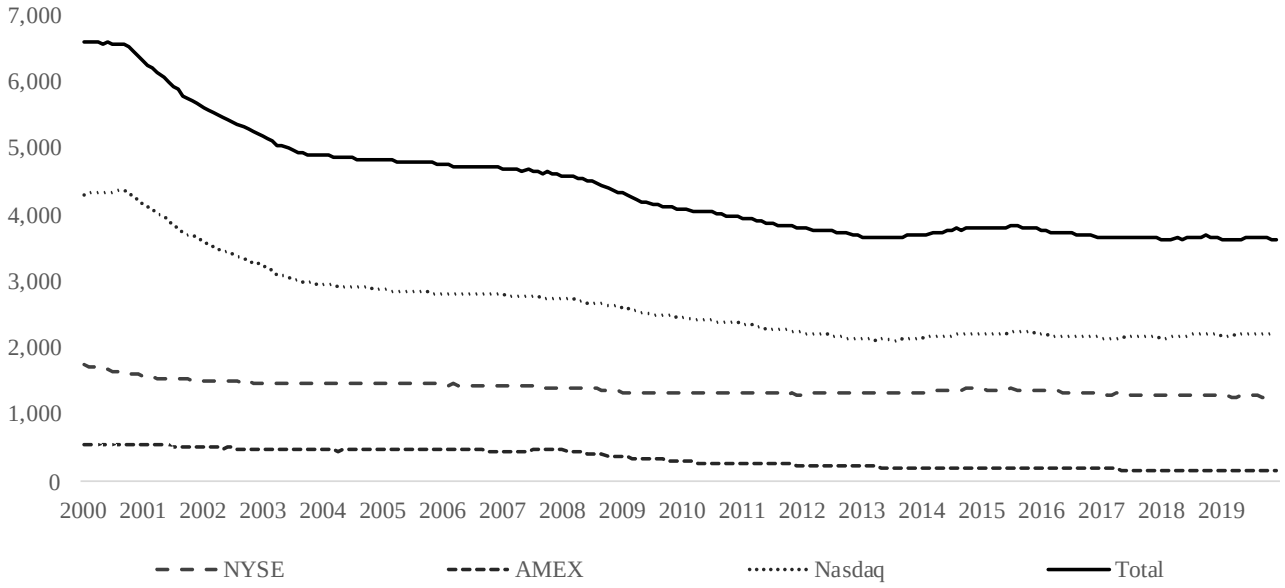
5.2.1 Description of data sample

The thesis data sample consists of daily and monthly market prices from CRSP between 1998-2019 and quarterly fundamentals from CCM, downloaded for the time period from 1993-2019. The data sample consists of all companies incorporated in the U.S. with ordinary common shares listed at NYSE, AMEX or Nasdaq in the investment period between 2000-2019. U.S.-based common stocks are identified by CRSP Share Code (CRSP variable SHRCD) 10 or 11, and the three stock exchanges are identified by the CRSP Exchange Code (CRSP variable EXCHCD) 1, 2 and 3. Thus, the data sample consists of 11,061 different companies.

Figure 5.1 shows the total number of stocks in the data sample at the end of each month from January 2000 through December 2019 by stock exchange, as the investment period lasts from 2000-2019.

Figure 5.1

Number of stocks in the data sample by stock exchange, at the end of each month from January 2000 through December 2019

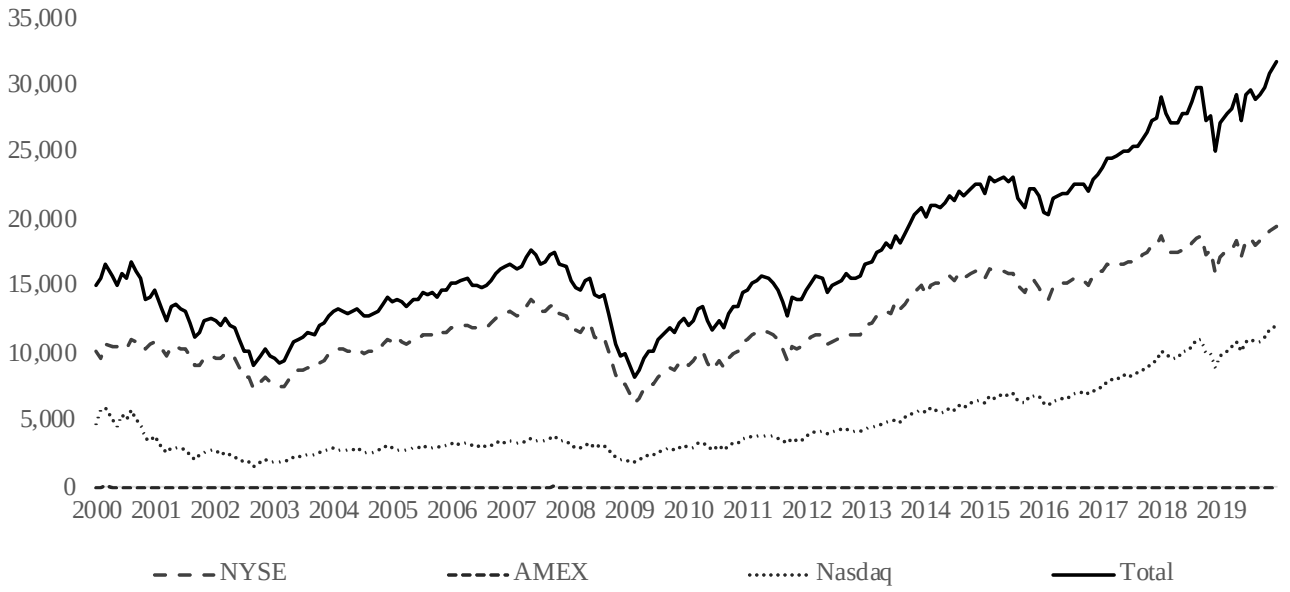


The data sample reaches its peak number of companies in March 2000, with a total of 6,615 stocks. Companies listed on Nasdaq make up around 60% of the total number of stocks during the entire time period. The number of total stocks is steadily declining throughout the sample period, ending with a total of 3,644 in December 2019. The main reason for this decline is that the number of stocks listed on Nasdaq were declining, but the two other exchanges were also experiencing a falling number of stocks. Doidge et al. (2015) found that the number of listed firms in the U.S. peaked in 1996 and 1997, with a rapid decrease in the beginning of the 21st century, due to a delisting rate up to five times the new list rate. The new list rate was higher than the delisting rate in most of the 1990's, but the delisting rate exceeded the new list rate in every year from 1998 to 2012. The delisting rate peaked at 13.3% in 2001, where mergers and acquisitions accounted for 6.6%, 6.3% were forced to delist and 0.4% delisted voluntarily (Doidge et al., 2015).

Figure 5.2 presents the total market value (in USD billions) of all stocks in the investment period of the data sample by stock exchange.

Figure 5.2

Total market value (in USD billions) of all stock in the data sample by stock exchange, at the end of each month from January 2000 through December 2019



Looking at Figure 5.2, the total market value of all stocks in the data sample sees a decline in the first two years. The total value thus reached its 2000 level in 2007, before the financial crisis of 2008 leaded to a large decline from 2008 through 2009. After 2009, the total market value was steadily increasing throughout the second half of the data sample. The peak market value at the end of 2019 was USD 31,787 billion, more than double the USD 15,078 billion value at the start in January 2000. Even though Nasdaq has had the largest number of stocks listed, the total market value has been higher on NYSE, representing a maximum of 80% of the total market value in 2002. This percentage has been declining until the end of the sample, where NYSE accounted for about 62% of the total market value.

Table 5.1 presents the total number of companies, and the average and median market capitalization per company in USD millions in total. Additionally, the figure displays fractions of the total number of stocks and total market capitalizations, as well as the average and median market cap per stock exchange.

Table 5.1

Descriptive statistics of the sample stock exchange composition, in % of total and USD millions

	Total			NYSE				AMEX				Nasdaq			
Year	Total No.	Average	Median	No.%	M.Cap%	Average	Median	No.%	M.Cap%	Average	Median	No.%	M.Cap%	Average	Median
2000	6,310	2,270	106	25%	75%	6,785	976	9%	0.5%	130	25	66%	24%	832	67
2001	5,619	2,251	143	27%	78%	6,541	1,140	9%	0.5%	111	27	64%	22%	764	86
2002	5,200	1,893	131	29%	80%	5,328	1,020	9%	0.5%	103	22	62%	19%	580	79
2003	4,879	2,632	268	30%	77%	6,781	1,466	10%	0.6%	156	45	60%	22%	958	166
2004	4,822	2,958	323	31%	78%	7,551	1,770	10%	0.5%	157	54	60%	22%	1,071	197
2005	4,751	3,118	339	31%	78%	7,954	1,854	10%	0.5%	151	57	59%	21%	1,118	212
2006	4,698	3,506	399	31%	79%	8,994	2,165	10%	0.4%	154	64	59%	21%	1,225	250
2007	4,603	3,592	346	30%	78%	9,234	2,089	10%	0.5%	174	68	59%	22%	1,310	208
2008	4,335	2,304	195	31%	78%	5,792	1,172	9%	0.4%	97	27	60%	22%	825	97
2009	4,083	3,083	305	32%	75%	7,115	1,713	7%	0.3%	120	46	60%	25%	1,271	162
2010	3,948	3,680	409	34%	75%	8,189	2,100	7%	0.3%	163	58	60%	25%	1,545	219
2011	3,794	3,713	392	35%	74%	8,003	1,935	7%	0.2%	129	38	59%	25%	1,599	190
2012	3,674	4,309	483	36%	73%	8,710	2,090	6%	0.2%	157	41	58%	27%	2,018	231
2013	3,679	5,678	707	36%	72%	11,293	2,841	6%	0.2%	237	52	58%	28%	2,692	323
2014	3,806	5,973	657	36%	71%	11,658	2,806	6%	0.2%	264	53	58%	29%	2,949	326
2015	3,789	5,771	585	36%	69%	10,940	2,252	5%	0.2%	206	50	59%	31%	3,085	303
2016	3,653	6,420	708	36%	69%	12,270	2,688	5%	0.2%	257	48	59%	31%	3,387	352
2017	3,630	7,603	799	36%	66%	13,952	3,050	5%	0.2%	294	55	59%	34%	4,389	400
2018	3,646	6,888	673	35%	64%	12,468	2,450	5%	0.2%	234	43	60%	36%	4,119	331
2019	3,616	8,794	769	35%	62%	15,609	2,977	4%	0.1%	274	44	61%	38%	5,512	396
Average	4,327	4,322	437	33%	74%	9,258	2,028	7%	0.3%	178	46	60%	26%	2,062	230
Median	4,016	3,636	395	33%	75%	8,450	2,090	7%	0.3%	157	47	60%	25%	1,427	215
Max	6,310	8,794	799	36%	80%	15,609	3,050	10%	0.6%	294	68	66%	38%	5,512	400
Min	3,616	1,893	106	25%	62%	5,328	976	4%	0.1%	97	22	58%	19%	580	67

Table 5.1 shows that NYSE firms were making up an increasing fraction of the number of companies, but a declining fraction of the market capitalization. The increase in the fraction of companies was due to a lower delisting rate compared to the other two exchanges. The decreased fraction of the market capitalization was mainly due to the increase of market capitalization on Nasdaq. Nasdaq experienced the opposite development in terms of market capitalization, while the fraction of total companies was somewhat stable around 60%. This shows an interesting change, as the largest companies were typically listed on NYSE at the beginning of the sample, while the largest stocks were listed on Nasdaq at the end of the sample. The size of AMEX was decreasing, as both the fraction of companies and the share of market capitalization declined over the sample period.

To further enhance the understanding of the data, an outline of the U.S. stock market sector exposure both in terms of number of listed stocks per sector and the market capitalization per sector is presented in Table 5.2. MSCI's (2021) global industry classification standard is used to assign the companies to their specific sectors, comprising 11 sectors in total.

Table 5.2

U.S. stock market sector exposure measured on number of stocks and market capitalization (%)

	Energy	Materials	Industrials	Consumer Discretionary	Consumer Staples	Health Care	Financials	Information Technology	Telecom Services	Utilities	Real Estate
Year	No./M.cap	No./M.cap	No./M.cap	No./M.cap	No./M.cap	No./M.cap	No./M.cap	No./M.cap	No./M.cap	No./M.cap	No./M.cap
1999	4 / 4	4 / 3	14 / 9	17 / 12	4 / 8	12 / 10	18 / 14	21 / 29	3 / 10	2 / 2	0 / 0
2000	4 / 5	4 / 2	13 / 9	16 / 8	4 / 8	13 / 15	17 / 18	23 / 24	3 / 7	2 / 3	0 / 0
2001	4 / 5	4 / 3	13 / 9	15 / 9	4 / 10	14 / 15	18 / 19	22 / 19	3 / 7	2 / 3	1 / 0
2002	4 / 6	4 / 3	13 / 10	15 / 10	4 / 11	15 / 15	19 / 21	21 / 15	3 / 7	2 / 3	1 / 0
2003	4 / 5	4 / 3	13 / 10	15 / 11	4 / 10	15 / 14	19 / 21	20 / 17	3 / 6	2 / 3	1 / 0
2004	4 / 6	4 / 3	13 / 11	15 / 11	4 / 9	16 / 13	19 / 21	20 / 15	3 / 6	2 / 3	1 / 0
2005	5 / 8	4 / 3	13 / 11	14 / 10	4 / 9	16 / 14	19 / 20	19 / 15	3 / 6	2 / 3	1 / 0
2006	5 / 9	4 / 3	13 / 11	14 / 10	4 / 9	16 / 12	19 / 21	18 / 14	3 / 7	2 / 4	1 / 1
2007	6 / 11	4 / 4	13 / 12	14 / 9	4 / 9	16 / 13	19 / 17	18 / 15	3 / 7	2 / 4	1 / 1
2008	6 / 11	4 / 4	14 / 11	14 / 8	4 / 11	15 / 15	19 / 14	17 / 14	3 / 6	2 / 4	1 / 0
2009	6 / 10	5 / 4	14 / 11	13 / 9	4 / 10	15 / 13	19 / 15	17 / 17	3 / 6	3 / 4	1 / 1
2010	6 / 10	5 / 5	14 / 12	13 / 10	4 / 9	15 / 11	19 / 15	17 / 17	3 / 6	2 / 3	1 / 1
2011	6 / 11	5 / 4	14 / 11	13 / 10	4 / 10	15 / 12	19 / 13	17 / 17	3 / 7	2 / 4	1 / 1
2012	6 / 10	5 / 4	14 / 11	13 / 11	4 / 10	14 / 12	19 / 14	17 / 17	3 / 7	2 / 3	1 / 1
2013	6 / 9	5 / 4	14 / 12	13 / 11	4 / 9	15 / 13	19 / 15	17 / 15	4 / 8	2 / 3	1 / 1
2014	6 / 7	5 / 4	14 / 11	13 / 11	4 / 9	17 / 15	18 / 15	16 / 16	4 / 8	2 / 3	1 / 1
2015	6 / 6	4 / 3	14 / 11	13 / 11	4 / 9	19 / 16	18 / 14	16 / 16	4 / 10	2 / 3	1 / 1
2016	5 / 7	4 / 3	14 / 11	12 / 10	4 / 9	19 / 14	18 / 16	15 / 16	4 / 10	2 / 3	1 / 1
2017	6 / 6	4 / 3	14 / 11	12 / 10	4 / 8	20 / 14	18 / 16	15 / 18	4 / 10	2 / 3	2 / 1
2018	6 / 5	4 / 3	14 / 10	12 / 11	4 / 8	21 / 15	18 / 14	14 / 20	4 / 10	2 / 3	2 / 1
2019	5 / 4	4 / 3	14 / 10	12 / 11	4 / 7	22 / 14	18 / 14	14 / 22	4 / 11	2 / 3	1 / 1

Health Care, Financials and Information Technology (IT) stand out as the historically largest sectors measured on both variables. Over recent years, the IT sector has been the largest, followed by Financials and Health Care, measured on market cap. Looking at the number of listed firms, Health care was the largest sector, followed by Financials and IT. Utilities and Real Estate stabilized as the smallest sectors, while the size of Energy and Telecommunication Services varied over the time period.

5.2.2 Risk-free rate

The risk-free rate is applied to examine excess returns instead of simple stock returns in the thesis, denoting the expected return an investor would expect from an investment with zero risk. As pointed out by Damodaran (2008), a challenge when working with risk-free rates is identifying risk-free assets. For an asset to be considered risk-free, there can be no reinvestment risk and no risk of default. The only securities that may fulfil these rules are certain government securities, where the government controls the currency printing and has the highest credit rating (Damodaran, 2008). Therefore, and since the thesis' scope is limited to the U.S. stock market, the applied risk-free rate is the one-month U.S. Treasury bill rate downloaded from Kenneth French's data library (French, 2021a). Excess returns are applied in the

factor regressions because the variation in the risk-free rate over the time period might impact the regression results (Bali et al., 2016). Thus, excess returns are applied and presented throughout the thesis.

5.2.3 Market portfolio

The market portfolio is one of the most important factors in asset pricing, and therefore in asset returns. According to the CAPM, the expected return on an asset is dependent on the covariance between the return of the asset and the return on the market portfolio (Bali et al., 2016). The market portfolio is a theoretical construction that contains the sum of all possible investments, including not just financial securities. As this portfolio is practically impossible to construct, it is normal to apply a proxy. According to Bali et al. (2016), most empirical research takes the market portfolio to be comprised by securities traded on the U.S. stock exchanges, as these are easily calculated from widely available security price data. Thus, the thesis applies the value-weighted portfolio of all U.S.-based common stocks in the CRSP database, consisting of stocks from NYSE, AMEX and Nasdaq, as the market portfolio, in accordance with Bali et al. (2016). The monthly excess return of the market portfolio is downloaded from Kenneth French's data library (French, 2021d).

5.2.4 Stock market index

Reinganum (1988) presented his returns in excess of the returns on the S&P 500 index in the same period. The S&P 500 is a value-weighted stock market index including 500 of the largest companies in the US, covers 80% of available market capitalization, and is widely regarded as the best single measure of the performance of large-cap U.S. Equities (S&P Dow Jones Indices, 2021). The S&P 500 index will also be used for comparison when evaluating the performance of the created portfolios. The return on the S&P 500 index is downloaded from CRSP, using monthly returns of the value-weighted index including distributions (CRSP variable VWRETM).

5.2.5 Factor portfolios

Benchmarking is used in the analysis to compare whether the constructed portfolios exhibit abnormal returns. Further explanations of the factor models applied will be presented in Section 6.9, while this section presents the data source. All factor portfolios are downloaded from Kenneth French's data library (French, 2021a). French (2021c) constructs the different factor portfolios using all NYSE, AMEX and Nasdaq firms available in the CRSP files at the start of month t, with shares and price data. Further data

items applied in the construction of the factor portfolios are market equity, book equity, total assets, revenue and at least one of the following: cost of goods sold, selling, general and administrative expenses, or interest expense. A complete description of the factor calculations is presented in Appendix C.

6. Methodology

This section will outline the methodological approach applied to fulfill the thesis' aim and objective. It entails presenting Reinganum's (1988) approach to create an investment strategy and how the thesis's draws on Reinganum's (1988) methodology to formulate a new investment strategy. The theories and principles behind the methodology are also presented to secure an approach that coincides with the field of research.

To begin with, Section 6.1 will describe the procedure for revisiting Reinganum's (1988) strategy today, before Section 6.2 details how the new strategy is constructed. Section 6.3 presents how the strategies are implemented, while Section 6.4 describes how data from CCM are adjusted and treated. The calculations of return, portfolio weighting and rebalancing and transaction costs are outlined in sections 6.5, 6.6 and 6.7, respectively. Next, performance measures and benchmark models are presented in sections 6.8 and 6.9. Finally, the statistical methodology applied can be found in Section 6.10.

6.1 The Anatomy of a Stock Market Winner revisited 2021

The research question asks whether the strategies created by Reinganum (1988) still produces excess returns above the S&P 500 between 2000-2019. Thus, following the method of Reinganum (1988), the strategies were recreated using quarterly fundamental data, and the investment returns were calculated on a quarterly basis, using monthly returns.

As explained in Section 3.1, Reinganum (1988) identified two different trading strategies with four and nine screens. Returns from the nine-screen strategy have not been investigated, due to the limited number of companies making the nine screens in the time period from 2000 through 2019. Thus, only returns from the four-screen strategy are presented. This is further explained in Section 7.2.1 and Appendix D.

The results of the strategy are presented in a corresponding way to that of Reinganum (1988). However, as this presentation is somewhat limited in showing the actual performance of a trading strategy, the four-

screen strategy is also traded as an actual portfolio. The performance of this portfolio is evaluated using different performance measures and benchmarks.

6.2 Construction of a new strategy

The research question subsequently seeks to answer whether it is possible to construct a trading strategy based upon shared characteristics of stocks that have at least doubled in price over one calendar year, inspired by the methodology of Reinganum (1988). The main difference in the framework of this thesis and Reinganum's (1988) article is the method of identifying the winner stocks. Reinganum (1988) analyzed 222 stocks that were predefined as "Stock market winners" by William O'Neil + CO and was therefore given his sample of stocks. This sample of stocks was already thoroughly analyzed and defined as stock market winners by O'Neil personnel. Even though they all shared the common price appreciation, other non-stated criteria had been applied to distinguish these particular stocks from the other stocks that had doubled in price over a calendar year (Reinganum, 1988). As these additional criteria are unknown, the exact same methodology is impossible to implement.

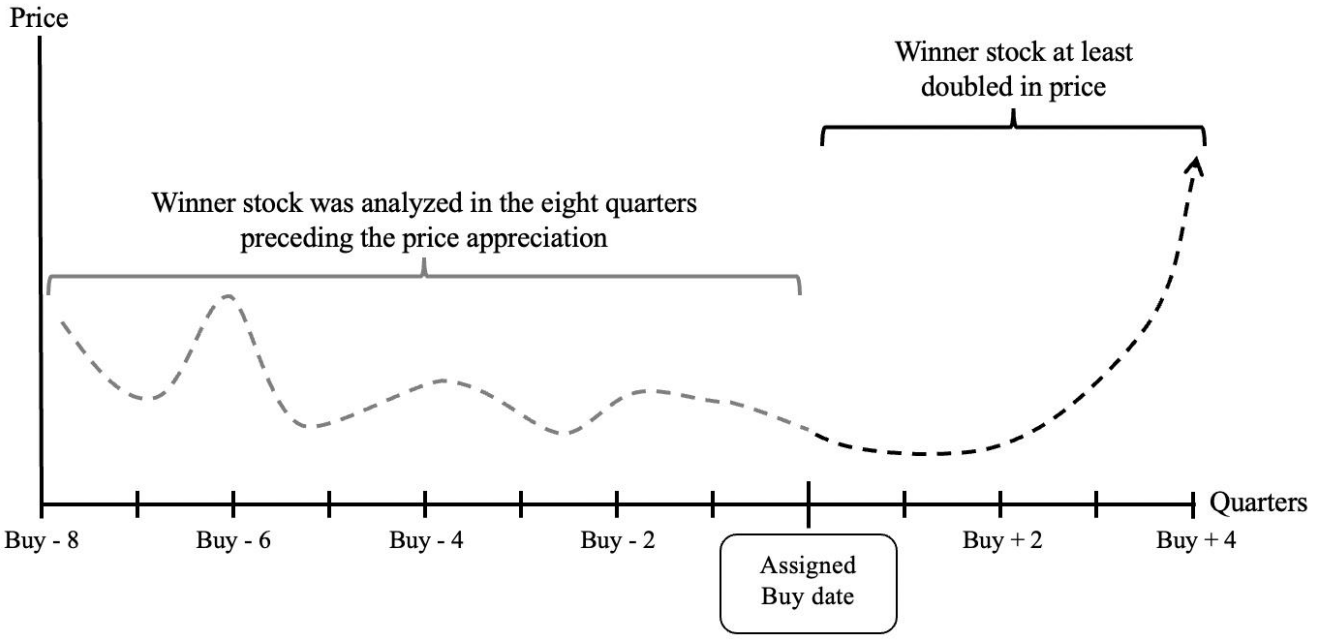
Due to the abovementioned, the thesis applied an adjusted approach from that of Reinganum (1998). First, all stocks in the data sample that at least doubled in price during one calendar year were identified. Then, a random sample of 200 stocks was analyzed, but the lack of consistency made it impossible to identify any common characteristics among the sample. Thus, to reduce the impact of extreme values and improve the coherency between the random sample of winners and all identified firms doubling in price, a new increased sample of 300 stocks was analyzed. Still, the findings were equally ambiguous.

Based on Reinganum's (1988) findings, it is evident that all of his 222 stock market winners had positive book equity, and approximately 5% had market cap below USD 20 million. It seems highly probable that the 222 winners had been sorted on positive book value of equity and a lower limit market cap. Therefore, and to increase the data consistency, the thesis sample of stocks doubling in price was filtered by two criteria: positive book equity and market capitalization of more than USD 20 million. After adjusting for the two filters, a random sample of 300 stocks was chosen, weighted by the yearly number of companies that doubled compared to the total of 4,081. To illustrate, if 2,000 of the companies doubled in price in 2006, 150 of these companies were randomly selected to the sample of stocks. This sample of stocks is hereafter referred to as the thesis' sample of winner stocks.

The winner stocks were assigned an imagined "buy date" at the beginning of the period the stocks doubled. Again, this means that if the company doubled in price in 2000, ultimo Q4 1999 was assigned as the buy date. The stocks were analyzed in the eight preceding quarters, which were named: "buy-1-…- buy-8". To derive five-year growth rates for the eight quarters preceding the buy date, seven years of fundamental data were needed, meaning that for winner stocks doubling in price in the calendar year 2000, quarterly data for the years 1993-1999 were collected. The method of assigning a buy date prior to the rapid price appreciation and analyzing the winner stocks in the preceding quarters is illustrated in Figure 6.1.

Figure 6.1

Method of analyzing winner stocks



After all companies were assigned buy dates, all of Reinganum's (1988) nine screens and more than 30 additional financial ratios and key figures were calculated for the preceding quarters (all analyzed ratios are listed in table Appendix B.3). This included valuation measures, technical indicators, earnings and profitability measures. As these stocks were all sorted on buy quarters, their metrics in the buy quarters were compared with their metrics in the eight quarters preceding the buy signal. This means that the stocks were compared independent of their actual time period. For example, if one stock doubled in 2000 and another doubled in 2010, their assigned buy dates were ultimo Q4 1999 and ultimo Q4 2009. Thus,

their buy-1 dates were ultimo Q3 1999 and ultimo Q3 2009, and metrics for these two dates were compared, along with the other seven quarters preceding the buy date.

Using this method, six common characteristics were identified. These six screens were then applied on the overall stock market, where the 300 analyzed firms were excluded from the stock market sample. With the holding period of two years, results are presented in the same way as in Reinganum (1988). Again, as this presentation is somewhat limited in showing the actual performance of a trading strategy, the six-screen strategy is also traded as an actual portfolio. The performance of this portfolio is evaluated using different performance measures and benchmarks.

6.3 Strategy implementation

In this section, the concept of backtesting is introduced, allowing investors to test a strategy using historical data before it is implemented in the real world. Further, a thorough explanation of the investment process is presented.

6.3.1 Backtesting strategies

One of the advantages of quant equity strategies is that they can be backtested, which is a powerful tool to simulate whether a trading idea would have worked in the past using historical data (Pedersen, 2015). Investors should know that historical returns are no predictor of future returns, but backtesting can still provide important knowledge of a simulated trading strategy. It is unlikely that investors will implement an investment strategy going forward that never worked in the past. Backtests are also valuable because they can give the investor an indication of the riskiness of the strategy. However, backtests are also subject to biases that must be accounted for, and it is important to note that backtests typically look unrealistically good. According to Pedersen (2015), four components are necessary to perform a solid backtest: a universe, signals, trading rules and time lags.

The thesis' universe consisted of the previously mentioned sample of U.S. ordinary common shares listed at NYSE, AMEX and Nasdaq between 2000-2019, a total of 11,061 different companies. Following the methodology of Reinganum (1988), the 300 winner stocks were withdrawn from the investable universe to secure that none of these analyzed stocks were possible investments, leaving the total investable universe at 10,761 different companies. However, this still left the methodology exposed to an in-sample bias, meaning that the strategy was created and invested based upon data from the same period, which

makes it plausible that the backtested performance was biased to look unrealistically strong. This is further discussed in Section 8.1.4. Another important measure to secure reliability in the backtest is to include all stocks that were listed at the time of investing, not only companies that are still active, to avoid the survivorship bias (Pedersen, 2015). The thesis thus included all companies listed on the exchanges at the time of trading and returns for companies that delisted were found in CRSP, further described in Section 6.3.2.

The signals in a backtest are explained as "The data used as input, the source of the data and how the data are analyzed" (Pedersen, 2015, p. 47). Thus, the signals in the two backtested strategies in the thesis were the four and six screens, that were created using both price and fundamental data from CRSP and Compustat. The trading rule determines how to trade on the signals, including weighting-methods and rebalancing (Pedersen, 2015). When a company fulfilled all the different screens, an investment was made, and held for two years. The portfolios were rebalanced monthly or quarterly, depending on whether they were equal-weighted or value-weighted. The investments were triggered by screens created using fundamental data, which is why the thesis applied a time lag of one quarter to secure that the data was publicly available. The trading rules and time lags are further described in Section 6.3.2. Finally, the backtested portfolios are presented both before and after transaction costs to make the backtests more realistic. The method of adjusting for transaction costs is presented in Section 6.7.

6.3.2 Investment process

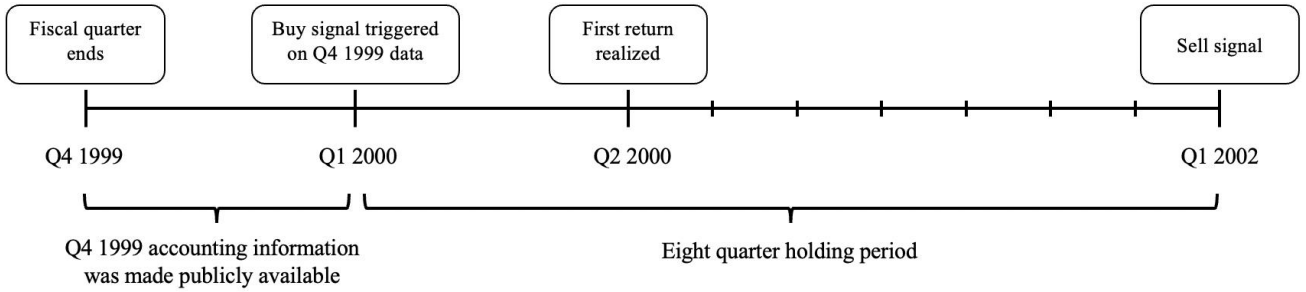
Using data from 1994-2019, all screens applied by Reinganum (1988) and the constructed six-screen strategy were calculated using either daily price data, monthly return data or quarterly fundamental data. Companies without the necessary data items for the calculation of all screens in either of the strategies were not available for investment. For example, if a company was missing shares outstanding data at the date of the screen calculation, the company was excluded from the investment universe that quarter. If the same company had all the necessary information available next quarter, it was included in the investment universe again.

In the original article, Reinganum (1988) used a time lag of 63 trading days, corresponding to a three-month delay. This time lag was implemented to ensure that the fundamental data was actually available at the time of the investment, and the thesis applied the same delay. Thus, as the strategies were implemented in 2000, the first investment decision was made in all stocks that met the investment screens

using Q4 1999 data, which were available ultimo Q1 2000. The stocks chosen by the strategy were then bought ultimo Q1 2000, with the first quarterly returns data available ultimo Q2 2000. The last investment was made ultimo Q3 2019, applying Q2 2019 data for the screens and with returns available ultimo Q4 2019. All positions were liquidated ultimo Q4 2019. Figure 6.2 illustrates the investment process.

Figure 6.2

Illustration of investment process



In line with Reinganum (1988), every investment was held for two years, with no other sell signal. The methodology of Shumway (1997) was used to handle situations were a company is delisted from the exchange during the two-year holding period. The delisting return from CRSP was taken as the correct delisting return, but if the value was missing, the return was taken to be either -30% or -100%, dependent on the delisting code in CRSP (Bali et al., 2016).

Returns on the invested companies were calculated using monthly returns. Cumulative quarterly returns were calculated and presented in the same way as Reinganum (1988), with a distribution of cumulative excess holding period returns in the eight quarters after the buy signal. In the presentation of the results, it is important to clarify that excess returns are defined as the difference between the holding period return on the security and the holding period return on the S&P 500 index.

To get a better view of the performance as an investment strategy, the two strategies were turned into portfolios, which were constructed both equal-weighted and value-weighted. Stocks entered or exited the portfolio every quarter following new buy signals and the lapse of two years, forcing the portfolio to be rebalanced at a minimum of every quarter. In cases where buy signals were triggered for a particular company at different times, each buy signal was tracked separately, making the company weighted more heavily (depending on the number of overlapping buy signals) in the portfolios.

Returns are presented both before and after transaction costs, which is further discussed in Section 6.7. The performance of the portfolios is evaluated using different performance measures and through regression analysis against multiple benchmarks.

6.4 CRSP/Compustat/CCM data processing

Working with data from CRSP, Compustat and CCM, it is important to note that these databases provide raw, unadjusted data (CRSP, 2021). Thus, some adjustments were necessary before the different screens are calculated, because the raw price and number of shares outstanding were not adjusted for split events like stock splits. Price and shares outstanding data were used to calculate screens in both the four-screen and six-screen strategies. For example, the calculation of RSR relies on adjusted prices. The four-screen strategy used shares outstanding as one of the screens, raising the question of whether raw or adjusted numbers should have been applied. As the goal is to find the actual number of shares outstanding at the data date, unadjusted number of shares was used for this screen. Further descriptions of the data items applied for screen calculations, formulas and an illustrative example are found in Appendix A and Appendix B.

6.5 Returns calculation

The following section will elaborate on the return calculation methods behind the replicating four-screen and the created six-screen strategy. In order to make the returns comparable to Reinganum's (1988) results, returns are calculated and presented in a similar fashion. To replicate Reinganum (1988), monthly excess returns over the S&P 500 were compounded to quarterly excess returns. Then, the quarterly excess returns were compounded over the eight-quarter holding period. This was done for all investments, before ending at the distribution of the strategies cumulative excess holding period return.

For evaluating the performance of the portfolios, monthly returns are presented both annualized and cumulated over the holding period, before and after transaction costs. For benchmarking purposes, monthly returns are utilized to calculate the excess returns over the risk-free rate.

The strategy involves long positions in stocks, hence the holding period return (HPR) represents the capital gain and dividend paid for each stock, where capital gain is the difference between the starting-price (P_{t-1}) and ending price (P_t). Monthly HPR are downloaded from CRSP, calculated using the following formula (Bodie et al., 2014, p. 128):

$$HPR_t = \frac{(P_1 - P_{t-1}) + D_t}{P_{t-1}}$$

While excess returns is obtained by subtracting the benchmark return from the given rate of return (Bodie et al., 2014, p. 129):

$$Excess\ HPR_t = HPR_t - HPR_{t,Benchmark}$$

The average cumulative holding period return over the eight quarters following the buy quarter is calculated is given by the arithmetic average of n returns (Bodie et al., 2014, p. 130):

$$Average\ quarterly\ return = \frac{1}{n}\sum_{t=1}^{n} r_t$$

The cumulative holding period return and the annualized returns are given by the geometric average of n returns (Bodie et al., 2014, p. 162):

$$Cumulative\ quarterly\ return_t = \left(\sum_{t=1}^{n}(1 + r_t)\right)^{\frac{1}{n}}$$

6.6 Portfolio weight and rebalancing

As mentioned, Reinganum (1988) reported the average return of stocks that met his filters but did not create a portfolio based on the investment strategies. Based in Reinganum's (1988) wording, it is highly probable that the average return of all stocks is an equal-weighted average, hence it made sense to create equal-weighted portfolios. Additionally, value-weighted portfolios were constructed to investigate the impact of the choice of weighting-method.

Stocks were traded on a quarterly basis because buy and sell signals for stocks were triggered every quarter. Therefore, and since the initial investment was the only capital inflow to the portfolios, the portfolios had to be rebalanced at a minimum of every quarter. The value-weighted portfolios, which were weighted based on each stocks market cap, were rebalanced quarterly. This was done by deriving the cumulative quarterly returns for all investments, which was multiplied with each investment's portfolio weight. The portfolio weight was given by the stocks market cap divided by the total market cap of all stocks.

The equal-weighted portfolios could either be rebalanced monthly or quarterly, dependent on whether it was assumed to be rebalanced every month or only when buy and sell signals were triggered. For monthly equal-weighted portfolios, returns were derived as a simple average of all investments. When rebalancing quarterly, the returns were the simple average of quarterly cumulative returns for all stocks. Results using monthly rebalancing of the equal-weighted portfolios are presented in Section 7, while the quarterly rebalanced equal-weighted portfolios are found in Appendix E.

6.7 Transaction costs

In order to create a portfolio which replicates Reinganum's (1988) investment strategy, frequent trading accompanied with monthly and quarterly rebalancing calls for an outline of how transaction costs were accounted for. According to Pedersen (2015), the direct costs of transaction costs amount to the commission most investors pays and other costs. However, there are also the indirect cost, namely the bid-ask spread and market impact. Investors buy to the ask price and sell to the bid price. The larger the spread, the larger is the indirect transaction costs, where the most liquid stocks usually have smaller spreads than illiquid stocks, hence costs can vary greatly. The market impact denotes the difference between the price that exists in the market before trading begins and the actual traded price, scaled by the traded amount. Thus, there are several variables to consider when estimating transaction costs. However, there are some empirical studies which have derived average total transaction costs paid by investors based on data broker data.

Frazzini, Israel and Moskowitz (2012) estimated that the average market equity transaction cost in the U.S. in 2011 was 9.47 basis points (bp), compared to 62 bp in 2000. Engle, Ferstenberg and Russel (2012) estimated that the average transaction cost for NYSE was 9 bps and 14 bps for Nasdaq in 2004. However, if one traded more than 1% of the free float adjusted number of shares outstanding, the cost increased to 27 bps. The significant drop in transaction costs during the 2000s was driven by intense competition and innovative high-tech trading tools introduced before and around the financial crisis (Akasie, 2011). Thus, the yearly average transaction cost is volatile and vary greatly with the market sentiment, and there is a lack of new research on average transaction costs which makes it problematic to estimate precise yearly transaction costs. Hence, the possibility of deriving an expected exponential yearly decline in transaction costs based on the historical costs provided by Frazzini et al. (2012) and Engle et al. (2012) is not favored.

Therefore, the thesis applied a method of assuming constant transaction costs rate over the time period, similar to what Ognar, Graczyk and Westwood (2016) does when backtesting.

Ognar et al. (2016) used an average of 20 bps for the American stock market for a portfolio backtest ranging from 1995-2015, covering 15 of the same years as the thesis' time period. This figure is also close to the average of an estimated yearly exponential decline in transaction costs from prior research until today. While this was the preferred method, it was also uncertain, hence sensitivity analyses based on two other methods of deriving transaction costs were carried out and discussed in Section 8.2.3. The first was the exponential yearly decline and the second was a scenario where the transaction costs were doubled to 40 bps, to test the portfolios sensitivity to changes in the level of costs applied.

Lastly, transaction costs were calculated on every trade separately. That implied that the size of the trade was tracked and adjusted for transaction costs. When buy or sell signals were triggered, the portfolio "paid" transaction costs equal to 20 bps of the full trade. However, for the portfolio investments that were merely held and did not enter or exit the portfolio, transaction cost would only apply to the amount that was adjusted.

6.8 Performance measures

The excess return is key when evaluating the attractiveness of an investment. For risky investments, the excess return tells an investor the expected return that can be earned, less the return of the risk-free rate. This is known as the risk premium. However, the risk premium does not say at what risk the excess return can be earned. Rational investors prefer large returns at low risk, thus it is relevant to derive the expected return relative to the risk carried by the investor. Several ratios analyze the relation between excess return and risk, where the Sharpe ratio are among the most used ratios. However, on more complex cases, other ratios such as skewness of returns and crash risk could enhance the explanation of portfolio performance (Pedersen, 2015). Therefore, several performance measures are introduced.

6.8.1 Sharpe ratio

A popular measure of quantifying the risk-adjusted return is the Sharpe Ratio, which denotes the reward per unit of risk. This is defined as the expected excess return over the risk (Pedersen, 2015, s. 29):

$$Sharpe\ ratio = \frac{E(r - r_f)}{\sigma(r - r_f)}$$

The expected return is measured as the expected portfolio return, less the risk-free rate above the standard deviation of the excess return. The ratio will be applied to compare performances across portfolios and benchmarks. The ratio is along with other performance measures sensitive to time horizons, hence time horizons will always be clearly specified (Pedersen, 2015).

6.8.2 Treynor ratio

Treynor ratio is similar to Sharpe ratio in the sense that it measures the risk/return tradeoff, but as seen from the equation below, it differs in its definition of risk. The Treynor ratio only incorporates systematic risk, hence assuming that unsystematic risk can be mitigated through diversification (Munk, 2019, s. 302):

$$Treynor\ ratio = \frac{E(r - r_f)}{\beta}$$

The ratio measures the excess return compared to the systematic risk, or the market risk. While the Sharpe ratio compares the excess returns to the volatility of portfolio returns, the Treynor ratio compares volatility of excess returns compared to market returns. The ratios are expected to be similar for fully diversified portfolios, but for sector dominated portfolios, the Sharpe ratio may be a more appropriate measure.

6.8.3 Sortino ratio

The Sortino ratio is another measure of risk-adjusted return that only accounts for downside volatility. The ratio looks at the excess returns above the downside risk, which is calculated as the standard deviation of negative excess returns (Pedersen, 2015, s. 32):

$$Sortino\ ratio = \frac{E(r - r_f)}{\sigma^{\text{downside}}}$$

The downside risk ignores the variation in positive excess returns, and hence implicitly assumes that investors for the most part care about the downside risk. This means that the ratio also assumes that the investor is indifferent whether a portfolio yields a 5% annual return over two years, or 1% the first year and 9% the second year (Pedersen, 2015). Sortino et al. (2010) claim that its popularity is partly due to hedge funds frequent use of the ratio, because it often makes the hedge funds look better than the Sharpe ratio.

6.8.4 Information ratio

The information ratio (IR) is another relevant measure of the risk-adjusted return, explaining the relationship between alpha and unsystematic risk. It measures the extra return obtainable by security analysis and active investing compared to added firm-specific risk from overweighting or underweighting securities relative to the benchmark. The IR is given by the following formula (Pedersen, 2015, s. 30):

$$IR = \frac{\alpha}{\sigma(\varepsilon)}$$

The formula measures the alpha, or excess return, over the benchmark compared to the variance in the alpha and is consequently a relevant indication of relative portfolio performance.

6.8.5 Drawdown

Another important measure of risk is drawdown. Drawdown is the cumulative loss since losses started, or how much the strategy is down from its cumulative all-time high. The measure is given by (Pedersen, 2015, s. 35):

$$DD_t = \frac{HWM_t - P_t}{HWM_t}$$

HWM is short for high water mark and is the highest price the strategy has achieved in the past and P_t is the price at time t. Simplified, if the investment strategy is at its all-time high, the drawdown is zero, otherwise it is positive. Drawdown is typically used by active fund managers, as large drawdowns could incite redemptions from investors and further elevate losses. Thus, large drawdowns are costly, where the largest loss from the peak price is denoted as the maximum drawdown, given by (Pedersen, 2015, s. 35):

$$MDD_t = max_{t \leq T} DD_t$$

6.9 Benchmarking

In this section, the different models applied for benchmarking in the analysis is presented. According to Pedersen (2015), the objective of an active manager is to add value to their investors by generating excess returns relative to a benchmark. To investigate whether the constructed portfolios are actually adding value to investors, they will be compared to the different benchmarks presented in this section. By comparing the portfolio returns to different benchmarks, the potential abnormal returns after accounting for exposures to the different factors are examined (Bali et al., 2016).

6.9.1 Capital Asset Pricing Model

The first factor model is the CAP (Sharpe, 1964). CAPM states that the expected return on a security depends on the risk-free rate, market return and its market risk, known as beta. Investors are only compensated for bearing market risk, implying that it is impossible for investors to systematically earn returns in excess of the market. Thus, consistent alpha would contradict the CAPM. CAPM is given by (Bali et al., 2016, p. 48):

$$r_{p,t} = \alpha + \beta_{mkt} MKT_t + \epsilon_t$$

Where $r_{p,t}$ is the excess return of the portfolio, β_{mkt} is the portfolios exposure to market risk and MKT_t is the excess return on the market portfolio during the period t.

6.9.2 Fama and French three-factor model

Another model often considered by academics was originally proposed by Fama and French (1993), known as the Fama and French three-factor model (hereafter FF3). This model uses two additional risk factors that proxy the returns associated with the size and value effects. The size effect is proxied through a zero-cost portfolio that is long small cap stocks and short high cap stocks. The value effect is proxied through a zero-cost portfolio that is long high book-to-market stocks and short low book-to-market stocks. The two factors and their returns are referred to as SMB and HML (Bali et al., 2016). Therefore, the FF3-model can be written as (Bali et al., 2016, p. 49):

$$r_{p,t} = \alpha + \beta_{MKT} MKT_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \epsilon_t$$

where β_{SMB} and β_{HML} are the portfolios exposure to the two risk factors, and SMB_t and HML_t are the returns of the two risk factor portfolios.

6.9.3 Fama, French and Carhart four-factor model

The third factor model applied in this paper is an extended version of the FF3-model, with an additional factor to capture the momentum effect, documented by Jegadeesh and Titman (1993) and Carhart (1997). The return of the momentum factor (UMD) is captured by a zero-cost portfolio that is long stocks with the highest recent performance and short stocks with the lowest recent performance. Recent performance is defined as the return of the stock over the 11-month period beginning 12 months ago and ending one month ago (Bali et al., 2016). The Fama, French and Carhart-model (hereafter FFC4) can be written as (Bali et al., 2016, p. 49):

$$r_{p,t} = \alpha + \beta_{MKT} MKT_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{UMD} UMD_t + \epsilon_t$$

where β_{UMD} is the exposure to momentum risk and UMD_t is the return of the momentum risk factor.

6.9.4 Fama and French five-factor model

The fourth and final factor model applied in this paper is another expansion of the original FF3-model, as Fama and French (2015) found that the FF3 did not sufficiently explain abnormal returns. Thus, they added two more factors directed at capturing the profitability and investment patterns in average stock returns called the Fama and French five-factor model (hereafter FF5). Profitability (RMW) is the difference between the returns on diversified portfolios of stocks with robust and weak profitability, and investments (CMA) is the difference between the returns on diversified portfolios of the stocks of low and high investment firms (Fama & French, 2015). The FF5-model can be written as (Fama & French, 2015, s. 3):

$$r_{p,t} = \alpha + \beta_{MKT} MKT_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{RMW} RMW_t + \beta_{CMA} CMA_t + \epsilon_t$$

where β_{RMW} and β_{CMA} are the portfolios exposure to the two risk factors, and RMW_t and CMA_t are the returns of the two risk factor portfolios.

Formulas and calculations behind the risk factors are presented in Appendix K.

6.10 Statistical methodology

Time-series regressions were used to risk-adjust and compare portfolio returns with the different benchmarks. Linear regression models with single and multiple regressors were applied, in which the constructed portfolios excess returns were the dependent variable Y, and the excess returns of the

different risk factors were the independent variables X_i. Both regression models were estimated using ordinary least squares (OLS) estimation. The OLS method estimates a regression line which minimizes the difference between the actual observed data and the predicted data, measured by the sum of squared residuals derived when predicting the independent variable given the explanatory variables (Stock & Watson, 2015). The application of linear regression models builds on four least square assumptions in the single regression model, and five least squares assumptions in the multiple regression model (Newbold, Carlson, & Thorne, 2013, p. 482):

1. The n observations of x_i are fixed numbers, or they are realizations of random variables, X_j, that are independent of the error terms, ϵ_i.
2. The expected value of the random variable Y is a linear function of the independent X_j variables.
3. The error terms are normally distributed random variables with a mean of 0 and constant variance, σ^2.
4. The random error terms, ϵ_i, are not correlated with one another.
5. There is no linear relationship between the X_j variables.

For OLS to be a reliable estimator of the unknown parameters, and hence applicable in large samples, these assumptions must be satisfied (Stock & Watson, 2015). Therefore, the different assumptions were tested through multiple statistical tests. First of all, time series analysis requires stationarity in the time series. Stationarity was tested with the augmented Dickey-Fuller test (Enders, 2015). The linearity assumption was examined through visual interpretations of scatter plots. The assumption of normality in the sample residuals was tested using a Jarque-Bera test, which tests whether the skewness and kurtosis of the model residuals follow a normal distribution (Jarque & Bera, 1980). Further, Breusch-Pagan test for heteroskedasticity was applied to test for constant variance in the residuals, homoskedasticity (Breusch & Pagan, 1979). The fourth assumption of no correlation in the random errors was tested through the Breusch-Godfrey test for autocorrelation (Breusch, 1979; Godfrey, 1978). The fifth and final assumption of no multicollinearity in the regression model was tested by examination of the variance inflation factor (James, Witten, Hastie, & Tibshirani, 2013). Results and further descriptions of the aforementioned tests are presented in Section 7.6 and Appendix L.

According to Bali et al. (2016), most researchers use a 5% level to determine statistical significance. Thus, if the p-value was less than 0.05 and the t-statistic was greater than 1.96 the null hypothesis of the

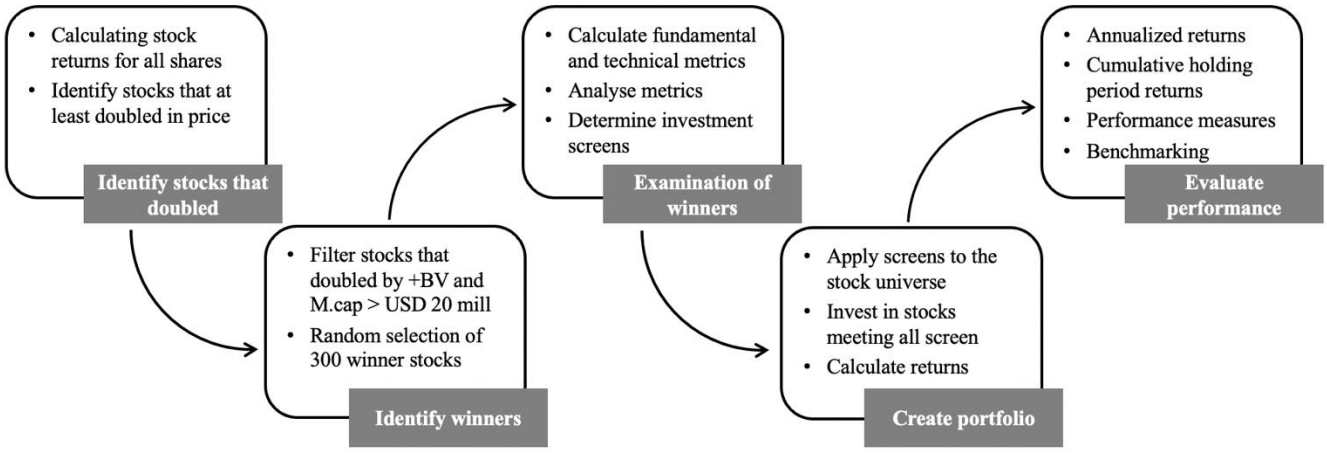
statistical test was rejected, and vice versa if the p-value was greater than 0.05 and the t-statistic was lower than 1.96. A statistically significant slope coefficient in the simple regression model indicates that one cannot reject the null hypothesis that the independent variable has explanatory power over the dependent variable, while if the coefficient is statistically insignificant, one can reject that the independent variable has any explanatory power over the dependent variable. In a multiple regression, a statistically significant coefficient indicate that the independent variable has an explanatory power over the dependent variable above what is explained by the other independent variables. Thus, this means that if a coefficient is significant in one regression model, and insignificant in another regression model with more independent variables, the variations in the dependent variable, Y is better explained by a linear combination of the additional independent variables (Bali et al., 2016). The interpretation of the estimated regression coefficients will be further explained in Section 7.5.

6.11 Section summary

This section has detailed the methodology behind the empirical analysis and results presented in the next section. A comprehensive understanding of the methods utilized to analyze the research question is fundamental to secure a friction-less interpretation. To summarize, the section is streamlined in Figure 6.2.

Figure 6.2

Structure of analyzing the research question



7. Empirical Results

The next part of the thesis will present the empirical results of Reinganum's (1988) replicating strategy and the new strategy. The section is further split into six sub-sections: Section 7.1 presents results after screening winner stocks. Section 7.2 displays an overview of all stocks meeting the chosen screens. Section 7.3 shows the distribution of cumulative holding period returns generated by the four-screen and six-screen strategies before and after transaction costs. Summary of performance measures are presented in Section 7.4, before benchmark analyses and regression diagnostics analyses are presented in Section 7.5 and Section 7.6.

7.1 Characteristics of winner stocks

The cornerstone of the six-screen strategy are the common characteristics and trends found by studying the eight quarters leading up to the buy date for the 300 randomly selected stocks. The mean, median, percentiles and number of positive/negative thresholds for more than 40 fundamental measures and technical indicators were studied, although only descriptive statistics for the six selected filters will be presented in this section. The six filters were chosen, as they showed the most consistent and credible results out of all the analyzed factors. The six filters are: 1) Price/book above 1, 2) Debt-to-equity below 2, 3) positive three-year annual growth rates, 4) positive EBITDA margin, 5) positive change in the year-over-year EBITDA margin and 6) positive change in the relative strength rank.

1. Price/book ratio above 1

The analysis of the 300 randomly selected companies showed that few stocks had a P/B ratio below 1 before the buy date. The mean is clouded by some very high values, illustrated by the percentiles, and you must look above the 10^{th} percentile before the P/B increases above 1. 73% of the stocks were selling at a P/B higher than 1 in buy-1 and 78% in buy-2. This indicates that one should seek out stocks trading for a P/B higher than 1, possibly because these stocks have more promising growth prospects.

Table 7.1

Price/book ratios in the buy and eight preceding quarters

			Percentile								
Quarter	**Mean**	**% > 1**	**1st**	**5th**	**10th**	**25th**	**50th**	**75th**	**90th**	**95th**	**99th**
Buy	3.49	72.96	0.27	0.41	0.56	0.94	1.70	3.58	6.95	12.00	30.73
Buy-1	3.13	72.90	0.21	0.39	0.55	0.97	1.75	3.28	6.41	11.59	21.63
Buy-2	3.45	77.69	0.22	0.47	0.67	1.10	1.77	3.36	6.28	9.79	23.24
Buy-3	3.19	78.29	0.12	0.39	0.66	1.15	1.93	3.48	6.13	8.96	20.10
Buy-4	3.25	78.43	0.17	0.39	0.60	1.11	2.02	3.44	5.68	8.21	19.85
Buy-5	2.89	76.38	0.19	0.41	0.62	1.08	1.79	3.13	5.40	8.28	18.06
Buy-6	3.04	83.27	0.24	0.57	0.75	1.19	2.16	3.64	7.03	9.58	13.86
Buy-7	2.99	78.69	0.31	0.53	0.70	1.14	2.05	3.31	6.17	9.21	15.88
Buy-8	3.26	79.92	0.32	0.61	0.72	1.18	2.11	3.74	6.66	10.00	20.10

The result is notably conflicting with Reinganum's (1988) reported results stating that 82% of the firms traded at P/B lower than 1 in the buy-1 quarter. This might suggest that expected growth to a larger extent is reflected in stock prices today than during the 1970s, and thus that it is more difficult to identify undervalued stocks. Also note that Reinganum (1988) studied winners during a period where value stocks outperformed, something both Basu (1977) and Chan and Lakonishok (2004) presents evidence in favor of, which might tilt Reinganum's (1988) sample towards value.

2. Debt-to-equity below 2

The debt-to-equity (D/E) ratio of the winning stocks measured below 2 for between 75% and 81% of the stocks in the eight quarters preceding the buy quarter. Again, it is difficult to conclude anything based on the mean, due to several extreme values, however the median (50^{th} percentile) also indicates that most firms operate with a D/E ratio below 2.

Table 7.2

Debt-to-equity ratios in the buy and eight preceding quarters

			Percentile								
Quarter	**Mean**	**% < 2**	**1st**	**5th**	**10th**	**25th**	**50th**	**75th**	**90th**	**95th**	**99th**
Buy	2.22	73.26	0.06	0.12	0.19	0.41	0.91	2.18	5.07	7.77	16.66
Buy-1	1.95	75.09	0.05	0.12	0.18	0.40	0.92	1.97	4.41	6.06	18.22
Buy-2	1.87	77.57	0.05	0.11	0.18	0.35	0.82	1.84	4.08	5.36	21.84
Buy-3	1.63	78.54	0.07	0.12	0.16	0.31	0.87	1.81	3.85	5.46	12.64
Buy-4	1.72	77.13	0.08	0.13	0.18	0.32	0.87	1.93	4.06	5.50	11.49
Buy-5	1.62	80.54	0.07	0.11	0.16	0.31	0.84	1.77	3.77	4.96	9.87
Buy-6	1.67	78.74	0.06	0.10	0.15	0.34	0.89	1.68	3.32	5.07	9.48
Buy-7	1.78	79.76	0.05	0.11	0.15	0.34	0.83	1.73	3.22	4.39	12.06
Buy-8	1.52	77.69	0.07	0.11	0.17	0.35	0.81	1.74	3.34	4.72	8.05

There is evidence supporting that companies with excessive debt are not rewarded by investors, likely due to high financial risk and should, in some cases be sidestepped in favor of less levered companies.

The evidence supports O'Neil's (2009) argument stating that a low D/E ratio indicates higher quality and is preferred due to safety, especially during downturns. Note that Reinganum (1988) does not present any results related to balance sheet measures, hence it is not possible to make a straight-forward comparison.

3. Positive three-year annual revenue growth rates

The three-year annual growth rates are calculated using the same formula as the five-year growth rate presented in Appendix B using only three years. The sample average equaled 29% in buy-1 and buy-2, while the median growth never dropped below 10%. Additionally, the 25th percentile is positive for all previous buy quarters. In the buy-1 quarter, 78% of the firms exhibited a positive growth rate, undermining a selection of stocks based on positive three-year growth rate in revenue.

Table 7.3

Three-year revenue growth rate in the buy and eight preceding quarters

			Percentile								
Quarter	**Mean**	**% > 0**	**1st**	**5th**	**10th**	**25th**	**50th**	**75th**	**90th**	**95th**	**99th**
Buy	26.0%	76.3%	-38.7%	-17.2%	-10.8%	0.4%	11.5%	31.0%	81.0%	143.3%	239.8%
Buy-1	28.9%	77.8%	-37.1%	-16.7%	-8.8%	1.2%	10.5%	29.2%	76.7%	128.7%	291.4%
Buy-2	29.4%	79.8%	-36.4%	-20.3%	-10.1%	1.4%	11.0%	34.3%	81.1%	127.8%	307.9%
Buy-3	28.6%	77.5%	-33.8%	-17.1%	-11.2%	0.8%	10.8%	33.1%	77.5%	123.6%	274.0%
Buy-4	27.6%	76.7%	-35.7%	-15.8%	-9.1%	0.8%	11.5%	36.1%	73.7%	112.9%	226.6%
Buy-5	33.8%	79.7%	-36.5%	-15.3%	-7.6%	1.3%	13.3%	47.0%	91.9%	158.0%	233.0%
Buy-6	36.1%	79.9%	-32.1%	-14.5%	-9.0%	1.5%	13.5%	38.5%	89.8%	165.7%	262.1%
Buy-7	46.3%	78.7%	-28.8%	-16.0%	-4.3%	2.8%	15.6%	45.2%	106.1%	160.2%	466.0%
Buy-8	33.3%	78.0%	-32.9%	-15.3%	-6.3%	1.5%	12.9%	34.8%	90.0%	147.1%	378.0%

Reinganum (1988) found that more than 85% of the firms exhibited positive five-year quarterly earnings growth. The thesis did not find convincing trends in the five-year earnings growth, however close to 80% of the 300 winners showed positive five-year quarterly revenue growth. Also, 80% showed a positive three-year quarterly revenue growth. Since the results of the three- and five-year growth rates are very similar, the three-year is favored for the purpose of not restricting the strategy to only account for firms with five or more years of data.

4. Positive EBITDA margin

Table 7.4 shows the EBITDA margins of the 300 companies. Note also that the data represents raw accounting data and is not adjusted in any way. The margin is positive for over 70% of the companies

the two quarters before the buy quarter, indicating that a seniority of the companies delivers positive operating earnings before depreciation and amortization.

Table 7.4

EBITDA margins in the buy and eight preceding quarters

			Percentile								
Quarter	**Mean**	**% > 0**	**1st**	**5th**	**10th**	**25th**	**50th**	**75th**	**90th**	**95th**	**99th**
Buy	0.9%	72.9%	-141.2%	-46.4%	-32.6%	-2.1%	7.9%	17.2%	31.3%	47.1%	83.5%
Buy-1	-2.1%	72.8%	-200.3%	-70.7%	-27.7%	-1.4%	7.6%	15.8%	29.0%	42.6%	77.9%
Buy-2	-5.4%	70.3%	-316.3%	-78.1%	-40.9%	-2.6%	7.9%	15.9%	27.1%	45.9%	81.0%
Buy-3	-6.3%	68.6%	-238.1%	-79.3%	-48.8%	-5.9%	5.9%	14.1%	26.2%	41.7%	79.2%
Buy-4	-6.1%	69.5%	-281.0%	-92.9%	-41.5%	-4.4%	6.5%	14.2%	28.6%	37.1%	74.7%
Buy-5	-4.0%	68.8%	-195.6%	-95.0%	-46.4%	-4.8%	6.5%	15.9%	31.4%	44.4%	74.7%
Buy-6	-4.0%	69.5%	-197.0%	-93.9%	-44.4%	-6.0%	8.0%	14.7%	33.3%	46.4%	77.8%
Buy-7	-5.2%	70.7%	-241.3%	-104.8%	-35.6%	-3.2%	7.5%	16.1%	28.1%	42.5%	80.2%
Buy-8	-4.3%	71.3%	-231.3%	-84.5%	-41.5%	-3.7%	7.7%	16.1%	32.4%	44.1%	75.4%

The difference between this thesis' results and Reinganum's (1988) findings is compelling. Out of Reinganum's (1988) 222 winners, 215 had a positive pre-tax margin in the buy-1 quarter and the average margin was 12%. The percentage of the thesis' winner stocks with a positive pre-tax margin is around 52% in buy-1, with an average margin of -41%, as seen from Appendix H.5

5. Positive change in the year-over-year EBITDA margin

Table 7.5 presents changes in EBITDA margins, representing the year-over-year change in EBITDA margins for each company. There is a notable increase in companies delivering margin expansions leading up to the buy quarter, from 44% in buy-3 to 64% in the buy quarter. Even though it appears to be some seasonality in the data, the two highest percentages occur during the buy quarter and the buy-1 quarter, indicating that firms improve their profitability leading up to the buy quarter. Hence, the second to last investment rule suggested by the winner stocks says that the investor should target stocks with a positive year-over-year change in the EBITDA margin.

Table 7.5

Change in year-over-year EBITDA margins in the buy and eight preceding quarters

			Percentile								
Quarter	**Mean**	**% > 0**	**1st**	**5th**	**10th**	**25th**	**50th**	**75th**	**90th**	**95th**	**99th**
Buy	0.08	64.3%	-0.63	-0.30	-0.14	-0.03	0.02	0.11	0.36	0.62	2.62
Buy-1	0.06	59.0%	-0.62	-0.30	-0.14	-0.04	0.02	0.09	0.26	0.61	1.23
Buy-2	0.01	55.1%	-1.32	-0.41	-0.19	-0.04	0.01	0.07	0.27	0.51	1.50
Buy-3	-0.01	44.2%	-1.39	-0.42	-0.25	-0.07	-0.01	0.06	0.20	0.38	1.14
Buy-4	-0.06	46.1%	-2.41	-0.82	-0.33	-0.08	0.00	0.06	0.18	0.40	1.12
Buy-5	-0.04	49.8%	-1.69	-0.82	-0.23	-0.08	0.00	0.05	0.17	0.37	0.87
Buy-6	0.00	52.6%	-1.54	-0.74	-0.31	-0.07	0.00	0.06	0.24	0.56	1.64
Buy-7	0.03	56.5%	-1.64	-0.58	-0.26	-0.06	0.01	0.08	0.26	0.62	2.23
Buy-8	0.17	56.0%	-1.16	-0.45	-0.19	-0.05	0.01	0.08	0.30	0.71	2.62

The change in EBITDA margins is not to be mistaken by Reinganum's (1988) accelerating earnings criteria, applied to the four-screen and nine-screen strategy, which analyses quarterly changes opposed to yearly changes. It should be mentioned that Reinganum (1988) uncovers convincing evidence of such earnings momentum in both revenue and earnings figures, while the thesis' sample showed no signs of such trends in neither revenue, operating income nor earnings (tables for these screens can be seen in Appendix H.1, H.2 and H.3).

6. Positive change in the relative strength rank

Jegadeesh & Titman (1993) reported alpha based on a study of buying the past 3-12 months winners, finding that this strategy would outperform the next year. Reinganum (1988) also found evidence in support of this well-known price momentum strategy after studying his winner stocks. Based on the thesis' sample of winners from 2000-2019, there are still indications supporting the price momentum anomaly, as both the mean and median RSR increases between the buy-4 quarter and the buy quarter. More precisely, the median jumps from 46 to 60 during the last year. Thus, the 300 winner stocks suggest that the last investment rule in the six-screen strategy should be to seek out stocks with a positive change in the relative strength rank. To be clear, this is the same rule as Reinganum (1988) implemented in both of his strategies.

Table 7.6

Relative strength rank

			Percentile								
Quarter	**Mean**	**Median**	**1st**	**5th**	**10th**	**25th**	**50th**	**75th**	**90th**	**95th**	**99th**
Buy	54.44	59.80	3.00	4.76	10.82	22.65	59.80	83.55	93.98	96.74	99.33
Buy-1	53.40	56.35	3.36	6.95	11.33	23.18	56.35	83.88	94.38	96.87	99.27
Buy-2	53.21	54.60	2.07	5.99	9.50	23.58	54.60	84.18	92.80	97.22	99.23
Buy-3	50.59	48.30	1.94	6.47	9.55	21.08	48.30	79.98	94.43	97.10	98.84
Buy-4	47.73	45.70	2.32	5.17	7.40	17.55	45.70	78.15	93.02	95.16	98.55
Buy-5	49.83	49.30	3.05	7.10	10.20	21.85	49.30	76.50	91.40	95.50	99.20
Buy-6	47.47	43.90	2.78	4.91	8.34	18.78	43.90	75.90	93.19	96.68	98.76
Buy-7	49.70	51.40	3.03	5.36	9.30	21.90	51.40	77.45	93.52	97.12	99.07
Buy-8	53.84	56.40	3.03	5.85	10.00	22.15	56.40	85.60	95.00	96.70	99.20

The results of screening the sample of winner stocks show that there are six common characteristics among the 300 winners. Important takeaways are that the results are less consistent compared to Reinganum's (1988) results and only one of his nine screens survived the screening process of the 300 winners. The six selected screens are: 1) Price/book above 1, 2) Debt-to-equity below 2, 3) positive three-year annual growth rates, 4) positive EBITDA margin, 5) positive change in the year-over-year EBITDA margin and 6) positive change in the relative strength rank. It is these screens that will be used to construct portfolios and test whether Reinganum's (1988) method of creating an investment strategy based on common characteristics among winner stocks generates excess returns today.

7.2 Overview of stocks meeting investment screens

As previously mentioned, Reinganum (1988) presented one four-screen strategy and one nine-screen strategy. However, this section will focus on presenting results from this thesis' implementation of the four-screen strategy, due to the fact that the nine-screen strategy generated a conservative number of two buy signals on average per quarter, on top of several quarters with zero buy signals in the thesis time period. The result is a strategy which is close to impossible to implement for a professional investor and therefore less relevant for the thesis. The overview of the stocks meeting the nine screens can be seen in Appendix D. Further, the section will present summary statistics for the four-screen and the constructed six-screen strategy, in addition to each strategy's sector exposure.

7.2.1 Reinganum's (1988) four-screen strategy

In the process of filtering out stocks that meet the various filters, all stocks on NYSE, AMEX and Nasdaq have been analyzed. The results can be seen in Table 7.7 below where the number of listed stocks and the number/percentage of stocks meeting the different filters are sorted by year. Yearly figures are

calculated as an average of the quarterly statistics, which can be found in Appendix C.1 and C2. Moreover, remember that the "Total companies" column in both Table 7.7 and Table 7.10 only include companies where CCM provides sufficient data to compute all filters, meaning that companies with missing data points are excluded from the sample.

Table 7.7

Overview of all stocks and percentage of stocks meeting filter rules of the four-screen strategy

Year	Total companies	Price-to-book		Shares outstanding		Change in RSR		Accelerated earnings		All filters	
	#	#	%	#	%	#	%	#	%	#	%
2000	5506	1720	31%	3222	59%	2798	51%	2612	47%	319	6%
2001	5330	1718	32%	2857	54%	2459	46%	2489	47%	265	5%
2002	5074	1504	30%	2516	50%	2450	48%	2424	48%	222	4%
2003	4715	1027	22%	2240	48%	2141	45%	2276	48%	138	3%
2004	4479	481	11%	1935	43%	2238	50%	2151	48%	66	1%
2005	4350	456	10%	1722	40%	2164	50%	2087	48%	56	1%
2006	4268	403	9%	1603	38%	2088	49%	2019	47%	53	1%
2007	4147	490	12%	1486	36%	2052	49%	1959	47%	50	1%
2008	4055	1267	31%	1429	35%	1942	48%	1834	45%	129	3%
2009	3946	1494	38%	1334	34%	1724	44%	1928	49%	142	4%
2010	3714	1006	27%	1200	32%	1848	50%	1756	47%	111	3%
2011	3574	1011	28%	1097	31%	1759	49%	1667	47%	104	3%
2012	3479	956	27%	1031	30%	1665	48%	1675	48%	112	3%
2013	3400	658	19%	970	29%	1614	47%	1617	48%	60	2%
2014	3352	566	17%	912	27%	1680	50%	1590	47%	57	2%
2015	3414	692	20%	910	27%	1646	48%	1613	47%	64	2%
2016	3422	724	21%	953	28%	1635	48%	1632	48%	69	2%
2017	3353	574	17%	911	27%	1589	47%	1621	48%	47	1%
2018	3309	624	19%	857	26%	1615	49%	1569	47%	41	1%
2019	3324	717	22%	871	26%	1616	49%	1608	48%	53	2%
Average	4010	904	22%	1503	36%	1936	48%	1906	48%	108	3%
Median	3830	721	21%	1267	33%	1803	48%	1795	47%	67	2%
Max	5506	1720	38%	3222	59%	2798	51%	2612	49%	319	6%
Min	3309	403	9%	857	26%	1589	44%	1569	45%	41	1%

The quarterly average number of stocks that meet all four filters across the time period is 108 (3%), corresponding to an average of 432 buy signals per year. However, the fraction varies greatly from 6% in 2000 and 1% in 2018. The main reasons are the drop in the total number of listed stocks with necessary data from 5,506 in 2000 to 3,324 in 2019, equivalent to 40%. As a consequence, fewer stocks are able to meet all the criteria in recent years. Secondly, the number of stocks with fewer than 20 million shares outstanding drops progressively close to every year over the sample period.

The price and earnings momentum filters, change in RSR and accelerated earnings, are relatively unchanged with several stocks satisfying both filters across the period. The number of companies meeting the price to book filter, however, is lower towards the end of the period, suggesting that it is harder to find undervalued stocks. An equally interesting observation is the large variation in the ratio, where the percentage of firms meeting the filter is largest in and after market downturns. This may indicate that it

is easier to find undervalued companies after downturns, in-line with De Bondt & Thaler (1985) and Shiller's (1992) documentation of the stock market's tendency to overreact to bad news. Another important takeaway is that even though the number of stocks meeting all filters declines sharply, a sample of 40-60 stock per quarter is still enough to pursue the strategy today. Additionally, it underlines that a potential addition or tightening of the current filters quickly renders the strategy impossible to implement, similar to the nine-screen strategy.

Table 7.8 below presents the stock exchange composition among the shares meeting all screens in the four-screen strategy. The numbers are presented as average per quarter each year. No.% represents the percentage of total stocks meeting the four screens listed on the exchanges, while M.Cap% represents the percentage of total market capitalization of the stocks that meet all four screens per exchange.

Table 7.8

Quarterly average number of companies and market capitalization of the four-screen strategy by stock exchange

	Total			NYSE				AMEX				Nasdaq			
Year	Total No.	Average	Median	No.%	M.Cap%	Average	Median	No.%	M.Cap%	Average	Median	No.%	M.Cap%	Average	Median
2000	319	46	21	13%	28%	108	73	14%	8%	28	14	73%	64%	42	20
2001	265	44	19	10%	21%	98	78	17%	12%	33	14	73%	67%	43	22
2002	222	35	16	11%	32%	112	63	19%	9%	19	11	70%	59%	33	18
2003	138	63	28	10%	28%	192	104	20%	11%	36	22	69%	61%	61	32
2004	66	78	30	10%	20%	155	110	26%	14%	43	19	63%	66%	85	41
2005	56	67	29	10%	29%	241	173	23%	10%	33	18	67%	61%	70	39
2006	53	68	36	11%	26%	189	164	23%	17%	53	26	66%	56%	65	40
2007	50	81	33	7%	17%	148	123	22%	25%	68	22	71%	58%	63	31
2008	129	50	20	8%	23%	142	95	16%	12%	38	9	77%	65%	44	21
2009	142	81	30	6%	21%	311	133	13%	20%	135	18	81%	58%	61	32
2010	111	86	49	4%	15%	306	153	11%	5%	36	30	85%	80%	83	49
2011	104	74	35	7%	27%	312	142	13%	6%	31	22	80%	68%	64	36
2012	112	87	44	8%	27%	381	149	12%	3%	23	17	81%	70%	75	49
2013	60	96	44	8%	19%	229	203	13%	3%	27	21	79%	77%	103	51
2014	57	102	44	7%	22%	398	364	11%	2%	16	14	82%	76%	105	55
2015	64	81	50	6%	16%	243	195	18%	4%	22	15	76%	80%	90	69
2016	69	88	51	14%	33%	240	131	14%	6%	38	24	72%	61%	81	53
2017	47	94	36	10%	34%	378	301	15%	14%	116	16	75%	53%	72	44
2018	41	97	28	15%	42%	319	71	13%	3%	25	17	71%	55%	82	31
2019	53	109	32	16%	50%	360	189	11%	2%	26	15	73%	47%	77	37
Average	108	76	34	10%	27%	243	151	16%	9%	42	18	74%	64%	70	38
Median	67	81	32	10%	26%	240	137	15%	9%	33	18	73%	63%	71	38
Max	319	109	51	16%	50%	398	364	26%	25%	135	30	85%	80%	105	69
Min	41	35	16	4%	15%	98	63	11%	2%	16	9	63%	47%	33	18

Table 7.8 shows that the strategy is dominated by stocks that are listed on Nasdaq, both in terms of number of stocks and market capitalization. Nasdaq stocks never account for less than 63% of the number of stocks in the portfolio, and never below 47% of the market capitalization. However, in the last three

years, there is evidence of a trend that NYSE captures a higher portion of the market capitalization, resulting in a weight of 50% in 2019. Another interesting finding is that companies listed on AMEX exceeds the number of stocks listed on NYSE. It is evident that the strategy is significantly tilted towards small cap stocks, with an average market capitalization between USD 35-109 million, and median ranging from USD 16-51 million for the four-screen strategy.

The four-screen strategy solely selects stocks based on quantitative factors, without considering industry exposure. Thus, one might expect that the strategy is dominated by a few industries. It is therefore interesting to look at the sector composition with emphasis on how well risk is diversified across industries, which is presented in Table 7.9.

Table 7.9

Four-screen strategy sector exposure by number of investments (MSCI sector classification)

Year	Energy	Materials	Industrials	Consumer Discretionary	Consumer Staples	Health Care	Financials	Information Technology	Telecom Services	Utilities	Real Estate
2000	3.6%	5.1%	13.0%	19.6%	4.4%	13.3%	18.3%	18.7%	2.1%	1.6%	0.5%
2001	3.5%	3.2%	12.6%	16.3%	4.0%	11.8%	20.5%	23.4%	3.0%	1.2%	0.5%
2002	4.1%	5.1%	11.6%	16.7%	4.0%	14.3%	19.8%	19.0%	2.9%	2.1%	0.5%
2003	3.2%	3.7%	14.9%	16.1%	3.4%	14.0%	20.5%	18.3%	2.6%	2.8%	0.6%
2004	2.9%	3.9%	14.6%	21.6%	2.9%	15.9%	18.8%	16.6%	0.5%	2.3%	0.0%
2005	0.9%	6.2%	15.8%	16.5%	3.1%	14.2%	15.3%	23.5%	1.5%	3.1%	0.0%
2006	2.1%	6.0%	14.0%	14.6%	4.3%	13.6%	17.5%	17.3%	4.8%	5.7%	0.0%
2007	1.7%	3.2%	24.4%	9.2%	2.2%	17.7%	21.0%	19.9%	0.0%	0.0%	0.6%
2008	7.8%	3.7%	11.6%	15.5%	2.7%	18.6%	21.6%	13.2%	4.7%	0.3%	0.4%
2009	5.3%	3.5%	13.1%	18.8%	3.1%	13.9%	22.2%	15.1%	3.6%	1.2%	0.3%
2010	9.6%	3.8%	9.0%	21.0%	2.5%	18.9%	15.2%	12.8%	3.8%	2.9%	0.4%
2011	10.8%	4.1%	21.0%	13.6%	1.5%	10.9%	21.6%	11.3%	2.2%	3.1%	0.0%
2012	7.9%	4.4%	19.7%	16.6%	4.0%	17.3%	14.7%	9.5%	3.5%	2.4%	0.0%
2013	11.5%	0.0%	23.8%	13.1%	2.1%	17.9%	13.4%	11.9%	6.3%	0.0%	0.0%
2014	10.8%	2.8%	17.4%	16.5%	2.1%	14.6%	19.6%	9.5%	2.9%	3.8%	0.0%
2015	8.9%	2.0%	19.0%	15.6%	6.8%	13.7%	19.9%	9.0%	2.9%	2.2%	0.0%
2016	5.7%	1.5%	20.3%	13.9%	8.7%	17.9%	15.1%	11.9%	3.5%	1.7%	0.0%
2017	10.9%	1.7%	14.5%	13.6%	8.3%	20.1%	19.2%	10.6%	0.0%	0.0%	1.1%
2018	8.5%	2.6%	11.5%	16.3%	2.4%	31.3%	18.4%	5.3%	0.0%	2.6%	1.1%
2019	4.6%	5.1%	19.7%	16.6%	2.3%	24.7%	18.1%	5.5%	3.6%	0.0%	0.0%
Average	6.2%	3.6%	16.1%	16.1%	3.7%	16.7%	18.5%	14.1%	2.7%	1.9%	0.3%
Max	11.5%	6.2%	24.4%	21.6%	8.7%	31.3%	22.2%	23.5%	6.3%	5.7%	1.1%
Min	0.9%	0.0%	9.0%	9.2%	1.5%	10.9%	13.4%	5.3%	0.0%	0.0%	0.0%

Overall, the four-screen strategy is dominated by Industrials, Consumer Discretionary, Health Care, Financials and Information Technology (IT) companies. This is not surprising, knowing these sectors are the largest sectors in the U.S. stock market, both in terms of number of listed stocks and market cap (Table 5.2). However, while IT is close to the largest sector in the U.S., the four-screen strategy has lower exposure to the sector, particularly during the second half of the investment period. Note that the exposure is only around 5-6% in 2018-2019. This might be a result of high growth expectations and the sector's strong run-up after the financial crisis, lifting the P/B above 1. Overall, Financials is the largest sector,

while Real estate, Telecommunication Services and Utilities are underweighted. The latter two sectors are considered to be defensive, which often yields lower gains during market upturns. Thus, the four-screen appears to be tilted towards cyclical stocks.

Looking at the average exposure to sectors throughout the sample period, the strategy is fairly well diversified across the largest sectors in the world, which would indicate high market risk. There are, however, some large yearly diversions, which could indicate otherwise. For example, in 2018 the exposure to Health Care is 31.3%, compared to the IT exposure of 5.3%. Also note the large exposure to Industrials before the financial crisis in 2007. This indicates periods of high unsystematic sector risk.

7.2.2 Six-screen strategy

Like the four-screen strategy, the overview of stocks meeting all screens are calculated based on all stocks on NYSE, AMEX and Nasdaq where CCM provides sufficient data for all screens to be calculated. In other words, for a firm to be included in the sample, data on book value of equity, liabilities, revenue, EBITDA, and price close must be available. Additionally, remember that the sample is filtered on positive book value of equity and firms with a market cap above USD 20 million, as introduced in Section 6.2. This explains why the "Total companies" figures in Table 7.10 differs from Table 7.7.

Table 7.10

Overview of all stocks and percentage of stocks meeting filter rules of the six-screen strategy

Year	Total companies	Price-to-book		Debt-to-equity		3-year revenue growth		EBITDA-margin		Change in EBITDA-margin		Change in RSR		All filters	
	#	#	%	#	%	#	%	#	%	#	%	#	%	#	%
2000	3913	2735	70%	2843	73%	3214	82%	2753	70%	355	46%	1961	50%	355	9%
2001	3731	2517	67%	2748	74%	2926	78%	2552	68%	235	40%	1675	45%	235	6%
2002	3595	2485	69%	2688	75%	2601	72%	2571	72%	317	51%	1714	48%	317	9%
2003	3552	2696	76%	2693	76%	2387	67%	2598	73%	309	50%	1625	46%	309	9%
2004	3448	3023	88%	2690	78%	2471	72%	2616	76%	466	55%	1720	50%	466	14%
2005	3283	2900	88%	2590	79%	2697	82%	2499	76%	472	49%	1622	49%	472	14%
2006	3092	2759	89%	2439	79%	2655	86%	2375	77%	429	49%	1524	49%	429	14%
2007	2974	2626	88%	2307	78%	2521	85%	2260	76%	421	49%	1499	50%	421	14%
2008	2878	2083	72%	2172	75%	2353	82%	2169	75%	283	44%	1372	48%	283	10%
2009	2815	1887	67%	2139	76%	1917	68%	2146	76%	228	50%	1271	45%	228	8%
2010	2779	2182	79%	2143	77%	1757	63%	2266	82%	338	60%	1368	49%	338	12%
2011	2693	2090	78%	2070	77%	1757	65%	2186	81%	285	50%	1337	50%	285	11%
2012	2565	1986	77%	1920	75%	1985	77%	2087	81%	281	50%	1211	47%	281	11%
2013	2523	2101	83%	1867	74%	1999	79%	2062	82%	300	50%	1199	48%	300	12%
2014	2486	2121	85%	1837	74%	1853	75%	2019	81%	306	51%	1247	50%	306	12%
2015	2444	1975	81%	1753	72%	1747	71%	1939	79%	259	52%	1151	47%	259	11%
2016	2402	1913	80%	1699	71%	1632	68%	1894	79%	209	51%	1149	48%	209	9%
2017	2413	1979	82%	1720	71%	1635	68%	1913	79%	223	50%	1174	49%	223	9%
2018	2407	1939	81%	1719	71%	1783	74%	1878	78%	240	51%	1165	48%	240	10%
2019	2368	1852	78%	1584	67%	1862	79%	1831	77%	206	48%	1134	48%	206	9%
Average	2918	2292	79%	2181	75%	2188	75%	2231	77%	308	50%	1406	48%	308	11%
Median	2797	2111	79%	2141	75%	1992	74%	2177	77%	292	50%	1352	48%	292	10%
Max	3913	3023	89%	2843	79%	3214	86%	2753	82%	472	60%	1961	50%	472	14%
Min	2368	1852	67%	1584	67%	1632	63%	1831	68%	206	40%	1134	45%	206	6%

There are 308 firms, or 11% on average that meet the six filters every quarter, a higher percentage compared to the four-screen strategy, even though there are two more filters. The main reason is that the four-screen strategy filters P/B and shares outstanding are stricter than any filters in the six-screen strategy. Further, the number of firms meeting all filters vary greatly across the time period from 14% down to 6% in 2001. Opposed to the four-screen, which triggered most buy signals the first half of the time horizon, the trend is less clear for the six-screen, but one could argue that the strategy triggers more buy signals in years following market downturns.

The P/B numbers move as expected, where it decreases during downturns and increases after, opposite of the four-screen. The percentage of firms having D/E below 2 decreases over the period, indicating that firms on average use more equity as a source of financing, as opposed to debt. The three-year revenue growth rate has a cyclical pattern, where it rebounds after periods of low growth and vice versa. The EBITDA margin is relatively low the first four years and stable for the residual period, suggesting that firms have improved their profitability after the dot-com bubble. The change in EBITDA, on the other hand, drops during the dot-com bubble and financial crisis.

Based on the percentage of firms meeting all screens, the six-screen strategy appears more cyclical than the four-screen strategy. There are considerably fewer firms, only 6-9%, meeting all screens during the dot-com bubble and the financial crisis. For periods of economic prosperity, however, the same number raises to 12-14%, which could be due to the six-screen strategy's fundamental filters, namely the D/E, revenue growth and EBITDA filters. This might result in a strategy with fewer firms that are vulnerable to downturns and less volatility in returns.

Table 7.11 presents the stock exchange composition among the shares that meet all screens in the six-screen strategy. The numbers are presented as average per quarter each year. Once again, No.% represents the percentage of total stocks meeting the six screens listed on the exchanges, while M.Cap% represents the percentage of total market capitalization of the stocks that meet all four screens per exchange.

Table 7.11

Quarterly average number of companies and market capitalization of the six-screen strategy by stock exchange

	Total			NYSE				AMEX				Nasdaq			
Year	Total No.	Average	Median	No.%	M.Cap%	Average	Median	No.%	M.Cap%	Average	Median	No.%	M.Cap%	Average	Median
2000	355	4,623	574	40%	76%	8,854	1,557	4%	0.8%	902	83	56%	23%	1,804	313
2001	235	3,367	428	32%	47%	5,034	1,172	5%	0.5%	299	163	62%	53%	2,517	290
2002	317	4,148	554	40%	81%	8,521	1,455	4%	0.1%	131	94	56%	19%	1,415	290
2003	309	4,278	643	35%	72%	9,324	1,857	6%	0.7%	572	82	60%	27%	1,968	408
2004	466	4,075	781	38%	72%	7,683	1,939	6%	0.6%	453	93	55%	27%	1,930	427
2005	472	4,649	781	40%	78%	9,101	2,369	5%	0.3%	292	81	55%	22%	1,960	423
2006	429	5,508	801	43%	85%	10,986	2,284	6%	0.5%	385	94	51%	15%	1,493	426
2007	421	5,881	834	41%	73%	10,563	3,142	6%	0.3%	282	90	53%	27%	2,772	485
2008	283	4,949	600	40%	73%	9,212	1,606	5%	0.2%	152	48	55%	27%	2,475	391
2009	228	5,216	942	34%	48%	7,016	2,710	4%	0.1%	139	88	62%	51%	4,538	587
2010	338	6,355	1,046	36%	76%	13,569	2,845	4%	0.1%	242	86	60%	24%	2,523	687
2011	285	6,434	1,086	39%	69%	11,495	3,104	4%	0.1%	261	113	57%	31%	3,683	761
2012	281	6,657	1,060	42%	59%	9,563	2,860	3%	0.1%	200	67	54%	40%	5,022	647
2013	300	8,267	1,481	43%	75%	15,071	3,712	3%	0.1%	199	96	54%	25%	3,658	956
2014	306	10,398	1,849	45%	67%	15,424	4,453	3%	0.2%	466	119	51%	33%	7,249	1,120
2015	259	8,556	1,366	40%	51%	10,702	3,246	3%	0.0%	124	113	57%	49%	7,738	938
2016	209	7,012	1,529	39%	59%	10,577	2,938	5%	0.1%	218	129	56%	41%	5,213	956
2017	223	12,969	2,333	40%	51%	16,460	5,460	3%	0.1%	274	176	57%	49%	11,586	1,531
2018	240	10,430	1,750	39%	64%	17,010	3,504	4%	0.1%	238	149	57%	36%	6,550	1,216
2019	206	12,496	2,612	46%	68%	18,235	5,168	4%	0.1%	178	135	50%	32%	8,794	1,672
Average	308	6,813	1,153	40%	67%	11,220	2,869	4%	0.3%	300	105	56%	33%	4,244	726
Median	292	6,118	994	40%	70%	10,570	2,853	4%	0.1%	252	94	56%	29%	3,215	617
Max	472	12,969	2,612	46%	85%	18,235	5,460	6%	0.8%	902	176	62%	53%	11,586	1,672
Min	206	3,367	428	32%	47%	5,034	1,172	3%	0.0%	124	48	50%	15%	1,415	290

There are some major differences in the stocks selected by the six-screen strategy compared to those of the four-screen strategy. AMEX stocks never account for more than 0.7% of the market capitalization, and 6% of the number of stocks. Thus, the influence of AMEX companies on the created portfolios is limited. Further, the average and median size of the companies selected by the six-screen strategy is significantly higher than those selected by the four-screen strategy, up to 100 times higher. There are two main reasons for this. The four-screen strategy only selects companies with less than 20 million shares outstanding, and the six-screen strategy does not invest in companies with a market capitalization of less than USD 20 million. Thus, the relevant universe of stocks differs significantly between the strategies.

Lastly, both the percentage number of stocks and market capitalization of NYSE increases almost every year. This participates in increasing the average and median market cap of the total strategy, as NYSE is shown to have the largest companies (Table 5.1). Hence, the strategy is less exposed to size risk than the four-screen strategy. Due to the large fraction of stocks listed on NYSE, the strategy results in both average and median market capitalizations above the overall market in every single year (Table 5.1).

Next up is the six-screen strategy's sector exposure, presented in Table 7.12. With P/B ratios above 1 and a D/E limit of 2, one would expect a different sector exposure from the four-screen strategy. Note that the exposure to a sector is determined by the number of stocks associated with the given sector, similar to Table 7.9.

Table 7.12

Six-screen strategy sector exposure by number of investments (MSCI sector classification)

Year	Energy	Materials	Industrials	Consumer Discretionary	Consumer Staples	Health Care	Financials	Information Technology	Telecom Services	Utilities	Real Estate
2000	3.6%	5.0%	13.2%	19.2%	5.4%	14.6%	16.3%	18.1%	1.9%	2.4%	0.3%
2001	5.2%	3.8%	14.8%	16.8%	3.6%	14.0%	19.1%	18.8%	1.5%	1.8%	0.6%
2002	3.6%	5.0%	12.1%	14.8%	5.3%	12.5%	19.1%	21.6%	2.3%	2.9%	0.7%
2003	3.8%	4.1%	13.4%	15.9%	5.7%	13.1%	17.0%	22.0%	2.2%	2.1%	0.7%
2004	4.0%	5.5%	12.4%	16.6%	5.3%	12.9%	18.8%	19.1%	2.3%	2.3%	0.9%
2005	4.1%	3.6%	15.0%	15.6%	6.0%	13.5%	15.7%	20.0%	2.5%	3.4%	0.7%
2006	4.6%	5.4%	15.4%	13.9%	5.1%	15.0%	17.1%	17.3%	1.9%	3.4%	0.9%
2007	4.4%	4.7%	15.8%	16.0%	5.6%	12.2%	17.2%	17.6%	2.2%	3.3%	1.0%
2008	5.5%	4.2%	16.8%	16.4%	2.7%	14.4%	16.2%	18.0%	1.6%	1.6%	2.6%
2009	6.1%	6.0%	16.5%	12.3%	3.7%	14.7%	19.7%	15.9%	1.2%	3.0%	0.8%
2010	6.6%	5.1%	12.5%	11.0%	3.6%	19.5%	20.0%	17.3%	1.6%	2.4%	0.5%
2011	7.7%	6.8%	15.7%	9.2%	4.1%	14.5%	22.2%	15.3%	1.9%	1.8%	0.7%
2012	8.3%	5.0%	13.6%	13.5%	4.5%	14.7%	19.6%	13.4%	1.9%	4.0%	1.5%
2013	7.9%	5.8%	15.0%	13.0%	4.0%	13.0%	18.3%	17.5%	2.3%	1.8%	1.6%
2014	4.1%	6.9%	14.6%	12.5%	4.2%	14.7%	20.8%	14.7%	2.2%	3.8%	1.6%
2015	3.9%	5.4%	14.7%	12.3%	4.1%	18.0%	21.7%	13.6%	3.1%	1.7%	1.5%
2016	3.7%	3.9%	14.6%	13.8%	2.7%	20.9%	17.5%	15.1%	2.9%	3.9%	1.0%
2017	7.9%	5.4%	14.7%	11.5%	2.1%	19.3%	13.5%	16.6%	4.9%	3.2%	0.9%
2018	5.9%	3.6%	15.9%	7.5%	3.2%	20.0%	18.5%	14.7%	4.8%	3.7%	2.1%
2019	6.6%	4.0%	14.7%	10.3%	2.9%	25.4%	17.7%	8.8%	3.7%	2.7%	3.1%
Average	5.4%	5.0%	14.6%	13.6%	4.2%	15.8%	18.3%	16.8%	2.4%	2.8%	1.2%
Max	8.3%	6.9%	16.8%	19.2%	6.0%	25.4%	22.2%	22.0%	4.9%	4.0%	3.1%
Min	3.6%	3.6%	12.1%	7.5%	2.1%	12.2%	13.5%	8.8%	1.2%	1.6%	0.3%

The same five sectors that weighted the largest in the four-screen, also make up the largest share of the six-screen portfolio. Financials is still the largest sector, with a close to unchanged weighting from the four-screen. According to Damodaran (2021), the sector has an average P/B just above 1, which means that the two strategies probably invest in several of the same stocks, although not at the same time. IT is the second largest, with a 16.8% average weighting, 2.8 pp higher than the four-screen strategy. Three out of the five largest remaining sectors make up lower fractions of the six-screen strategy, while the smaller sectors make up larger fractions, compared to the four-screen. Additionally, the six-screen has a positive exposure to all sectors every year and the gap between the maximum and minimum exposure is smaller for every sector except real estate. Thus, the sector diversification is arguably improved in the six-screen.

The lower average and maximum exposure to Industrials, Consumer Discretionary and Health Care is likely a consequence of the D/E ceiling of 2. The industries are characterized by capital-intensive

businesses with substantial fixed costs associated with property, plant and equipment and R&D. The Energy and Telecommunication sectors are also relatively levered sectors with low exposure in the six-screen. Moreover, the IT exposure is considerable larger after the financial crisis, which could contribute to excess return compared to the four-screen given the strong performance of IT-stocks over the decade.

7.2.3 Section summary

The composition of stocks in the two screen strategies is quite different. The four-screen has stricter filters, hence it executes considerable fewer trades and invest in fewer companies, even though the six-screen utilizes two more filters. The four-screen also shows a declining trend in stocks meeting all filters, while the six-screen has a cyclical pattern. The four-screen invests more in AMEX and Nasdaq listed firms, compared the six-screen where NYSE and Nasdaq are overweighted. The smallest firms, in terms of market cap, is listed on AMEX, meaning that the four-screen invests in more small cap stocks. Overall, both strategies are quite well diversified across all MSCI sectors, however there are large yearly deviations. Financials is the largest sector in both strategies, Health Care is the second largest four-screen sector, while IT is the second largest six-screen sector. Lastly, note that the four-screen reduces the IT exposure significantly towards the end of the period.

7.3 Portfolio holding period returns

This section will present the returns for the four-screen and six-screen strategy. In order to provide a comprehensive view of the performance, the returns are displayed using four different designs. The first is an overview over the returns sorted on buy quarters, an exact copy of Reinganum's (1988) preferred method for comparable benefits. To better present the results of an actual investment, the two strategies are created as portfolios. Then, the annual returns are shown, before the cumulative holding period returns are illustrated. Lastly, the two portfolios' holding period returns after transaction costs are presented. Remember that the four-screen portfolios are formed based on an exact copy of Reinganum's (1988) four investment screens, while the six-screen portfolios are created based on the thesis's analysis of stock market winners between 2000-2019.

7.3.1 Overview of the cumulative return per buy quarter

The four-screen strategy triggered 8,911 buy signals in total, distributed across 2,843 unique companies. The number of buy signals is similar to Reinganum's (1988) number of 10,543 buy signals, but since he

studied a shorter time period, the annual number of buy signals were much higher. The excess holding period return is displayed as an average of every cumulative returns for all stock over the eight-quarter holding period. Hence, Table 7.13 shows the distribution of cumulative excess returns between the time of purchase (buy) and the sell date (buy + 8). The excess return is defined as the difference between the four-screen return and the S&P 500 return over the same time period.

Table 7.13

Distribution of cumulative excess (of S&P 500) holding period returns from the four-screen strategy

Quarter	Average	1st	5th	10th	25th	50th	75th	90th	95th	99th
Buy+1	3.6%	-72.0%	-43.6%	-30.6%	-12.1%	1.7%	16.0%	40.3%	62.1%	125.6%
Buy+2	9.0%	-82.1%	-56.3%	-40.3%	-15.8%	5.0%	27.1%	61.0%	96.1%	214.1%
Buy+3	14.7%	-85.6%	-63.3%	-45.5%	-16.9%	8.9%	35.5%	80.8%	131.0%	282.3%
Buy+4	21.4%	-87.4%	-66.6%	-48.5%	-16.9%	13.0%	44.0%	99.7%	158.1%	348.4%
Buy+5	28.6%	-89.9%	-69.8%	-50.8%	-17.9%	16.5%	55.3%	120.6%	190.8%	442.6%
Buy+6	34.6%	-92.2%	-70.6%	-52.7%	-16.1%	21.3%	63.6%	136.7%	217.3%	523.5%
Buy+7	40.6%	-93.4%	-73.1%	-54.2%	-15.6%	26.3%	72.5%	156.2%	258.8%	520.9%
Buy+8	45.9%	-94.0%	-73.9%	-55.6%	-15.1%	30.0%	81.7%	174.7%	284.2%	588.9%

Looking at the average cumulative return per stock, the four-screen strategy produces an impressive result compared to the S&P 500. The one-year average cumulative excess return for all stocks is 21.4% and 45.9% after two years. The performance is superior to Reinganum's (1988) results of 37.1% after two years and close to the cumulative excess return of 50.7% generated by Reinganum's (1988) nine-screen strategy. The median gain after two years is 30%, implying that the majority of stocks generate excess returns before sale. Another interesting observation is the 1st percentile return, which is much lower than Reinganum's (1988) 1st percentile, indicating that several firms go bankrupt or experience severe financial distress over the holding period.

Table 7.14 displays the distribution of the cumulative excess (of S&P 500) holding period returns from the six-screen strategy. The six-screen generated 24,970 buy signals across 3,754 unique companies, much more than the four-screen. Put in perspective, Reinganum's (1988) four-screen generated 10,543 buy signals between 1970-1983, seven years less than the thesis' sample period, and over a sample of companies which was about 20% of the thesis' sample of companies.

Table 7.14

Distribution of cumulative excess (of S&P 500) holding period returns from the six-screen strategy

Quarter	Mean	1st	5th	10th	25th	50th	75th	90th	95th	99th
Buy+1	1.4%	-45.6%	-28.5%	-21.0%	-10.2%	0.1%	11.0%	24.2%	35.4%	66.6%
Buy+2	2.7%	-58.0%	-38.3%	-28.8%	-14.4%	-0.2%	15.8%	34.9%	51.9%	101.2%
Buy+3	3.5%	-66.1%	-45.1%	-34.3%	-17.9%	-0.6%	18.7%	42.9%	64.5%	127.8%
Buy+4	4.5%	-71.9%	-49.7%	-39.1%	-20.2%	-0.8%	20.8%	49.7%	75.3%	149.6%
Buy+5	5.6%	-76.6%	-54.5%	-42.7%	-22.1%	-0.9%	23.4%	55.9%	83.2%	174.9%
Buy+6	6.8%	-80.1%	-58.1%	-45.6%	-23.8%	-0.8%	25.9%	62.1%	94.5%	192.6%
Buy+7	8.1%	-83.4%	-61.2%	-48.3%	-25.5%	-0.7%	28.3%	68.0%	104.6%	212.4%
Buy+8	9.1%	-86.0%	-64.6%	-50.6%	-26.6%	-0.5%	30.6%	72.1%	110.2%	235.1%

The average cumulative excess returns for all stocks were 9.1% over the holding period of two years. While an average excess return per investment of 9.1% over a two-year period is noteworthy, it is still significantly lower than the four-screen. The six-screen, however, has fewer outlier returns, likely because the six-screen ignores stocks with lower than 20 million in market capitalization. The D/E filter could also contribute to less volatility in returns by avoiding the riskiest stocks.

7.3.2 Annual returns

Next up is a summary of the annual returns between 2000 and 2019 for the equal-weighted (EW) and value-weighted (VW) portfolios. The returns are compared to the S&P 500 and the market portfolio, which are widely used benchmark indexes for the U.S. equity market. Note that the S&P 500 consists of 500 large companies, while the market portfolio includes a much wider selection of stocks and are therefore not perfectly comparable to the strategies.

7.3.2.1 Equal-weighted portfolios

Table 7.15 below illustrates the annual returns, arithmetic and geometric mean, standard deviation and the number of positive return years for the EW four-screen and EW six-screen strategy. The S&P 500 and market portfolio are also included for benchmark performance purposes. Annual returns are derived by assuming that every position is rebalanced monthly, entailing that yearly returns are equivalent of the cumulative average monthly return of all stocks.

Table 7.15

Annual returns for the EW portfolios

Years	Four-screen	Six-screen	S&P 500	Market
2000*	-19.5%	-7.8%	-10.8%	-15.1%
2001	40.3%	14.1%	-11.9%	-11.4%
2002	7.8%	-14.5%	-21.8%	-21.1%
2003	86.8%	49.6%	28.7%	31.8%
2004	35.3%	20.0%	11.0%	11.9%
2005	5.5%	11.5%	5.2%	6.1%
2006	26.0%	16.6%	15.7%	15.4%
2007	-11.3%	4.2%	5.7%	5.7%
2008	-56.3%	-37.7%	-36.5%	-36.7%
2009	50.7%	45.8%	26.5%	28.3%
2010	28.4%	30.3%	15.2%	17.5%
2011	-9.3%	-0.2%	1.8%	0.5%
2012	32.0%	16.9%	16.1%	16.3%
2013	48.0%	40.9%	32.5%	35.2%
2014	6.8%	6.7%	13.5%	11.7%
2015	-5.1%	-2.9%	1.5%	0.1%
2016	22.0%	21.7%	11.8%	13.5%
2017	7.6%	19.2%	22.0%	22.3%
2018	-23.9%	-9.8%	-4.5%	-5.1%
2019	6.3%	25.8%	31.5%	30.4%
Arithmetic mean	10.6%	11.7%	7.0%	7.2%
Geometric mean	9.4%	10.6%	6.1%	6.2%
Standard deviation	18.3%	18.2%	14.4%	15.1%
Max return	86.8%	49.6%	32.5%	35.2%
Min return	-56.3%	-37.7%	-36.5%	-36.7%
Positive years	14	14	15	15
Negative years	6	6	5	5

*2000 returns are calculated based on Q2-Q4 data, since the first reported portfolio return is ultimo Q2

The geometric mean is 9.4% for the four-screen and 10.6% for the six-screen, 3.3 pp and 4.5 pp better than the S&P 500, respectively. Thus, both portfolios significantly outperform the S&P 500 over the 20-year period and the six-screen is the best performer. This seems to be in contrast with the results from Table 7.13 and Table 7.14. The explanation is that the respective tables show the average return for all stocks 1-8 quarters after buy, which for instance implies that buy+2 returns are an average of cumulative two-quarter returns of every single investment generated in every quarter ranging from 2000 Q3 until 2019 Q3. Thus, the impact of negative returns from market downturns will be evened out from positive returns in market upturns. However, when a portfolio is constructed based on the strategies, most of the negative returns are suffered in the same period. For the four-screen, the negative returns are diluted when looking at the buy quarter averages, because the strategy holds fewer stocks, and thus fewer

negative returns, compared to studying the portfolio holding period return, where most of the negative returns occurs at the same time.

For most of the years, the two portfolios generate negative returns over the same years as the benchmarks. However, especially in 2001 and 2002, when the market decreases in light of the dot-com crash, the four-screen sees large yearly gains of 40% and 8%. Moreover, both portfolios outperform the market, but the extra return comes at a price, namely higher risk exemplified by a standard deviation of 18.3% and 18.2%, versus 14.4% and 15.1% for the two benchmarks. The higher risk is also particularly evident after studying the maximum and minimum returns for the four-screen portfolio, ranging from +87% in 2002 and -56% in 2008. The maximum return for the six-screen portfolio is 50%, also much higher than the benchmarks, yet the minimum return of -37.7% is in-line with the benchmarks.

7.3.2.1 Value-weighted portfolios

The same statistics that are shown in Table 7.15 are illustrated for the VW portfolios in Table 7.16 but note that the value-weighted portfolios are rebalanced quarterly. Remember that the four-screen and six-screen holds on average 900 and 2,400 investments per year, respectively, so value-weighting the returns after market cap could alter the results.

Table 7.16

Annual returns for the VW portfolios

Years	Four-screen	Six-screen	S&P 500	Market
2000*	-5.8%	-18.5%	-10.8%	-15.1%
2001	35.1%	-12.6%	-11.9%	-11.4%
2002	3.6%	-20.3%	-21.8%	-21.1%
2003	63.4%	26.8%	28.7%	31.8%
2004	25.7%	11.1%	11.0%	11.9%
2005	2.3%	7.6%	5.2%	6.1%
2006	23.6%	13.5%	15.7%	15.4%
2007	-1.3%	14.8%	5.7%	5.7%
2008	-49.3%	-31.0%	-36.5%	-36.7%
2009	20.6%	33.1%	26.5%	28.3%
2010	23.9%	14.5%	15.2%	17.5%
2011	-10.7%	5.5%	1.8%	0.5%
2012	23.5%	15.1%	16.1%	16.3%
2013	37.8%	32.1%	32.5%	35.2%
2014	4.7%	12.8%	13.5%	11.7%
2015	-11.6%	-2.0%	1.5%	0.1%
2016	29.0%	10.0%	11.8%	13.5%
2017	5.7%	32.4%	22.0%	22.3%
2018	-17.3%	-3.4%	-4.5%	-5.1%
2019	17.1%	31.7%	31.5%	30.4%
Arithmetic mean	9.5%	7.9%	7.0%	7.2%
Geometric mean	8.2%	7.1%	6.1%	6.2%
Standard deviation	17.9%	14.4%	14.4%	15.1%
Max return	63.4%	33.1%	32.5%	35.2%
Min return	-49.3%	-31.0%	-36.5%	-36.7%
Positive years	14	14	15	15
Negative years	6	6	5	5

*2000 returns are calculated based on Q2-Q4 data, since the first reported portfolio return is ultimo Q2

After value-weighting the portfolios, the results differ substantially from the EW portfolio. The annual return averages 9.5% for the four-screen and 7.9% for the six-screen, close to the market's average of 7.2%. Interestingly, both screen portfolios perform worse when value-weighting returns, however the four-screen only drops 1.1 pp on average, opposed to the six-screen which sees a drop of 3.8 pp. The overall trend seems to be that the returns follow the market more closely, with less extreme positive and negative annual returns. Especially in 2001, the VW six-screen underperforms the EW, with a return of -12.6%, closer to the S&P 500. The four-screen also exhibits some notable differences in 2018 and 2019 where the VW portfolio outperforms the EW. However, the four-screen still performs worse than the six-screen and the market over these two years.

The estimated standard deviation for the six-screen drops parallelly with the annual return down to 14.4%, approximately the same as the S&P 500. This is not surprising as the larger and traditionally less volatile companies accounts for a larger share of the portfolio. The standard deviation of returns for the four-screen, however, is close to unchanged, only down 0.3 pp to 17.9%. The four-screen singles out companies with fewer than 20 million shares outstanding. This could explain why the difference in the EW and VW four-screen portfolio returns are smaller than the difference between the six-screen portfolio returns, as the effect of value-weighting the four-screen portfolio is diluted due to the tilt towards small cap stocks.

7.3.3 Portfolio cumulative holding period return

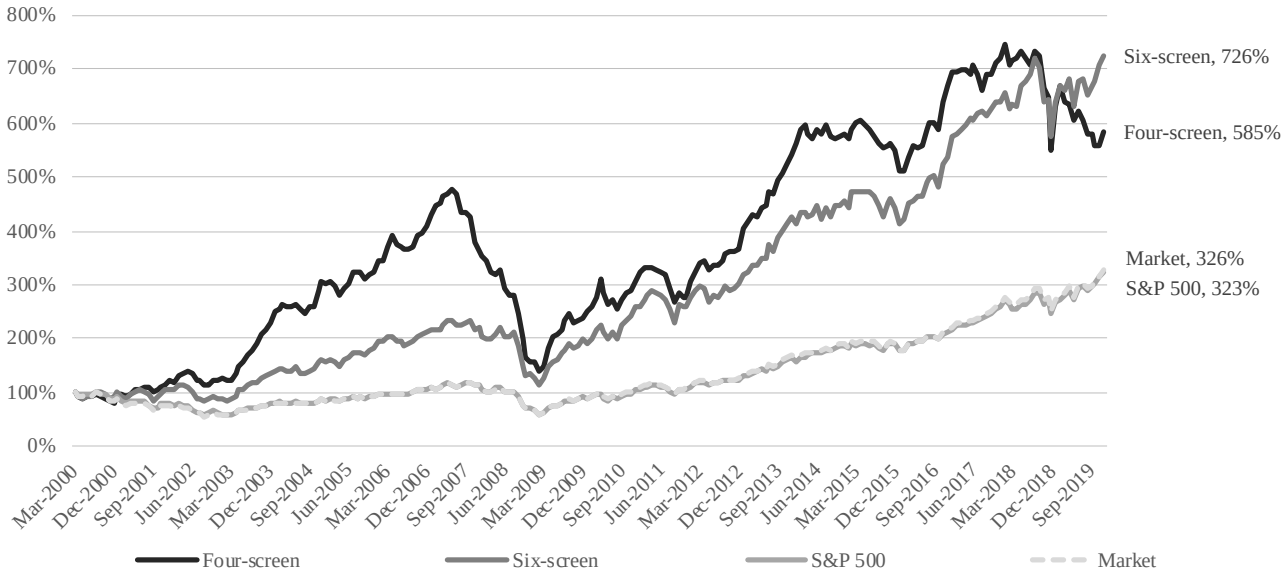
To improve the perception of how the strategies perform over time, the cumulative performance for the EW and VW portfolios is presented for the entire 2000-2019 period. Both sections will address the raw holding period return indexed to 100% in March 2000 and the holding period return after transaction costs. The latter is relevant since investors generally take transaction costs into account when calculating returns. Again, the S&P 500 is used as a benchmark for the U.S. stock market to easier asses the relative performance.

7.3.3.1 Equal-weighted portfolios

Figure 7.1 presents the cumulative holding period returns of the EW portfolios, together with the market portfolio and S&P 500. Note that the portfolios are indexed at 100%, meaning that the ending cumulative holding period return is 100% higher than the realized return on the investment.

Figure 7.1

EW portfolio indexed cumulative holding period returns

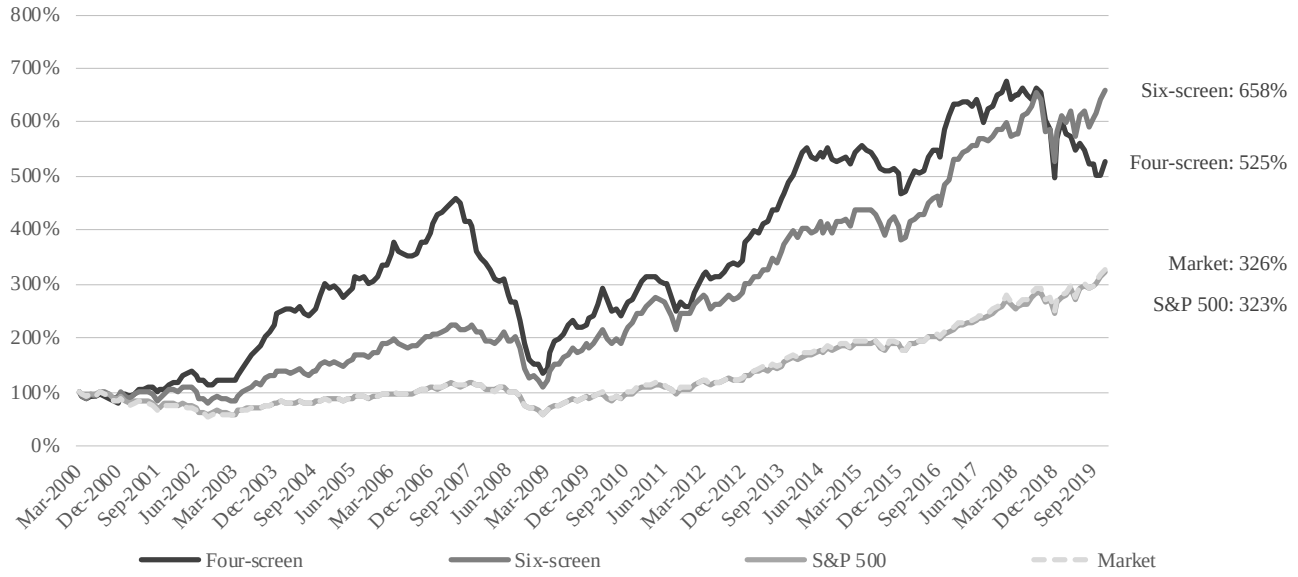


As seen from Figure 7.1, the EW four-screen and EW six-screen portfolios severely outperform the S&P 500 over the 20-year period, with a cumulative holding period return of 485% and 626%, respectively. As stated above, the four-screen seems rather unaffected by the dot-com bubble, before declining considerably during the financial crisis. The six-screen saw a more gradual outperformance before the financial crisis and dropped approximately the same as the market during the downturn. After the crisis, both strategies gained traction much faster than the S&P 500 and followed suit until after the US-China trade war in 2018, where the six-screen outperformed. The six-screens heavier exposure to growth stocks, led by the IT-sector is a possible explanation. Additionally, the large fluctuations strengthen the beliefs that both strategies are associated with excessive risk compared to the market.

To simulate what returns an investor would get by constructing portfolios based on the strategies, the returns are calculated after transaction costs, presented in Figure 7.2. As discussed in Section 6.6, the portfolio is rebalanced monthly to secure an equally weighted portfolio and transaction costs are assumed to be 20 basis points every year. Thus, the impact of transaction cost is larger during the intersection between quarters, since shares are traded quarterly. Portfolio sensitivity to transaction costs is discussed further in Section 8.2.3.

Figure 7.2

EW indexed cumulative holding period returns after transaction costs



If an investor invested USD 1 million in the six-screen strategy, the equity would have compounded to USD 6.58 million in Q4 2019 after transaction costs, translating into a holding period return of 558%. That is close to twice what the investor would have gained by investing in an instrument that follows the S&P 500 and 25% more than the four-screen. Thus, when adjusting for transaction costs the holding period return drops 68 pp for the six-screen and 60 pp for the four-screen. Accordingly, the four-screen is slightly more sensitive to transaction costs, which is explained by the higher volatility in returns, which call for higher transaction costs when rebalancing the portfolio. Note also that if an investor allocated USD 1 million to the four-screen portfolio, the investor would have to see the equity value decline from USD 4.5 million in July 2007 to USD 1.3 million just 1 ½ years later. That is close to the initial investment of USD 1 million and illustrates the risk of the strategy which is elaborated on in Section 7.4.

7.3.3.2 Value-weighted portfolios

Figure 7.3 presents the cumulative holding period returns of the VW portfolios before transaction costs, together with the market portfolio and S&P 500.

Figure 7.3

VW portfolio indexed cumulative holding period returns

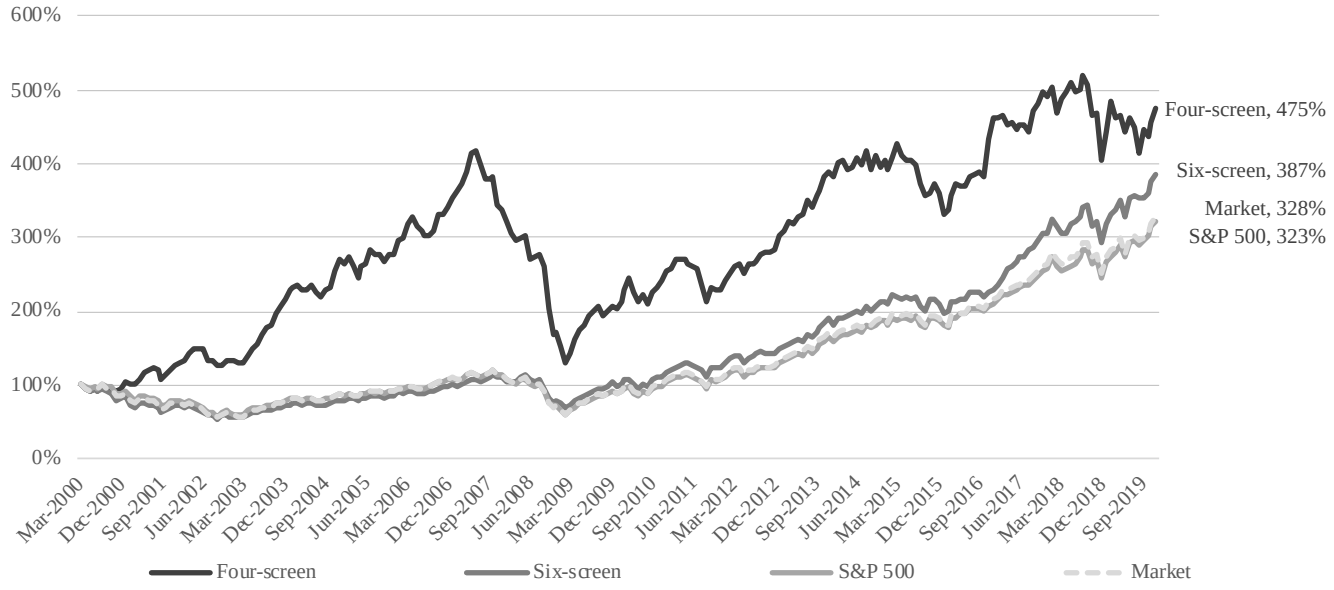


Figure 7.3 shows that the VW four-screen and VW six-screen portfolios outperform the market, with a holding period return of 375% and 287%, respectively. However, the holding period return is less impressive than what the EW portfolios show, especially for the six-screen which sees a significantly lower return over the 20-year period. The six-screen slightly underperforms the market the first half of the investment period, but performs better in the second half, and finishes the investment period with an all-time high cumulative return. Overall, the six-screen follows the market closely when value-weighting returns. The performance of the VW four-screen portfolio, however, is not so different from the EW portfolio. The return is accelerating significantly in the first half of the investment period, before dropping almost 300 pp in 2008. The second half of the period is also similar to the EW portfolio, but with higher returns the last two years.

Figure 7.4 presents the cumulative holding period returns of the VW portfolios after transaction costs. Transaction costs are still assumed to be constant at 20 bps per year.

Figure 7.4

VW indexed cumulative holding period returns after transaction costs

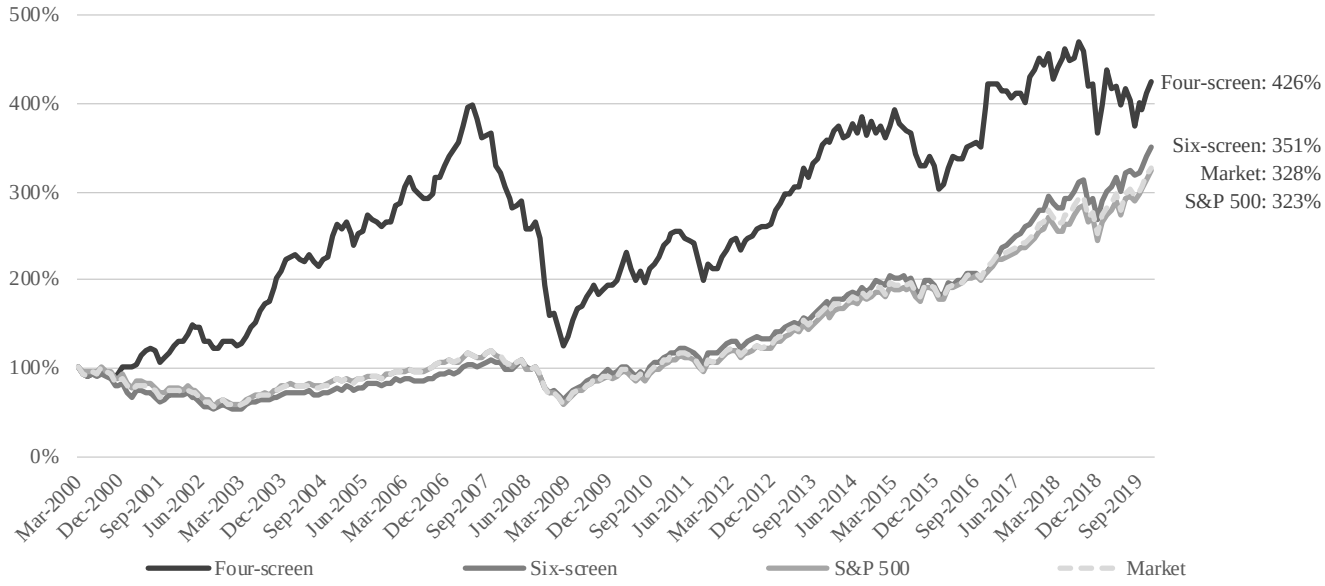


Figure 7.4 shows that if the investor invested USD 1 million in the VW four-screen portfolio, the portfolio would increase the equity value to USD 4.26 million over 20-years, more than what the investor would gain by investing in the six-screen portfolio. The six-screen compounds the value to USD 3.51 million, still better than the S&P 500, but not by the same margin. The VW portfolios rebalances quarterly, when new shares are bought and sold, meaning that the total transaction costs are lower than for the EW portfolios. Yet, the EW still outperforms the VW portfolios. Thus, if the investor chooses portfolios solely based on optimizing returns, the EW portfolios are superior, led by the six-screen. However, if VW portfolios are preferred, the four-screen is the best choice, based on returns.

7.3.4 Section summary

Based on Reinganum's (1988) method of presenting returns, the four-screen sees considerably higher returns than the six-screen. However, when plotting the cumulative returns over the investment period, the EW six-screen portfolio outperforms the EW four-screen portfolio and the market significantly, with a cumulative return of 626%, compared to 485% and 228%, respectively. After adjusting for transaction costs, the same numbers drop to 558% and 425%, still creating significant value for the investor. The conclusions change when estimating the VW portfolio returns, where the four-screen outperforms the

six-screen and the market with a cumulative return of 375%, versus 287% and 228% respectively. After adjusting for transaction costs, the six-screen delivers returns close to the market of 251%, while the four-screen delivers 326%. Thus, both EW portfolios outperform the VW portfolios, however, there are large differences in volatility between the portfolios. The estimated risk in the EW portfolios is close to identical, but higher than the market. The estimated VW four-screen portfolio risk is comparable to the EW portfolios. However, the VW six-screen, which showed the lowest return also showed the lowest risk out of all portfolios, including the market and the S&P 500.

7.4 Performance measures

All portfolios have outperformed the market and S&P 500 over the sample period. However, all portfolios, with the exception of the VW six-screen, have displayed indications of high volatility in returns. Hence, to conclude about the performance, it is critical to assess the risk-adjusted return, to see whether the investors are compensated for the higher risk of the portfolios. To enhance the understanding of the portfolios' performance, the S&P 500 and market is still included as benchmarks. As described in Section 6.8, there are several measures of performance, which all will be presented to secure an optimal outline of the performance, starting off with the EW portfolios.

7.4.1 Equal-weighted portfolios

Table 7.17 illustrates the performance measures for the EW four-screen and six-screen portfolios before and after transaction costs.

Table 7.17

Performance measures for the EW portfolios

	Four-screen		Six-screen		S&P 500	Market
	Before TC	After TC	Before TC	After TC		
Arithmetic mean	10.6%	10.1%	11.7%	11.2%	7.0%	7.2%
Geometric mean	9.4%	8.8%	10.6%	10.0%	6.1%	6.2%
Excess return	7.8%	7.2%	9.0%	8.4%	4.5%	4.6%
Standard deviation	18.3%	18.3%	18.2%	18.2%	14.4%	15.1%
Market beta	0.89	0.89	1.13	1.13	0.95	1.00
Beta p-value	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	-
Unsystematic risk	12.5%	12.5%	6.5%	6.5%	1.69%	-
Sharpe ratio	0.50	0.47	0.56	0.53	0.38	0.37
Treynor ratio	0.10	0.10	0.09	0.09	0.06	0.06
Sortino ratio	0.70	0.66	0.79	0.75	0.49	0.50
Alpha to market	4.1%	3.6%	3.9%	3.4%	0.1%	-
Alpha p-value	*0.27*	*0.21*	*0.01*	*0.02*	*0.77*	-
Information ratio	0.33	0.29	0.59	0.52	0.07	-
Max drawdown	71%	71%	51%	51%	50%	50%
Skewness	-0.15	-0.15	-0.46	-0.46	-0.63	-0.63
Kurtosis	2.15	2.15	1.12	1.12	1.15	0.98

Studying the performance of the four EW portfolios, the standard deviations of 18.3% and 18.2% are considerably higher than the S&P 500's and the market's estimates of 14.4% and 15.1%, respectively. Thus, the higher returns come at a price of higher risk for the investor. However, adjusting for the excess return and risk, both strategies still deliver Sharpe ratios above the benchmarks. Thus, the strategies not only generate higher excess returns than the S&P 500, but also higher risk-adjusted excess returns. This holds both before and after transaction costs, which causes a 0.03 Sharpe ratio drop for both strategies. Both with and without transaction costs, the six-screen's Sharpe ratio is superior, thus assuming that an investor could only hold one portfolio, the six-screen is the optimal choice.

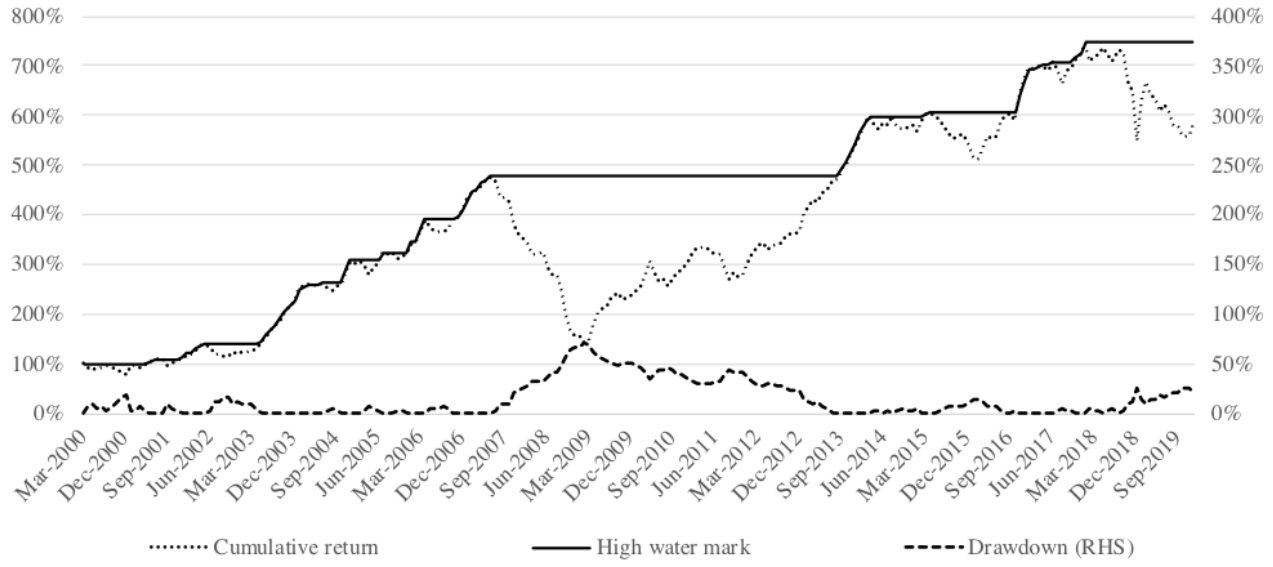
Standard deviation is a measure of each portfolio's total risk, however, some investors aim most of their attention towards the systematic risk, measured by the market beta. Despite the strategies higher excess returns, the betas are 0.89 and 1.13, close to the market beta of 1. Consequently, the Treynor ratios are almost twice the S&P 500's ratio. However, the unsystematic risk is considerable, making the ratio less relevant. Another extension of the Sharpe ratio is the Sortino ratio, which only considers the payoff between the excess return and downside risk. The Sortino ratio, as the Sharpe ratio, estimates a higher ratio for the two strategies. However, the difference between the four-screen and six-screen's Sortino ratios is larger, which indicates larger downside risk in the four-screen EW portfolios.

The four-screen portfolio generates alpha of 3.6% after transaction costs, 0.2 pp above the six-screen. However, the four-screen's high alpha p-value is statistically insignificant which suggests that the estimate of alpha is noisy and therefore could be a result of luck (Pedersen, 2015). The six-screen portfolio, however, has a statistically significant alpha before and after transaction costs, indicating that the alpha is positive and reliably estimated. The significant alpha defies the CAPM, as the strategy earns returns above the compensation for bearing systematic risk. Adjusting the alpha for unsystematic risk, the six-screen still outperforms with an information ratio of 0.52, compared to the four-screen's estimate of 0.29. The six-screen has considerably lower unsystematic risk, telling the investor that more return is generated from the acquired excess risk.

Plotting the cumulative returns, high water marks (HWM) and drawdowns of the two equal-weighted portfolios before transaction costs show some interesting differences between the two in Figure 7.5. The HWM is the highest cumulative return a portfolio has achieved in the past, and the drawdown is the cumulative loss since losses started (Pedersen, 2015). Notice that the maximum possible value for drawdown (right axis) is 100%, but the axis is extended for illustrative purposes.

Figure 7.5

Cumulative return, high water mark and drawdown for the EW four-screen portfolio



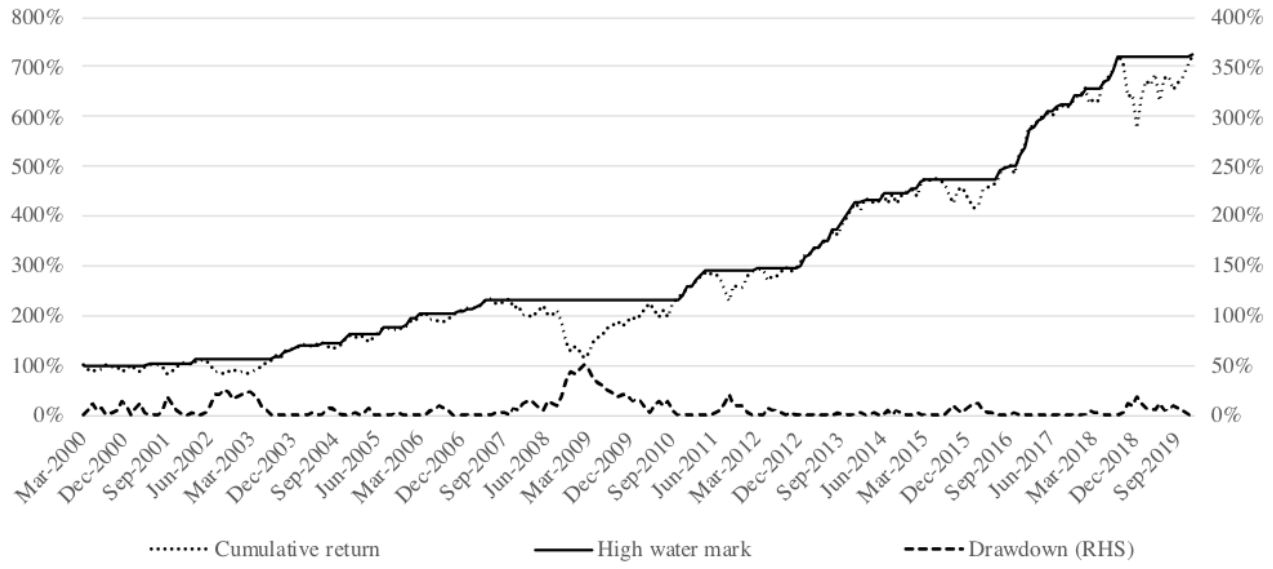
The four-screen portfolio delivers high cumulative return over the time period, but there are time periods where the portfolio is experiencing significant losses. From the time period from portfolio formation in

2000 until mid 2007, the portfolio delivers cumulative returns of almost 500%, more than double that of the six-screen portfolio. The maximum drawdown in this period is 19.1%, where the portfolio experienced four months of negative returns. The entire period of successive drawdown lasts for 11 months from June 2002 until April 2003. However, halfway through 2007, the portfolio experiences severe losses, with negative returns for 18 out of the next 20 months, resulting in a maximum drawdown of 71% in February 2009. A total of six years pass by before the portfolio reaches its previous HWM again in September 2013. The last two years of the investment period results in 15 months with negative returns, resulting in an ending drawdown of 22% from the HWM in January 2018.

Figure 7.6 presents the cumulative return, HWM and drawdown for the EW six-screen portfolio before transaction costs. Once again, note that the maximum possible value for drawdown (right axis) is 100%, but the axis is extended for illustrative purposes.

Figure 7.6

Cumulative return, high water mark and drawdown for the EW six-screen portfolio



As mentioned earlier, the six-screen portfolio delivers even higher cumulative returns. The first lasting period of drawdown starts in May 2002, and persists for 14 months, compared to the 11 months of the four-screen portfolio. After the portfolio reaches its previous HWM, the cumulative return rises steadily until it once again experiences a period of subsequent drawdown in July 2007. The portfolio reaches it maximum drawdown of 51% in February 2009, the same month as the four-screen portfolio. However,

the major difference between the two portfolios except from the difference in maximum drawdown is the time period before the portfolios reaches their HWM again. The six-screen portfolio did so in October 2010, almost three years earlier than the four-screen portfolio. Both portfolios experience a drawdown in February of 2018, but the six-screen portfolio outperforms the four-screen portfolio and ends the time period with a cumulative return at all-time high, in contrast to the four-screen portfolio that ends with a 22% drawdown.

7.4.2 Value-weighted portfolios

Table 7.18 shows the performance measures for the VW four-screen and six-screen portfolios.

Table 7.18

Performance measures for the VW portfolios

	Four-screen		**Six-screen**		**S&P 500**	**Market**
	Before TC	After TC	Before TC	After TC		
Arithmetic mean	9.5%	9.0%	7.9%	7.4%	7.0%	7.2%
Geometric mean	8.2%	7.6%	7.1%	6.6%	6.1%	6.2%
Excess return	6.6%	6.0%	5.5%	5.0%	4.5%	4.6%
Standard deviation	17.9%	17.9%	14.4%	14.4%	14.4%	15.1%
Market beta	0.96	0.96	0.93	0.93	0.95	1.00
Beta p-value	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	-
Unsystematic risk	10.5%	10.5%	3.6%	3.6%	1.69%	-
Sharpe ratio	0.45	0.42	0.44	0.40	0.38	0.37
Treynor ratio	0.08	0.08	0.07	0.06	0.06	0.06
Sortino ratio	0.58	0.54	0.59	0.54	0.49	0.50
Alpha to market	2.6%	2.1%	1.1%	0.6%	0.1%	-
Alpha p-value	*0.28*	*0.39*	*0.16*	*0.43*	*0.77*	-
Information ratio	0.25	0.20	0.32	0.18	0.07	-
Max drawdown	69%	69%	47%	48%	50%	50%
Skewness	-0.74	-0.73	-0.63	-0.63	-0.63	-0.63
Kurtosis	1.68	1.68	0.86	0.86	1.15	0.98

The VW four-screen portfolio has higher risk than the six-screen, where the standard deviation is in-line with the S&P 500 and lower than the market. Despite the higher risk in the four-screen portfolio, the Sharpe ratio is slightly better before and after transaction costs. Thus, the VW four-screen also delivers the highest risk-adjusted return, contrary to EW portfolio, where the six-screen delivered the highest risk-adjusted return. The main reason for the lower Sharpe ratio is lower excess returns alongside the close to unchanged standard deviation between the VW and EW four-screen portfolios. Overall, the EW portfolios delivered higher excess returns and better Sharpe ratios, compared to the VW portfolios.

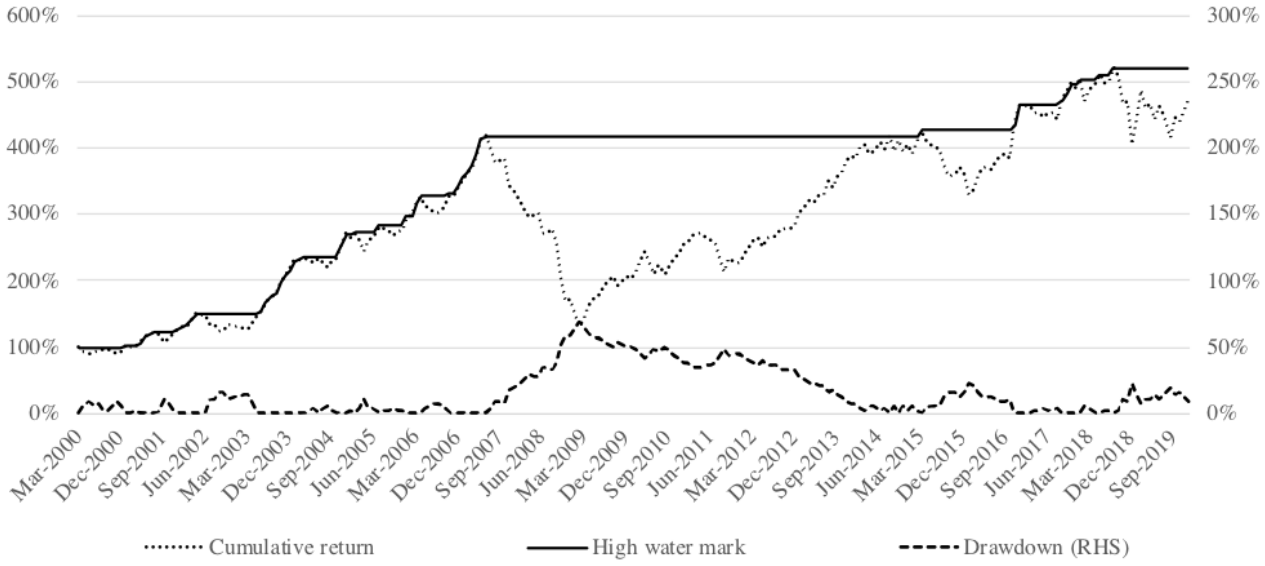
The portfolio betas have moved closer to one after value-weighting and is nearer S&P 500's beta value of 0.95. This is not surprising due to the S&P 500 and market portfolio both being value-weighted. Thus, with a lower return the Treynor ratio has decreased for both strategies, but the four-screen still delivered the highest Treynor ratio. This time, it is driven by higher returns, while the EW portfolio's higher Treynor ratio was due to lower beta. The Sortino ratio, on the other hand, suggests that the six-screen delivers the best risk-adjusted return, despite the notably lower excess return. The reason is the four-screens relatively large volatility in negative returns, while the six-screen has the lowest downside risk out of all portfolios, including the S&P 500 and the market.

Again, the four-screen produces higher alpha than the six-screen, with 2.6% before transaction cost and 2.1% after. The six-screen yielded 1.1% before and 0.6% after transaction cost. However, all alphas for the VW portfolios are insignificant, indicating that the alphas are not reliable. The VW four-screens unsystematic risk is close to the EW portfolio's unsystematic risk, while the VW six-screens unsystematic risk is almost halved from the EW. Hence, the six-screen's information ratio before transaction cost is higher than both the EW and VW four-screen portfolio. However, note that the insignificant alpha deems the information ratio unreliable.

As seen in Figure 7.7, the drawdowns experienced by the VW portfolios are somewhat similar to the EW portfolios. However, there are some noteworthy differences especially in the six-screen portfolios. Note again that the maximum possible value for drawdown (right axis) is 100%, but the axis is extended for illustrative purposes.

Figure 7.7

Cumulative return, high water mark and drawdown for the VW four-screen portfolio

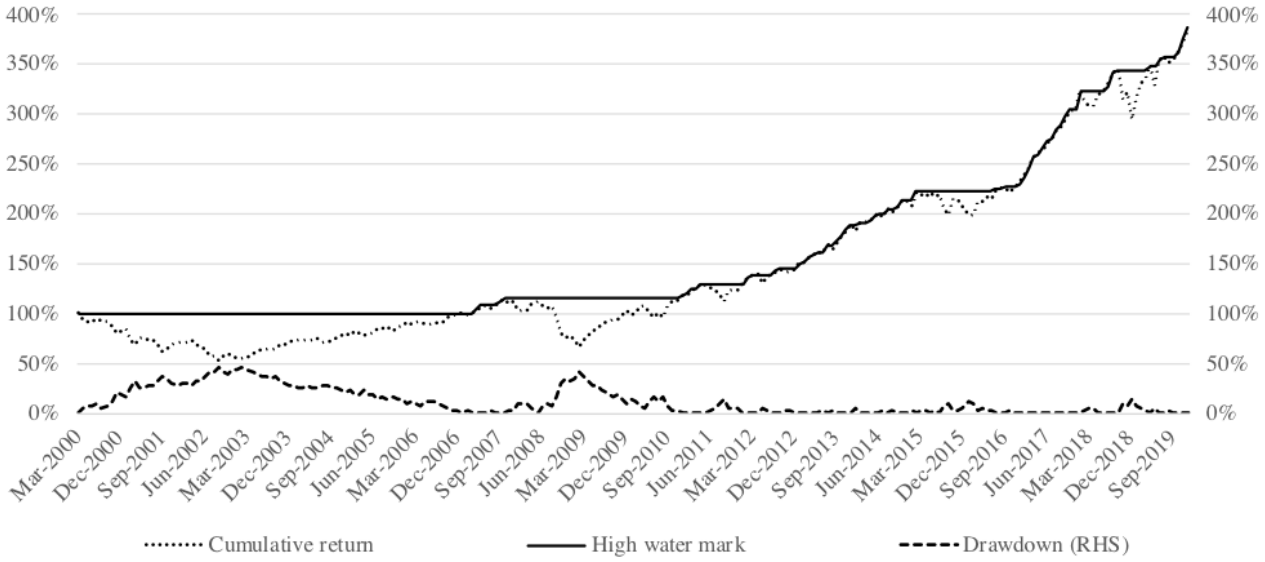


Looking at the plot of the cumulative return, high water mark and drawdown of the VW four-screen portfolio, it seems like the strategy performs somewhat similar to the EW four-screen portfolio with regards to portfolio drawdowns. The VW four-screen portfolio experiences some minor drawdowns in the years preceding the financial crisis. The biggest difference between the portfolios occurs after the financial crisis, where the EW portfolio reaches a new HWM around four years after the losses started, while the VW portfolio needs additional time to recover. First, it takes 11 months longer to recover, but then it experiences another two years of drawdowns. Thus, the VW portfolio sees only a minor increase in the HWM in the 10 years following the downturn.

Figure 7.8 plots the cumulative return, HWM and drawdown of the VW six-screen portfolio, and portrays some notable differences compared to the EW six-screen portfolio. Note again that the maximum possible value for drawdown (right axis) is 100%, but the axis is extended for illustrative purposes.

Figure 7.8

Cumulative return, high water mark and drawdown for the VW six-screen portfolio



The VW six-screen portfolio also shows some major differences compared to the EW portfolio, and performs more like the S&P 500 (Appendix F). While the largest drawdown during the dot-com bubble for the EW strategy was 22.6%, the VW portfolio experiences a drawdown of 46.8%, which is the maximum drawdown for the VW portfolio over the entire period. Thus, while the EW portfolio's maximum drawdown of 50% during the financial crisis is more than twice as high than during the dot-com bubble, the VW portfolio experiences a higher drawdown during the dot-com bubble than the financial crisis. This affects the HWM as well, as seven years pass by before the portfolio delivers any positive cumulative returns. As with the EW portfolio, the VW portfolio recovers from the financial crisis after approximately four years.

7.4.3 Section summary

All measures for risk-adjusted returns show that both EW and VW portfolios perform better than the S&P 500 and the market over the time period. The best performing portfolio is the EW six-screen, based on the Sharpe ratio, Sortino ratio and Information ratio. This was also the only portfolio that produced significant alpha over the investment period. The EW four-screen portfolio was the second-best performer, hence the EW portfolios outperformed the VW portfolios. The VW six-screen, which showed the by far lowest cumulative returns of the portfolios, delivered risk-adjusted returns close to the four-

screen portfolios. This illustrates previous identified trends, that the four-screen portfolios are associated with high risk, where a majority of the risk is categorized as unsystematic risk. This is additionally underlined by the portfolio's drawdowns and HWMs. Both four-screen portfolios stand out with high drawdowns, which consequently causes prolonged periods of negative cumulative returns between each HWM.

7.5 Benchmark performance

This section presents the results from the regressions on the different factor models used for benchmarking. Section 7.5.1 presents the results from the equal-weighted portfolios both in the complete period and in the individual sub-periods. Section 7.5.2 presents the corresponding results for the value-weighted portfolios. Following the methodology of Bali et al. (2016), all models with autocorrelation and/or heteroskedasticity are estimated using Newey and West adjusted standard errors (Newey & West, 1987).

7.5.1 Equal-weighted portfolios

Table 7.19 shows the output from the four regressions of the complete period from 2000-2019 with the risk-adjusted annualized alphas and factor sensitivities for the EW portfolios.

Table 7.19

Benchmark performance of EW portfolios for the complete period from 2000-2019

Equal-weighted	Four-screen strategy portfolio				Six-screen strategy portfolio			
	2000-2019				2000-2019			
	Estimate	*t*-statistic	*p*-value		Estimate	*t*-statistic	*p*-value	
Panel A: Capital Asset Pricing Model								
Alpha	4.12%	1.1026	0.2713	*	3.86%	2.6160	0.0095	
Coefficient of Market excess return	0.8857	12.2731	0.0000	*	1.1290	40.0500	0.0000	
Adjusted R-squared	0.5296				0.8717			
Panel B: Fama and French three-factor model								
Alpha	2.53%	0.8679	0.3863	*	3.03%	3.1102	0.0021	*
Coefficient of Market excess return	0.7553	12.2005	0.0000	*	1.0127	50.4528	0.0000	*
Coefficient of SMB	0.6792	7.1657	0.0000	*	0.5686	9.6245	0.0000	*
Coefficient of HML	0.3390	4.3697	0.0000	*	0.1246	3.1059	0.0021	*
Adjusted R-squared	0.6573				0.9479			
Panel C: Fama, French and Carhart four-factor model								
Alpha	3.28%	1.1070	0.2694	*	3.33%	3.6070	0.0004	
Coefficient of Market excess return	0.6773	8.9785	0.0000	*	0.9826	48.4760	0.0000	
Coefficient of SMB	0.7026	7.7494	0.0000	*	0.5776	19.1650	0.0000	
Coefficient of HML	0.2982	3.5078	0.0005	*	0.1089	4.2630	0.0000	
Coefficient of UMD	-0.1566	-2.4205	0.0163	*	-0.0604	-3.7450	0.0002	
Adjusted R-squared	0.6757				0.9507			
Panel D: Fama and French five-factor model								
Alpha	3.09%	0.9446	0.3459	*	2.42%	2.5370	0.0118	
Coefficient of Market excess return	0.7224	8.7087	0.0000	*	1.0235	47.0700	0.0000	
Coefficient of SMB	0.6573	7.1638	0.0000	*	0.6078	19.4920	0.0000	
Coefficient of HML	0.2443	2.7102	0.0072	*	0.0188	0.5470	0.5849	
Coefficient of RMW	-0.1273	-1.1073	0.2693	*	0.0688	1.7380	0.0835	
Coefficient of CMA	-0.0085	-0.0483	0.9615	*	-0.0692	-1.3900	0.1659	
Adjusted R-squared	0.6554				0.9524			

* Newey and West (1987) adjusted standard errors

The results using the CAPM risk model indicate that the four-screen portfolio does not generate abnormal returns that are statistically significant, as the t-statistic is 1.1026. A non-significant alpha indicates that the excess returns generated by the portfolio is a manifestation of the portfolio's exposure to market risk. None of the other three factor models estimate significant alpha for the four-screen portfolio either, indicating that the strategy does not produce any abnormal returns above these well-known risk factors. Looking at the slope coefficient in the CAPM regression, the estimated value of 0.8857 indicates that the portfolio is somewhat less sensitive to market risk than the overall market. The value of the adjusted R-squared is 0.5296, which is the lowest fit of all models, meaning that the additional factors in the following models are contributing to explaining the portfolio returns.

The six-screen portfolio produces a positive and significant annualized alpha-value in all four regression models, with an estimate of 3.86% using CAPM. The slope coefficient of 1.1290 is higher than the four-screen portfolio, indicating that the six-screen portfolio is more sensitive to market risk than the overall market.

Looking at the estimated coefficients in the FF3-model, it is evident that the four-screen portfolio has a high exposure to SMB and HML, with estimated significant coefficients of 0.6792 and 0.3390. This means that the portfolio is positively exposed to size and value risk. As the strategy seeks to find relatively small stocks that are cheap, these results are as expected. The six-screen portfolio is also positively exposed to these two factors, but with lower estimated coefficients. The six-screen portfolio produces statistically significant annualized alpha of 3.03%, which is lower than the estimated alpha in the CAPM-regression. This is as expected as the explanatory power of the FF3-model is higher, thus indicating that the two additional factors help explain some of the returns from the portfolio.

FFC4 is the factor model with the highest explanatory power for the four-screen strategy. The alpha-value is still insignificant, but the additional UMD-factor increases the explanatory power of the model. There are some small adjustments in the exposure to the three original FF3-factors, as the UMD-factor is significant and thus helps explain the returns. A negative and statistically significant coefficient of UMD for both portfolios indicates that they are somewhat exposed to buying recent losers. This might seem odd as one of the screens applied in the portfolio is an increase in relative strength rank. However, the reason for this might be that the difference in calculation between the relative strength rank and the momentum factor, as the relative strength rank gives more weight to the recent quarter compared to the momentum factor.

The FF5-model for both portfolios estimates non-significant coefficients for the two additional factors RMW and CMA. However, the t-statistic for the six-screen strategy of 1.7380 for the RMW indicates that it is significant on a 10% level. The reason for this exposure is probably the EBITDA screens used in constructing the portfolio, only buying stocks with positive EBITDA and a positive change in the year-over-year EBITDA margin. The FF5-model is the model with the highest adjusted R-squared and thus the highest explanatory power for the six-screen portfolio.

7.5.1.1 Sub-period from 2000-2009

Table 7.20 shows the output from the four regressions of the sub-period from 2000-2009 with the risk-adjusted annualized alphas and factor sensitivities for the EW portfolios.

Table 7.20

Benchmark performance of EW portfolios for the sub-period of 2000-2009

Equal-weighted	**Four-screen strategy portfolio**				**Six-screen strategy portfolio**			
	2000-2009				2000-2009			
	Estimate	*t*-statistic	*p*-value		Estimate	*t*-statistic	*p*-value	
Panel A: Capital Asset Pricing Model								
Alpha	10.50%	1.7109	0.0898	*	9.06%	3.8840	0.0002	
Coefficient of Market excess return	0.9247	9.5744	0.0000	*	1.1661	28.8120	0.0000	
Adjusted R-squared	0.5235				0.8773			
Panel B: Fama and French three-factor model								
Alpha	4.42%	1.0480	0.2969		4.82%	3.3597	0.0011	*
Coefficient of Market excess return	0.7966	10.5200	0.0000		1.0457	37.9583	0.0000	*
Coefficient of SMB	0.7138	5.9340	0.0000		0.5960	7.7468	0.0000	*
Coefficient of HML	0.3377	3.4500	0.0008		0.1785	3.8849	0.0002	*
Adjusted R-squared	0.6414				0.9583			
Panel C: Fama, French and Carhart four-factor model								
Alpha	4.10%	0.8737	0.3842	*	4.72%	3.5630	0.0005	*
Coefficient of Market excess return	0.6658	5.8570	0.0000	*	1.0094	26.5264	0.0000	*
Coefficient of SMB	0.7628	6.1649	0.0000	*	0.6107	9.6723	0.0000	*
Coefficient of HML	0.3081	2.7984	0.0060	*	0.1696	3.8464	0.0002	*
Coefficient of UMD	-0.1796	-2.2877	0.0240	*	-0.0538	-1.9135	0.0582	*
Adjusted R-squared	0.6678				0.9607			
Panel D: Fama and French five-factor model								
Alpha	4.43%	0.9870	0.3260		3.88%	2.8433	0.0053	*
Coefficient of Market excess return	0.7839	7.6110	0.0000		1.0752	36.2912	0.0000	*
Coefficient of SMB	0.7133	5.5600	0.0000		0.6425	9.7827	0.0000	*
Coefficient of HML	0.1906	1.3290	0.1860		0.0311	0.5856	0.5593	*
Coefficient of RMW	-0.0445	-0.2600	0.7950		0.0915	2.6502	0.0092	*
Coefficient of CMA	0.0018	0.0090	0.9930		-0.0546	-0.9142	0.3626	*
Adjusted R-squared	0.6350				0.9638			
* Newey and West (1987) adjusted standard errors								

As in the overall period, the four-screen portfolio fails to produce significant alpha in any of the factor models, while the six-screen portfolio does so in all four. The estimated alpha-values of the six-screen portfolio are higher in the early sub-period compared to the overall period, indicating that the portfolio generates the highest abnormal returns in the beginning of the sample. Both portfolios have increased coefficients to the market excess return compared to the overall period, but the four-screen portfolio is still less exposed to market risk than the overall market, while the six-screen portfolio is more exposed to market risk than the overall market.

The FF3-model estimates higher coefficients to all three factors in both portfolios compared to the overall period, indicating that the strategies are more exposed to market, value and size risk in the first half of the overall period. After adding UMD to the model, the explanatory power of the model increases for both strategies. The main difference from the overall period is that the UMD factor is no longer significant at the 5% level in the six-screen portfolio with a t-statistic of -1.9135. The alpha-value decreases, and the explanatory power of the model increases, indicating that the UMD factor helps explain the returns of the strategy, even though it is not significant at the 5% level.

The HML factor in the FF5-model for the four-screen portfolio is no longer significant in the sub-period. Thus, both portfolios have non-significant exposure to the HML factor in the FF5-regression. This is in line with the findings of Fama and French (2015), indicating that the exposure to the HML factor is better explained by the other factors in the regression, making the HML factor insignificant. Once again, the FF5-model has the highest explanatory power for the six-screen portfolio, while the FFC4-model presents the highest adjusted R-squared for the four-screen portfolio.

7.5.1.2 Sub-period from 2010-2019

Table 7.21 presents the output from the four regressions of the sub-period from 2010-2019 with the risk-adjusted annualized alphas and factor sensitivities for the EW portfolios.

Table 7.21

Benchmark performance of EW portfolios for the sub-period of 2010-2019

Equal-weighted	Four-screen strategy portfolio			Six-screen strategy portfolio			
	2010-2019			2010-2019			
	Estimate	*t*-statistic	*p*-value	Estimate	*t*-statistic	*p*-value	
Panel A: Capital Asset Pricing Model							
Alpha	-1.81%	-0.5600	0.577	-0.84%	-0.4810	0.6310	
Coefficient of Market excess return	0.8695	12.5100	0.0000	1.1071	29.4370	0.0000	
Adjusted R-squared	0.5666			0.8791			
Panel B: Fama and French three-factor model							
Alpha	1.32%	0.4740	0.6362	0.81%	0.6607	0.5101	*
Coefficient of Market excess return	0.7078	11.0760	0.0000	0.9907	39.4987	0.0000	*
Coefficient of SMB	0.5854	5.5260	0.0000	0.5240	7.6741	0.0000	*
Coefficient of HML	0.3731	3.8100	0.0002	0.0019	0.0315	0.9749	*
Adjusted R-squared	0.6873			0.9401			
Panel C: Fama, French and Carhart four-factor model							
Alpha	1.55%	0.5490	0.5841	1.15%	0.9572	0.3405	*
Coefficient of Market excess return	0.7001	10.7670	0.0000	0.9789	39.8294	0.0000	*
Coefficient of SMB	0.5880	10.7670	0.0000	0.5280	7.5173	0.0000	*
Coefficient of HML	0.3449	3.2420	0.0016	-0.0413	-0.7248	0.4700	*
Coefficient of UMD	-0.0530	-0.6870	0.4935	-0.0812	-3.5110	0.0006	*
Adjusted R-squared	0.6859			0.9424			
Panel D: Fama and French five-factor model							
Alpha	1.64%	0.5760	0.5655	0.80%	0.6590	0.5112	*
Coefficient of Market excess return	0.6919	10.4490	0.0000	0.9864	42.0226	0.0000	*
Coefficient of SMB	0.5474	4.8390	0.0000	0.5401	8.1768	0.0000	*
Coefficient of HML	0.2905	2.2570	0.0259	-0.0329	-0.5912	0.5555	*
Coefficient of RMW	-0.1740	-1.0410	0.3002	0.0640	1.2608	0.2100	*
Coefficient of CMA	0.0216	0.1080	0.9143	-0.0710	-1.1100	0.2693	*
Adjusted R-squared	0.6849			0.9397			

* Newey and West (1987) adjusted standard errors

The regressions on the four factor models on the second sub-period presents some interesting results compared to the overall period and the first sub-period. First, none of the portfolios are able to produce any statistically significant alpha in either of the regression models. Thus, the six-screen portfolio does no longer generate any abnormal returns above the different risk exposures. The estimated coefficients of the market excess return are lower for both strategies compared to the first sub-period, but still below and above the market.

Looking at the FF3-model, the four-screen portfolio is somewhat less exposed to market and size risk than in the first sub-period, with a higher exposure to value risk, while all coefficients are still significant. The HML factor is no longer significant in the six-screen portfolio, indicating that the portfolio is less exposed to value risk in the second sub-period. Adding the UMD factor to the regression model does not

make any noteworthy change in the factor coefficients in the four-screen portfolio, and UMD is insignificant in the FFC4. The six-screen portfolio is however negatively exposed to UMD, indicating that the strategy is buying recent losers. In the FF5-model, both RMW and CMA are insignificant for both strategies. HML is significant in the four-screen portfolio in contrast to the findings of Fama and French (2015), while it is insignificant in the six-screen portfolio.

7.5.2 Value-weighted portfolios

Table 7.22 shows the output from the four regressions of the complete period from 2000-2019 with the risk-adjusted annualized alphas and factor sensitivities for the VW portfolios.

Table 7.22

Benchmark performance of VW portfolios for the complete period of 2000-2019

Value-weighted	**Four-screen strategy portfolio**				**Six-screen strategy portfolio**			
	2000-2019				2000-2019			
	Estimate	*t*-statistic	*p*-value		Estimate	*t*-statistic	*p*-value	
Panel A: Capital Asset Pricing Model								
Alpha	2.61%	0.8167	0.4149	*	1.15%	1.4090	0.1600	
Coefficient of Market excess return	0.9581	12.6201	0.0000	*	0.9283	59.6050	0.0000	
Adjusted R-squared	0.6505				0.9377			
Panel B: Fama and French three-factor model								
Alpha	0.36%	0.2310	0.8180		1.60%	2.5203	0.0124	*
Coefficient of Market excess return	0.8239	26.3040	0.0000		0.9287	57.6633	0.0000	*
Coefficient of SMB	0.7382	14.6030	0.0000		-0.0304	-0.8762	0.3819	*
Coefficient of HML	0.5356	12.6290	0.0000		-0.1365	-4.4052	0.0000	*
Adjusted R-squared	0.8551				0.9471			
Panel C: Fama, French and Carhart four-factor model								
Alpha	0.37%	0.2400	0.8110		1.44%	2.3048	0.0221	*
Coefficient of Market excess return	0.8222	24.0540	0.0000		0.9460	43.7962	0.0000	*
Coefficient of SMB	0.7388	14.5350	0.0000		-0.0356	-0.9874	0.3245	*
Coefficient of HML	0.5347	12.4100	0.0000		-0.1275	-4.1687	0.0000	*
Coefficient of UMD	-0.0034	-0.1250	0.9010		0.0347	1.5614	0.1198	*
Adjusted R-squared	0.8544				0.9484			
Panel D: Fama and French five-factor model								
Alpha	-0.27%	-0.1640	0.8700		0.60%	1.0025	0.3171	*
Coefficient of Market excess return	0.8345	22.4380	0.0000		0.9661	54.0189	0.0000	*
Coefficient of SMB	0.7605	14.2590	0.0000		0.0181	0.5893	0.5563	*
Coefficient of HML	0.3785	6.4490	0.0000		-0.1512	-4.8812	0.0000	*
Coefficient of RMW	0.3376	0.4980	0.6190		0.1695	5.5598	0.0000	*
Coefficient of CMA	-0.0020	-0.0230	0.9810		-0.0700	-2.0743	0.0392	*
Adjusted R-squared	0.8556				0.9530			

* Newey and West (1987) adjusted standard errors

The results of the regressions show that the six-screen portfolio generates significant annualized alpha in FF3 and FFC4, while the four-screen portfolio does not produce any significant alpha. The six-screen

portfolio has a market exposure using CAPM of 0.9283 and is therefore somewhat less exposed to market risk than the overall market, in contrast to the six-screen EW portfolio which has a higher exposure.

The four-screen portfolio is still sensitive to size and value risk, with positive and significant coefficients in all three factor models. Thus, the effect of weighting the portfolio returns is limited in terms of factor exposure for the complete period. For the six-screen portfolio however, the estimated coefficients for SMB are no longer significant in any of the models, indicating that the strategy is less exposed to size risk. This makes sense as the larger stocks in the portfolio are weighted higher, reducing the portfolios exposure to small caps. Another interesting finding is that the six-screen portfolio is negatively exposed to value risk as opposed to the EW six-screen portfolio, indicating that the VW six-screen portfolio is tilted towards growth stocks. A sensible explanation for this difference is that many of the larger companies in the portfolio also have a lower book-to-market ratio, reducing the exposure to value risk when returns are value-weighted. The six-screen portfolio is also tilted towards profitable stocks, with a positive and significant RMW coefficient of 0.1695.

7.5.2.1 Sub-period from 2000-2009

Table 7.23 presents the output from the four regressions of the sub-period from 2000-2009 with the risk-adjusted annualized alphas and factor sensitivities for the VW portfolios.

Table 7.23

Benchmark performance of VW portfolios for the sub-period of 2000-2009

Value-weighted	Four-screen strategy portfolio				Six-screen strategy portfolio			
	2000-2009				2000-2009			
	Estimate	*t*-statistic	*p*-value		Estimate	*t*-statistic	*p*-value	
Panel A: Capital Asset Pricing Model								
Alpha	8.85%	1.7723	0.0790	*	0.81%	0.6130	0.5410	
Coefficient of Market excess return	0.9644	8.4958	0.0000	*	0.9122	39.5730	0.0000	
Adjusted R-squared	0.6571				0.9310			
Panel B: Fama and French three-factor model								
Alpha	1.00%	0.3019	0.7633	*	1.90%	1.6556	0.1006	*
Coefficient of Market excess return	0.8565	13.4397	0.0000	*	0.9079	37.4010	0.0000	*
Coefficient of SMB	0.7220	8.1531	0.0000	*	-0.0331	-0.6836	0.4956	*
Coefficient of HML	0.5518	9.0404	0.0000	*	-0.1156	-3.0062	0.0033	*
Adjusted R-squared	0.8522				0.9378			
Panel C: Fama, French and Carhart four-factor model								
Alpha	0.98%	0.2941	0.7692	*	1.96%	1.6443	0.1029	*
Coefficient of Market excess return	0.8486	11.4298	0.0000	*	0.9295	24.0608	0.0000	*
Coefficient of SMB	0.7250	8.2901	0.0000	*	-0.0412	-0.8514	0.3964	*
Coefficient of HML	0.5500	8.6096	0.0000	*	-0.1107	-2.8072	0.0059	*
Coefficient of UMD	-0.0108	-0.2565	0.7980	*	0.0296	0.9795	0.3295	*
Adjusted R-squared	0.8510				0.9387			
Panel D: Fama and French five-factor model								
Alpha	-0.31%	-0.0960	0.9237	*	0.77%	0.8035	0.4234	*
Coefficient of Market excess return	0.9053	13.6185	0.0000	*	0.9586	26.6241	0.0000	*
Coefficient of SMB	0.7609	8.5570	0.0000	*	0.0147	0.3155	0.7529	*
Coefficient of HML	0.3307	3.8775	0.0002	*	-0.1405	-2.9149	0.0043	*
Coefficient of RMW	0.1143	1.2235	0.2237	*	0.1658	3.1746	0.0019	*
Coefficient of CMA	0.0321	0.2472	0.8052	*	-0.0693	-1.8161	0.0721	*
Adjusted R-squared	0.8534				0.9431			
* Newey and West (1987) adjusted standard errors								

The results for the four-screen portfolio are similar to the complete period, with high coefficients towards market, size and value risk, and no significant alpha. Further, the six-screen portfolio no longer generates alpha in either of the regression models. The six-screen portfolio is less exposed to market risk with an estimated coefficient of 0.9122, compared to the coefficient of 1.1661 in the EW six-screen portfolio. As seen in the overall period, the SMB factor is insignificant in explaining the excess returns of the six-screen portfolio while the exposure to RMW is significant and positive. The estimated coefficient of HML is significant and negative as in the complete period. None of the portfolios have significant coefficients for UMD or CMA in the first sub-period, however, the CMA factor is close to significant for the six-screen portfolio. The model with the highest explanatory power in terms of adjusted R-squared is the FF5 for both portfolios. All estimated factor coefficients in both portfolios are similar to the complete period.

7.5.2.2 Sub-period from 2010-2019

Table 7.24 presents the output from the four regressions of the sub-period from 2010-2019 with the risk-adjusted annualized alphas and factor sensitivities for the VW portfolios.

Table 7.24

Benchmark performance of VW portfolios for the sub-period of 2010-2019

Value-weighted	Four-screen strategy portfolio			Six-screen strategy portfolio			
	2010-2019			2010-2019			
	Estimate	*t*-statistic	*p*-value	Estimate	*t*-statistic	*p*-value	
Panel A: Capital Asset Pricing Model							
Alpha	-3.94%	-1.3010	0.1960	1.13%	1.1490	0.2530	
Coefficient of Market excess return	0.9941	15.3200	0.0000	0.9521	45.1160	0.0000	
Adjusted R-squared	0.6626			0.9447			
Panel B: Fama and French three-factor model							
Alpha	0.22%	0.1130	0.9110	0.33%	0.3990	0.6910	
Coefficient of Market excess return	0.7804	17.0950	0.0000	0.9738	51.8620	0.0000	
Coefficient of SMB	0.7713	10.1910	0.0000	-0.0146	-0.4680	0.6410	
Coefficient of HML	0.4993	7.1370	0.0000	-0.2174	-7.5310	0.0000	
Adjusted R-squared	0.8575			0.9624			
Panel C: Fama, French and Carhart four-factor model							
Alpha	-0.03%	-0.0170	0.9870	0.24%	0.2860	0.7760	
Coefficient of Market excess return	0.7894	17.0510	0.0000	0.9770	51.0590	0.0000	
Coefficient of SMB	0.7683	10.1560	0.0000	-0.0157	-0.5020	0.6170	
Coefficient of HML	0.5321	7.0240	0.0000	-0.2058	-6.5730	0.0000	
Coefficient of UMD	0.0616	1.1220	0.2640	0.0219	0.9640	0.3370	
Adjusted R-squared	0.8578			0.9624			
Panel D: Fama and French five-factor model							
Alpha	0.26%	0.1280	0.8980	0.23%	0.2914	0.7713	*
Coefficient of Market excess return	0.7718	16.2860	0.0000	0.9776	59.0540	0.0000	*
Coefficient of SMB	0.7765	9.5910	0.0000	0.0101	0.3918	0.6959	*
Coefficient of HML	0.4162	4.5180	0.0000	-0.1839	-5.6172	0.0000	*
Coefficient of RMW	0.0048	0.0410	0.9680	0.1122	2.4116	0.0175	*
Coefficient of CMA	-0.0292	-0.2030	0.8400	-0.0749	-1.1506	0.2523	*
Adjusted R-squared	0.8559			0.9638			
* Newey and West (1987) adjusted standard errors							

The regression results from the second sub-period show that none of the VW portfolios generate any significant alpha in either of the four regression models. The factor exposures are similar to those of the first sub-period and complete period for both strategies. The four-screen portfolio is characterized with a high exposure to market, size and value risk, while the six-screen portfolio is explained by the exposure to market, value and profitability risk. One can notice that the estimated coefficient to HML is even more negative in all factor models for the six-screen strategy, indicating an even higher tilt towards growth stocks in the second sub-period.

7.5.3 Section summary

None of the EW or VW four-screen portfolios produce any significant alpha in either of the regression models across the different time periods. Thus, the excess returns generated by the portfolios are a result of the portfolios' exposure to the different risk factors. The four-screen portfolios have a high exposure to market, size and value risk over the time period. The EW six-screen portfolio produces significant annualized alpha values in the complete period and in the first sub-period in all four regression models, but in none of the models in the second sub-period. There are large differences in the exposure to the different factors between the EW and VW six-screen portfolios. The EW portfolio has a higher exposure to market, size and value risk, while the VW portfolio is insignificant towards size and negatively exposed to value risk.

7.6 Diagnostic checks

In this section, diagnostic checks for the regression models will be performed to evaluate and investigate whether the models fulfill the model assumptions stated in Section 6.10. This is to strengthen the validity of the models and secure that the OLS estimators are the best linear unbiased estimators (BLUE). In total, 48 different regressions are executed, however this section will mainly address the results of the diagnostic checks for the EW four-screen FFC4 model for the 2000-2019 time period, due to reasons of convenience. However, diagnostic checks are uniformly checked across all regression models and the test results can be found in Appendix L. The assumptions are analyzed using statistical tests in R.

The linearity assumption is checked by plotting the respective independent variables against the dependent variable for all regression models. That is each portfolio's excess return against the market portfolio's excess return, SMB, HML, UMD, RMW, CMA and the SMB five-factor portfolio. All portfolios display a clear linear trend, expect for the HML portfolio which shows a weak linear trend against both the four-screen and six-screen excess returns (Appendix L.2 linearity). However, all estimated HML coefficients make intuitive sense, as it for example indicates a strong positive relationship between the four-screen excess return and the HML between 2000-2009, a period of value upswing. Therefore, the linearity assumption is assumed fulfilled.

Multicollinearity occurs when two or more explanatory variables are linearly correlated. A model with multicollinearity can still be correctly specified and estimate unbiased OLS regressors, however, a

situation of perfect or imperfect multilinearity makes precise estimation difficult (Stock and Watson, 2015). Multicollinearity is a multivariate issue, meaning that a correlation analysis cannot detect the issue, hence the attention is turned to the variance inflation factor (VIF) (Bali et al., 2016). According to literature, there is no clear-cut consensus of what the VIF threshold is before multicollinearity requires attention, but papers suggested that a VIF below 5 does not cause for concern (Hair, 1995; Everitt & Skrondal 2008). The highest VIF in the EW FF4 model is 1.5, while the highest value across all regression models is 2.6 (Appendix L.4). Thus, multicollinearity does not cause for concern in either of the models and the assumption is assumed fulfilled.

Next up is the assumption of normality in the sample residuals, which says that the expected value of the residuals is assumed equal to zero. This is tested by Jarque-Bera tests, which simultaneously checks whether there are skewness and kurtosis in the sample residuals. The null hypothesis of normality is rejected for 36 out of the total 48 regression models, indicating a violation of the assumption (Appendix L.3 of test-tables). This means that the frequency of extreme value is higher than predicted by the normal distribution. This is, however, not uncommon when running regressions on stock returns and is a widely known phenomenon in literature (Bale et al, 2016; Enders, 2015). Even though the model has nonnormal errors, it is important to note that OLS estimator still could be BLUE, according to Gauss-Markov Theorem (Schönfeld, 1975). The conditions for BLUE coefficients are zero mean, uncorrelated and constant variance in the residuals, and not normality. Nevertheless, as Enders (2015) points out, nonnormal errors could cloud p-value calculations, where a possible solution is to be more conservative when conducting significance tests. That is, look for lower p-values closer to 1%, rather than 5% when evaluating coefficient significance. Ultimately, the implications of nonnormal errors evaluated to be negligible and the OLS estimators are assumed to be close to the true values of the parameters.

Constant variance in the residuals for all regressors, or homoskedasticity is another assumption. This implies that the data are equally spread out over the entire data sample, otherwise, there is heteroskedasticity. Breusch-Pagan tests are applied to test for constant variance, where the null-hypothesis is homoskedasticity. The p-value for the EW four-screen FFC4 regression model is close to zero, meaning that the null hypothesis is rejected, hence the residual variance is not constant. This is not overly surprising, as stock markets historical show shorter periods of high volatility, for example during the financial crisis. When the long run variance is constant, which arguably is the case here, this is known

as conditionally heteroskedasticity (Enders, 2015). Consequences include possible inaccurate t-statistics and p-values. Empirical asset pricing researchers frequently employ Newey and West standard errors to correct the issue. The method produces new standard errors to correct for heteroskedasticity, altering the standard errors slightly, but leaving the coefficients unchanged (Bali et al., 2016). Several models suffer from homoskedasticity, and the Newey and West standard errors are therefore employed in all these cases (Appendix L.3). These cases are also marked with a "*" in the regression output in Section 7.5.

The final assumption is no autocorrelation, meaning that the residuals are independently distributed across time. Using the Breusch-Godfrey test, the null hypothesis of no autocorrelation can be rejected on 5% significance level. Several other models also show signs of autocorrelation in the residuals. Similar to the issue of heteroskedasticity, Newey and West adjusted standard errors are used to correct the possibility of autocorrelation and hence, to fit the regression models (Bali et al., 2016).

8. Discussion

The next section will discuss the results presented in Section 7. Firstly, in Section 8.1, the winner characteristics and results presented as in Reinganum's (1988) study are commented on. Secondly, Section 8.2 will discuss the implementation and performance of the portfolios created based on the four-screen and six-screen strategies. The screening results of the four-screen strategy compared to the literature is addressed in Section 8.3, before finishing off with a discussion of other limitations in Section 8.4.

8.1 Results presented as in Reinganum (1988)

This section will discuss the results of the common characteristics found after analyzing the 300 winner stocks and the cumulative buy quarter returns. Thus, the focus of this section is aimed towards the part of the empirical results that is presented almost identical to Reinganum (1988). This includes a discussion of data consistency among the 300 winner stocks, a comparison of Reinganum's (1988) presented winner characteristics and the thesis's winner characteristics, the implications of presenting buy quarter cumulative returns and the challenges of testing a strategy created on an analysis of stocks over the same time as the stock analyses were conducted.

8.1.1 Methodology behind selecting winner stocks

Before discussing the methodology behind the selection of the winner stocks, a short summary of Reinganum's (1988) methodology is repeated to ensure a comprehensive understanding of his approach. Reinganum (1988) gathered his set of winners from an O'Neil publication, *The greatest stock market winners: 1970-1983,* which contained 272 occasions of stocks at least doubling in price during that period listed on the NYSE, AMEX and OTC markets. This list was then merged with a file containing historical information of firms listed on NYSE and AMEX, resulting in 222 matched firms. However, several firms which doubled in price where not considered in Reinganum's (1988) sample, due to O'Neil filtering them out of the named publication. O'Neil's exact method was unknown to Reinganum (1988), but he suspects that firms selling for less than USD 10 per share were excluded. There were 4,049 occasions of firms doubling in price between 1970-1983, however, the number dropped to 1,311 after adjusting for share prices. Still, this leaves 1,039 firms excluded from the 272 winners, for which the purpose is uncertain, forcing some assumptions and alterations to be made when revisiting the strategy.

There were 4,081 episodes of stocks doubling in price between 2000-2019 on the NYSE, AMEX and Nasdaq, corresponding to 2,857 different companies. Since winner stocks were excluded from the investable universe when applying the trading strategy, the thesis argues that if all these stocks were considered as winners, the investable universe would be adversely affected by removing 2,857 companies. Therefore, of all the 2,857 stocks that at least doubled, 300 were selected from a weighted random selection. This raises the issue of over-representation of some years in the sample of 300 winners. 611 and 476 stocks doubled in price in 2003 and 2009, respectively, while a conservative 28 stocks doubled in 2008 (Appendix G). Thus, the characteristics found when analysing winners are dominated by firms doubling in price between 2000-2009, which might impact the performance adversely in the long run. Since value performed well in this period, there could be an overrepresentation of value stocks among the winners. The possible impact of this is discussed further in Section 8.1.4.

Reinganum (1988) analysed 222 winners and to best mirror his methodology, 200 random winners were initially analysed. However, when screening for common characteristics among the 200 companies, the data was inconsistent at best. To illustrate the inconsistency, statistics for six common characteristics identified among the 300 winner stocks, are also displayed for the 200 winner stocks in Appendix I. The main takeaway is that large positive and negative values are much more frequent, hence it is problematic

to argue in favour of any form of common trend among the stocks. Thus, a sample of 300 random shares were selected and analysed, but the results were equally ambiguous, as seen in Appendix J. Therefore, a new and final sample of 300 shares were studied, however, this time conditions of positive book value of equity and market capitalization larger than USD 20 million were applied before the analysis.

Excluding firms with negative book value of equity could imply that certain trends among the winners are overlooked. The condition is not something Reinganum (1988) deliberately did, however, it is highly likely that O'Neil applied this filter to his winner sample, based on the statistics Reinganum (1988) presented. This is addressed and discussed thoroughly in the next section where the characteristics of the 300 winners are compared to Reinganum's (1988) winners. Firms with negative book values of equity might be associated with severe risk, particularly when investing solely based on six quantitative measures. Another argument in favour of excluding these firms is the risk of overlooking trends among the 300 winners, because negative book values of equity might contribute to increasingly inconsistent data.

The condition of excluding firms with a market capitalization of less than USD 20 million is not something Reinganum (1988) addressed either. Again, there might be a risk of missing winner stocks and moving even further away from Reinganum's (1988) method of screening winners. However, this thesis argues, based on Reinganum's (1988) presented results that O'Neil applied a minimum market capitalization threshold for his winners. This is not unlikely as his customers were institutions (Reinganum 1988). According to the U.S. Securities and Exchange Commission (SEC), stocks with a market cap below USD 50 million are categorized as micro-cap stocks. These stocks are associated with a lack of public information, business risk, liquidity risk and risk of fraud, which could cause investor groups to shy away (SEC, 2013).

Further, is should be mentioned that including these stocks would only cause minimal result changes, where the number of buy signals would increase with 591 (2.4%), and 104 (2.8%) new companies would be added. Other studies of stock market winners also applied similar filters, for example when Mayer (2014) used minimum USD 50 million in market cap and Martelli (2014) used USD 100 million. In this case, USD 20 million might be too conservative. However, considering that the median market capitalization of the four-screen was just above USD 20 million, the degree of comparability would arguably suffer notably by increasing the minimum level. Thus, since the scope of this study is aimed at

professional investor, the smallest stocks are not considered. However, the boundary used is slightly lower than previous studies, to avoid moving too far from Reinganum's (1988) method, as he did not include any lower limit.

8.1.2 Characteristics of stock market winners

The characteristics of the 300 stock market winners in the thesis' sample is significantly different from what Reinganum (1988) discovered. Above all, the data consistency among the thesis' sample of winners is questionable, making it challenging to argue with a desired degree of substance when constructing the six-screen portfolio. The difference in data consistency could be due to a number of factors, for example that the 300 winners are not representable for the other 3,561 winners. However, this is unlikely, because the same inconsistency recurred in the 200 and 300 random stock selection analyses. A second explanation is that the information to a larger extent is reflected in prices. A last explanation is that O'Neil had excluded certain groups of stocks before Reinganum (1988) started analyzing winners. The latter will be a topic in the next section where the winner characteristics are discussed and compared to Reinganum's (1988) statistics.

Of the six investment rules included in the six-screen strategy, only one, the change in RSR, was included in Reinganum's (1988) strategies, despite that all nine screens were applied to the 300 winners. The data indicated that the thesis' sample of winners are not characterized by the same common characteristics as Reinganum's (1988) sample. His sample had a lower average P/B, with a mean of 0.95 in buy-1, versus the thesis' sample mean of 3.13. Reinganum's (1988) data appeared to be much more concentrated, as his 95^{th} percentile had a lower P/B than the thesis' 50^{th} percentile. Also, Reinganum (1988) presented zero negative P/B values, indicating that O'Neil also filtered on positive book value of equity. It is important to note that the time period Reinganum (1988) studied was a period of value outperformance (Chan & Lakonishok, 2004), hence his winners might have been dominated by value stocks, which could have muted the performance in periods of stronger growth performance. Another interesting observation is Reinganum's (1988) table of P/E ratios, which also presented zero negative values, indicating that companies with negative earnings also were filtered out. Among the thesis' sample of 300 winners, around half of the stocks had negative earnings in the eight quarters before the buy quarter. The distinction is striking, and it renders the P/E ratio and other measures of profitability much less meaningful for the 300 winners.

The 300 winners have an average number of shares outstanding of slightly more than 50 million Appendix H.4) and a median around 22 million for all quarter preceding the buy quarter, hence the 20 million shares outstanding filter is arguably not relevant for the 300 winners. Reinganum's (1988) winners, on the other hand, showed an average of around 13.8 million and a median of 5 million. Reinganum (1988) claimed that his strategies were not tilted towards small cap stocks due the winner's average market capitalization of USD 500 million and average share price of USD 28 on the buy date. However, when creating a portfolio based on the four-screen in the time period from 2000-2019, the SMB factor explains much of the returns, indicating that his strategy exploits this known investment strategy in today's stock market.

Reinganum (1988) presented convincing evidence of earnings acceleration among the winners leading up to the buy date. The average change in quarterly earnings increased from 22% in buy-3 to 61% in buy-1, suggesting that the investor should seek out stocks with a positive change. However, for the 300 winners the data shows predictable changes that recur every quarter. That is, both the mean and median is positive every other quarter (Appendix H.3). Also, the 1st percentile and 99th percentile show large negative and positive values, opposed to Reinganum (1988) where the negative values are small, but the positive values are large. Several other researchers have documented abnormal returns following earnings announcements, where excess returns were found upwards of 90 days after the earnings announcement date (Watts, 1978; Rendleman et al., 1982). However, this does not seem to be the case when studying the 300 winners.

There is evidence of price momentum among the 300 winners, as displayed in Section 7.1, however, the pattern is less clear than what Reinganum (1988) found. His winners experienced an average relative strength of 90 in the buy-1 quarter, compared to the 300 winners average of 54 in buy-1. This number is obviously much lower than what Reinganum (1988) reported, and the trend is less convincing. Still, the increasing number over the four quarter prior to the buy quarter, indicates that more stocks exhibit a positive change before buy. The large distinction in RSR could also be influenced by O'Neil's investment philosophy which revolved around investing in past winners, rather than losers. Thus, Reinganum's (1988) argument that the strategy was not contrarian could be a result of O'Neil's investment philosophy. Nevertheless, the RSR estimates a high number regardless of price appreciation or depreciation, provided that the price increases more, or declines less than the market. Therefore, the RSR considers market

downturns and since a majority of the 300 winners are pulled from 2003 and 2009, both the four-screen and six-screen likely exhibit contrarian movements. Exposure to contrarian movements is also indicated by the negative exposure to the momentum factor (UMD).

In addition to the EBITDA margin, EBIT, PTP and profit margins are studied, including quarterly and yearly changes in the margins. Off the 300 winners, 73% show positive EBITDA margins in the buy-1 quarter, however, no other trends are discovered. Again, the results differ greatly compared to Reinganum (1988) as he reported that 216 of his 222 winners delivered a positive PTP-margin, i.e., several expense posts below EBITDA on the income statement. Thus, close to 100% of his winners probably delivered positive EBITDA margins. This thesis argues that the fact that close to ¾ of the 300 winners shows a positive EBITDA margin supports the investment rule, however it is important to note that the consistency is lower than Reinganum's (1988) findings. The consequence is that the created six-screen strategy might overlook cases of stock price accelerations.

The last investment filter to be discussed is the D/E ratio below 2. This rule stands out from the other five, because it might cause the six-screen strategy to consistently disregard sectors categorized of high leverage. In such a scenario, both the risk and return could suffer, due to missed out opportunities and lower diversification. Studying Damodaran's (2021) overview of average D/E ratios across industries in the US, the undoubtedly highest ratios are within bank and insurance, with averages just above 2, which could be a problem. However, according to the sector exposure presented in Section 7.2, the six-screen strategy is always invested in every MSCI sector. The large exposure to the financial sector, which is comprised of three sub sectors (Banks, Diversified insurance and insurance) is equally interesting, because it indicates that the most levered sectors are within the reach of the six-screen strategy (MSCI, 2021).

One possible criticism of the chosen filters could be that they are too general. For P/B, D/E, 3-year revenue growth and EBITDA margin, around 65-89% of the total companies fulfill each of these single criteria (Table 7.10). Hence, one can discuss whether a filter that matches 89% of the total companies is a necessary filter to include in the strategy. However, the purpose of the methodology is to find a combination of filters that is able to identify stocks with a rapid price appreciation, and every filter is chosen because it is a characteristic of the sample of winners. Thus, including a filter even though it singlehandedly does not filter away a larger part of the universe arguably makes sense in combination

with the other filters. The six-screen strategy is presented in Table 8.1 below removing one screen from the strategy, making it a five-screen strategy, to illustrate the effect from each single filter on the number of invested companies and buy signals.

Table 8.1

Number and percentage increase of companies and buy signals when removing one single screen

	All filters	P/B		D/E		3-year revenue growth		EBITDA margin		Change in EBITDA margin		Change in RSR	
	no.	no.	%-increase	no.	%-increase	no.	%-increase	no.	%-increase	no.	%-increase	no.	%-increase
Companies	3,754	3,977	6%	4,622	23%	4,395	17%	4,234	13%	4,092	9%	4,137	10%
Buy signals	24,970	27,066	8%	33,202	33%	32,291	29%	27,921	12%	43,529	74%	49,917	100%

Table 8.1 shows that the effect of the different screens on the entire strategy differs significantly. Removing P/B from the strategy increases the number of companies by 6%, and the number of buy signals by 8%, which is the smallest increase of all the screens. The D/E screen reduces the number of companies by 23% and the number of buy signals by 33%. This is the highest number of companies among all screens and excluding such a large fraction of the companies could influence the effect of diversification if certain sectors are ruled out. However, as previously mentioned, the strategy is exposed to companies in all sectors, implying that the screen simply reduces the risk of the portfolio without reducing the effect of diversification by excluding the most leveraged companies.

The two screens with the highest impact on the strategy is the change in EBITDA margin and change in RSR. The impact is especially significant in terms of the number of buy signals, which increases by 74% and 100% if each of the two screens are removed. This shows an interesting impact. Without these two filters, the strategy would be remarkably more tilted towards buying the same stocks over and over, as the number of buy signals increases up to 10 times more than the number of companies. This would entail holding the same stocks with low debt, revenue growth and positive EBITDA margins, without identifying the stocks that are most likely to experience a rapid price appreciation. Thus, these two filters tilt the strategy towards the companies that are currently experiencing improved EBITDA margins and higher price appreciation than the overall market.

Finally, in the discussion of the winner characteristics, the inclusion of Nasdaq firms is elaborated upon. As known, Reinganum (1988) only studied firms listed on AMEX and NYSE. The reasoning behind ignoring Nasdaq remains unknown, however it is assumed to be because the CRSP database does not

offer data on Nasdaq prior to December 1972 (Bali et al., 2016), which does not cover Reinganum's (1988) entire sample period. For the first decades after Nasdaq launched in 1971, NYSE did not allow small, new companies to be listed, hence Nasdaq served as a substitute for the newer companies, according to Etheridge (2016). It was and still is cheaper to list on Nasdaq, which has contributed to the growth of smaller and more volatile stocks (Nasdaq, 2021; NYSE, 2021). It is important to highlight this since it enlightens why the consistency of the 300 winners differs substantially from Reinganum's (1988) 222 winners. Note that Nasdaq today is the largest stock exchange in terms of number of listings with ~1,000 more than NYSE, hence as the aim of the thesis is to identify the characteristics of a stock market winners, it is argued that one cannot ignore the largest stock exchange.

8.1.3 Buy quarter returns

When reading the empirical results, one might question how a portfolio created based on the six-screen strategy manages to outperform the four-screen portfolio significantly between 2000-2019, when each firm's average cumulative return over the holding period return is 9%, compared to the four-screen's average of 46%. The reason is that most of the negative returns are suffered over a few bad years, where much fewer stocks meet all the four-screen filters, compared to the six-screen that still generate several buy signals during downturns. When looking at the cumulative distributed returns over the time period, the negative returns have larger impacts on the cumulative returns, because they mostly occur during the same year. However, when Reinganum (1988) presented results as cumulative returns over the buy quarters, these few, but large negative returns were diluted. Therefore, it is important to note that when Reinganum (1988) stated that his strategies outperformed the S&P, it was not based on cumulative holding periods return between 1970-1983. However, if an investor seeks to replicate the strategy in practice, an overview over the cumulative return would arguably be informative. That is why the thesis argues that screen portfolios enrich the research questions, even though it is something Reinganum (1988) steered clear off in his article.

8.1.4 Implications of in-sample bias

Reinganum's (1988) method of creating an investment strategy based on analyzing characteristics of past stock market winners was accompanied with a bias. This is because the performance of the investment strategy was influenced by an in-sample bias. Reinganum (1988) seeked to reduce this bias by removing the analyzed stocks from the sample available for investment, so that the winner stocks were excluded

from the presentation of the excess returns. However, this does not solve the issue with the in-sample bias.

When Reinganum (1988) presented returns of a strategy constructed on optimal filters over the same period these filters were estimated, the performance was biased to look unrealistically good. The filters were chosen to be optimal for this time period, but he could not have known this in advance, nor did he know if these filters would be optimal in the future. Thus, if the same analysis was performed on stocks that performed well in the 1960's and the strategy was tested in the 1970's, the results could have been different, due to the dynamic nature of financial markets.

The four-screen strategy constructed by Reinganum (1988) was based on market anomalies that are well-known today, with screens that capture both size, value and momentum. These market anomalies were less researched when he wrote the article, which might be the reason that Yu (2009) found that the strategy was producing significant and positive alpha-values over FF3 and FFC4 from 1984-2006. The results presented in this paper shows that the strategy does not create any significant alpha in the complete sample period of 2000-2019, nor in the first sub-period of 2000-2009, indicating that these market anomalies are to a larger extent reflected in stock prices today.

The evidence of the in-sample bias is also present in the constructed six-screen strategy, as this paper follows the methodology of Reinganum (1988). As previously mentioned, a majority of the winners are found in the first sub-period from 2000-2009. The results presented in Section 7.5.1 shows that the constructed EW six-screen portfolio generates positive and significant alpha values in the complete period from 2000-2019. However, the evidence of in-sample bias is visible when the two sub-samples are analyzed, because the EW six-screen portfolio generates positive and significant alphas in the first sub-period, but no longer in the second sub-period. As the strategy is constructed by analyzing an overweight of companies from the first sub-period, it is tilted towards the characteristics these stocks have in common. These characteristics might have been shared by other well-performing stocks in the first sub-sample but might fail to identify the same high-performing stocks in the second sub-sample.

The purpose of analyzing common characteristics and backtesting strategies is to find trading strategies that will perform well in the future, not strategies that perform well in a backtest. Thus, the methodology

suffers from a weakness that could have been avoided, for example by an out-of-sample analysis or a rolling-sample that is frequently updated (Pedersen, 2015).

8.1.5 Section summary

It is important to note some of the obstacles met when attempting to replicate Reinganum's (1988) methodology. The main challenge is the unknown filters that O'Neil have applied to Reinganum's (1988) winner sample, which are also unknown to the author himself. Particularly, the data consistency between his winners and the thesis' winners differs greatly, which could be a result of the unknown filters. However, it could also be a natural result of a dynamic stock market. The consequence is that the shared characteristics among the thesis's winner stocks is backed up by less convincing data. It is also interesting that just one out of Reinganum's (1988) nine winner characteristics are common to the thesis' winner stocks. Further, it is highlighted that the results are influenced by in-sample bias, which could make the returns look unrealistically good because the strategy is tested over the same period as the winner stocks are analyzed.

8.2 Interpretation of portfolio returns

The following section will present an interpretation of the results of the constructed portfolios in this thesis. Thus, the discussion moves on from discussing the results compared to Reinganum's (1988) reported result, towards discussing the implications of creating a portfolio based on his strategy. The results give raise to several interesting discussion points such as performance measures, impacts of weighting on portfolio returns, portfolio sensitivity to transaction costs and the portfolio turnover.

8.2.1 Interpretation of performance measures

The optimal portfolio is the portfolio that minimizes the risk for the given expected return. Looking at the portfolios before and after transaction costs, the EW six-screen portfolio offers the highest returns, and it also offers superior risk-adjusted returns. Measured on Sharpe, Sortino and Information ratio, this portfolio stands out as the optimal choice for the investor. The main reason is that the investor by taking on slightly lower risk than the four-screen portfolio earns higher returns. The EW four-screen has the highest Treynor ratio of all portfolios, however, it is argued that this ratio paints an inaccurate picture of the performance, due to high unsystematic risk in the four-screen portfolios. Looking at the plots of the holding period returns, in Section 7.3.3.1 and Section 7.3.3.2, it might come as a surprise that the

volatility between the EW four-screen and EW six-screen is so similar, based on the large fluctuations in the four-screen. However, the explanation lays in the two risk components, systematic and unsystematic. The six-screen has a significantly lower unsystematic risk. According to CAPM, investors are only compensated for the systematic risk and the large unsystematic risk could therefore serve as a red flag for investors.

The reason for the high unsystematic risk can partly be traced back to the four-screens large exposure to small caps. As pointed out in Section 8.1.2, there are types of unsystematic risks that are more prominent in small caps, such as business risk and financial risk. Business risk could be a result of limited public historical data or unproven business models. These risks are arguably reduced in the six-screen through the 3-year revenue filter, which demands that firms have at least three years of data and a business model that has proven its worth through sales growth. The financial risk is also lower because of the D/E filter. Avoiding the most levered firms during the financial crisis might have been key in reducing drawdown to the S&P 500's level, despite being more exposed to small caps than the S&P 500 is.

The six-screens diversification is arguably better, partly because of lower unsystematic risk. Another reason for the better diversification and superior performance, might be that the four-screens P/B filter excludes some industries. The EW four-screen portfolio delivered higher cumulative returns than the six-screen portfolio every year until 2018, and thereafter experienced a weak 2018 and 2019 compared to the six-screen. This might be because the P/B excluded high performing growth stocks such as IT and contributed to reducing exposure significantly in 2018 and 2019. Another interesting element of the P/B filter is the risk of investing in substandard companies, rather than undervalued companies. When Reinganum (1988) analyzed winners and found that most stocks traded at a P/B below 1, it indicated that most companies were undervalued. However, when implementing this screen on all companies, one runs the risk of investing in companies with poor expected performance, which justifies a P/B below 1. This might increase the downside risk of the four-screen, as for example illustrated by the high Sortino ratio.

The two EW portfolios and the VW four-screen are all associated with high risk for the investor. Thus, for investors who prefer lower risk, the VW six-screen is the best choice. The portfolio delivers higher return than the market and S&P to the same risk, and hence slightly better risk-adjusted return. This portfolio stands out, likely because the effect of small caps is significantly reduced when value-weighting, reducing the risk and return. The EBITDA margin filter and D/E filter are interesting in this

case, as margin robust companies should fare better during market downturns, possibly reducing the systematic risk. Also, less exposure to small caps is believed to reduce the unsystematic risk, as discussed above. Although, it is important to notice that the VW six-screen experiences more than six years of drawdown in the beginning of the time period, which might want investors to reallocate their capital elsewhere. However, the patent investor will see strong gains in the second half of the period. The impact of weights is elaborated on in detail in the next section.

8.2.2 Impact of weighting methods and rebalancing

The choice of weighting method results in major differences for the performance of the two different strategies. While the six-screen strategy outperforms the four-screen strategy both in terms of cumulative return and Sharpe ratio for the EW portfolios, the results are completely opposite in the VW portfolios. The cumulative return of the six-screen strategy drops from 626% to 287% when the portfolio is adjusted from EW to VW, and the Sharpe ratio decreases from 0.56 to 0.44. The same adjustment reduces the cumulative return of the four-screen strategy from 485% to 375%, and the Sharpe ratio from 0.5 to 0.45.

The main reason for this drop in performance is due to the reduced exposure to small cap firms in both strategies. However, this effect is especially noticeable in the six-screen portfolios compared to the four-screen portfolios. As the four-screen strategy is filtered to only invest in companies with less than 20 million shares outstanding, the strategy is significantly tilted towards small cap stocks, as larger companies tend to have more shares outstanding. Table 7.8 showed that the average and median market cap of the companies selected by the four-screen strategy is lower than the average and median of the total market. The implication of this is that the effect of value-weighting the four-screen portfolio is less noticeable, and the estimated coefficient of the SMB factor is increasing in the FF3, FFC4 and FF5 factor models.

The six-screen portfolio sees a significant decline in cumulative returns after value-weighting. The EW portfolio has a statistically significant exposure to the SMB factor in all three factor models, and in all time periods. This contrasts with the VW portfolio, which has no significant exposure to the SMB factor and size risk in any of the time periods. As the six-screen portfolios holds stocks with an average and median market capitalization up to 100 times that of the four-screen portfolios, the impact of value-weighting is greater in the six-screen portfolios. That is, the portfolio weights of the largest stocks will increase considerably more in the six-screen portfolios compared to the four-screen portfolios. Thus, the

higher returns in the EW six-screen strategy are related to the outperformance of small cap stocks, and this effect is removed when the portfolio is value-weighted. This result is in line with the findings of Pae and Sabbaghi (2015), as they found that EW portfolios outperformed VW portfolios in a normal economy.

Pae and Sabbaghi (2015) also found that EW portfolios had higher systematic risk than VW portfolios in normal markets. This is consistent with the results of the six-screen portfolio, where the estimated beta using CAPM changes from 1.13 in the EW portfolio to 0.93 in the VW portfolio. An interesting finding is that the results from the four-screen strategy contradicts this finding, as the beta coefficient increases in the VW portfolio. Beta increases in the VW portfolio likely due to lower returns, which makes the portfolio returns somewhat more similar to market returns. This is also reflected in an increased adjusted R-squared in the VW portfolio. Pae and Sabbaghi (2015) claimed that EW portfolios had lower systematic risk than VW portfolios when the market premium was negative. This might explain why the four-screen strategy experiences its highest beta in the VW portfolio in the first sub-period where the market is characterized by multiple periods of negative returns.

In the VW four-screen portfolio, the maximum weight of one single stock is 14.5%, which is relatively high compared to the total number of 376 investments at that time. The results of value-weighting the portfolios might lead to a reduced effect of diversification, if a few large stocks account for a majority of the portfolio weight. One possible action to mitigate this risk is to introduce a maximum weight limit for each stock in the portfolio.

After discussing the effects of the two weighting-methods, a short discussion of portfolio rebalancing is needed. The portfolios are constructed based upon the starting amount of money made available to implement in the strategy, and no more money is invested after this initial investment. Hence, the portfolios must be rebalanced at a minimum of every quarter when stocks enter or exit the portfolios. This frequent rebalancing of the portfolios might lower the chances of experiencing the full effect of the rapid price appreciation that the strategies are designed to capture, as cumulative returns are narrowed by the frequency of rebalancing.

The EW portfolios of both strategies are calculated with both monthly and quarterly rebalancing, presented in Appendix E. The difference in performance between the two rebalancing frequencies is

almost not present in the six-screen portfolios, while the monthly rebalanced four-screen portfolio deliver 19 pp higher cumulative returns than the quarterly rebalanced portfolio. Wise (1996) found that rebalanced portfolios outperformed passive strategies over short time horizons with a probability of about two-thirds. This seems to be the case for the four-screen portfolio, but the difference in returns between the two frequencies is somewhat limited as the strategy is forced to rebalance every quarter.

8.2.3 Transaction costs

With several trades and frequent rebalancing, the portfolios are exposed to transaction costs. The EW portfolios inquire higher transaction costs due to more frequent rebalancing than the VW portfolios. Total transaction costs over the period for the EW portfolios are approximately twice the size of the VW, but due to higher returns investors are compensated for the larger costs. What is also notable is how much higher transaction costs for the four-screen portfolios are compared to the six-screen. This is due to the volatile nature of four-screen, causing the stocks to deviate much further from the average investment in every stock, which increases transaction costs when rebalancing the portfolios. Looking at whether it is profitable for an investor to invest in the strategies compared to investing in the S&P 500, it is the VW six-screen portfolio that is most exposed to higher transaction costs, as it only generates 10% excess returns above the S&P 500 over the time period.

The method behind calculating transaction costs is associated with uncertainty. More precisely, whether it is reasonable to assume a constant average cost of 20 bps over the period and whether a yearly approximation should be incorporated instead. O'Neil Global Advisors (2016) applied 20 bps, when conducting backtesting estimations of portfolio performance. Additionally, the average of the yearly estimated transaction costs over the period is 25bps, building on Elkins/Mcsherry (2011). Thus, 20 bps is arguably a sensible estimate. However, O'Neil Global Advisors (2016) could have incentives to use lower transaction costs due to their role as financial advisors, and the exponential yearly estimate is also uncertain. A sensitive analysis of the portfolio performance relative to changes in the transaction costs is therefore displayed in Table 8.2 and discussed further.

Table 8.2

Holding period returns with different transaction costs

	Equally weighted	Value weighted
Constant 20 bps		
Four-screen	425%	326%
Six-screen	558%	251%
Exponential bps		
Four-screen	405%	318%
Six-screen	535%	240%
Constant 40 bps		
Four-screen	372%	283%
Six-screen	497%	218%
S&P 500		223%

The EW portfolios deliver high excess returns over the investment period regardless of which transaction cost scenario applied. However, the difference is notable as the EW six-screen portfolio's returns drops 61 pp when doubling the transaction costs from 20 bps to 40 bps. Doubling the cost also alters the conclusion of the VW six-screen portfolio from outperform to underperform compared to the S&P 500, as the return dwindles to 218%. Note, however, that 40 bps is arguably unlikely since it assumed a transaction cost level equal to what was seen in 2008. The transaction costs have dropped severely since then, because of technological advancements and was 11.4% on average in 2010, according to Elkins/McSherry (2011). The exponential scenario makes for only minor diversion from the base case of 20 bps. Further, remember that the VW portfolios showed risk-adjusted returns close to the S&P 500. Thus, minor changes in transaction costs could imply that both VW portfolios generate lower returns and risk-adjusted returns compared to the S&P 500. The EW portfolios saw much higher returns and risk-adjusted returns and are robust to larger increases in transaction costs.

Lastly, with regards to transaction cost, liquidity and the assumption of stocks being traded immediately at the closing price are discussed. According to Pedersen (2015) the total transaction cost can be split into two indirect costs, the bid-ask spread and market impact costs. Illiquid securities are said to have higher transaction costs, meaning a larger bid-ask spread, i.e., the difference between the buy price and sell price. A larger spread has an adverse effect on portfolio returns, particularly when trades are being executed frequently. Knowing that the median market capitalization for the four-screen is ranging from USD 16-51 million, the assumed transaction cost of 20 bps might be in the lower end of what is realistic.

Several of the stocks held are likely illiquid, meaning that the investor must by at a higher price than the price close and subsequently sell below the price close. However, as illustrated above, one must see a severe increase in the transaction costs before the holding period return drops to the market's level. As the six-screen ignores stocks trading at a market capitalization below USD 20 million, the strategy is most likely less exposed to this issue.

The market impact costs are arguably less relevant for the portfolios, since the investment is spread over several hundreds or thousands of stocks, implying that the investor does not buy a large number of the shares outstanding in each security. Again, this becomes a larger challenge when looking at the smallest stocks and if the strategy is upscaled significantly. Additionally, it is important to be aware of the liquidity premium during market downturns, where one could be exposed to cases where there are no bid prices, meaning that the investor must find a counterparty willing to take the other side (Pedersen, 2015). Remembering that both strategies are heavily exposed to small caps (except for the VW six-screen) and high maximum drawdowns, this might have a serious impact on the strategies, if several investors pull their investment at the same time. Ultimately, the transaction cost estimates are based on research and professional investors, but it is important to be aware of the potential downside risks.

8.2.4 Holding period

A key rule for the strategy is that the stocks must be sold after two years, in-line with Reinganum's (1988) instructions. However, he did not clarify why two years was chosen as a sell signal. The arguably most apparent reason is subject to the goal of the strategy which was to invest in firms which were expected to see a rapid price appreciation and subsequently exit the investment, in order to reallocate the capital to other cases of expected rapid price appreciation. Also knowing that the strategy was based on stocks that at least doubled in price over one year, it becomes clear that the strategy seeked to exploit quick price gains, opposed to, for example a more traditional buy-and-hold strategy. Another part of the explanation might be anchored in the theories of contrarian strategies, as literature provides evidence of contrarian behavior among stocks that have outperformed over a period of 3 or more years, as discussed in Section 4.4.1. As the scope of the thesis implies replicating Reinganum's (1988) strategy, the thesis has not analyzed other potential sell signals than the lapse of two years.

8.2.5 Section summary

Taking all the performance measures into consideration, the EW six-screen stands out as the most attractive portfolio for investors. For investors with a lower risk-appetite, the VW six-screen is preferred. This portfolio assigns higher weights to the larger companies, reducing the exposure to the volatile small caps significantly. For the investor, it is important to be aware of the high small cap exposure in both the EW and VW four-screen portfolios. This exposure is a likely driver of the impressive returns, but it also leads to negative side-effects in the form of high unsystematic risk and drawdowns. This creates significant downside risk, possibly larger than most investors are willing to undertake. Further, changes in transaction costs causes notable impacts on all strategies, particularly for the four-screen due to frequent trading and high volatility in returns. However, the portfolios are robust to large changes, as all portfolios except the VW six-screen outperforms when doubling transaction costs. In general, investors should have a long-term perspective, as all strategies could need at least 4 years to recover from a stock market crash.

8.3 Results compared to literature

As mentioned in Section 4.1.1, one other article that implements and tests the four-screen strategy created by Reinganum (1988) has been identified. One of the main findings in Yu's (2009) article was the increased difficulty in implementing the four-screen strategy through the 1990's and up to 2006, due to a decreasing number of stocks with less than 20 million shares outstanding. Yu (2009) found that the percentage of stocks meeting this filter declined from 4.8% in year 2000 to 2.5% in 2006, while this thesis finds that 59% of stocks in year 2000 and 38% of stocks in year 2006 meet the same filter.

There might be multiple reasons for this deviation, but it seems strange that the difference is that large. First of all, the total number of companies in Yu's (2009) article was somewhat higher than this thesis' sample. The number of companies in this thesis is based upon the stocks that have all the necessary data to calculate the four different screens available, while Yu (2008) included "available stocks", without further specifications. Regardless, the difference in the number of companies is not enough to explain the difference in companies meeting the filter.

Another possible explanation might be the source of data. Yu (2009) described her data sample:

> We begin with all stocks in that are in both the Standard and Poor's Compustat North America files (Compustat) and the Center for Research in Security Prices (CRSP) monthly database. We require earnings data for at least five consecutive quarters and 15 months of returns data in the period 1970-2006. (p. 359)

These are the same databases as those applied in this thesis. The number of shares outstanding in this thesis is downloaded from CCM, which relies on XBRL data (see Section 2.5 and Section 5.1 for further descriptions of the data sources). As the differences in results are of that magnitude, random samples of stocks from the overall period in this paper have been investigated further and compared to the companies' quarterly and annual reports (SEC Form 10-Q and SEC Form 10-K), Yahoo! Finance and Refinitiv. The overall results of the random samples are that the reported number from CCM corresponds with those of the abovementioned sources. Some minor discrepancies are identified, but none of any significant magnitude.

As the data source is considered to be reliable, another possible explanation might be the data processing. CCM provides users with an actual number of shares outstanding at the data date, and an adjustment factor which is used to adjust the historical number of shares outstanding and share price to the level of today. This paper applies the actual number of shares outstanding at the data date, to ensure that the information applied when forming the portfolio is that which was available at the time of formation. A significant portion of the companies in the data sample have adjustment factors over 1, meaning that they have increased the number of shares outstanding over time, for example through corporate actions such as seasoned equity issues and stock splits. Thus, a possible explanation could be that Yu (2009) adjusted the reported number of shares outstanding, however this was not explicitly stated.

Moving on to the performance of the portfolio, Yu (2009) replicated the four-screen strategy in a sub-period from 1984-2006, which is overlapping the time period of this thesis. She did not provide details into how the portfolio is constructed, other than that it was equal-weighted. Yu (2009) found that the original four-screen strategy produced significant and positive alphas from CAPM and FFC4, but not from FF3. The four-screen EW portfolio constructed in this thesis does not produce significant alpha in any of the regression models in either the overall period or the first sub-period, which is overlapping Yu's (2009) period. There are multiple similarities in the factor exposures compared to this thesis in

terms of somewhat lower but still positive and significant exposure to SMB and HML, and negative and significant exposure to UMD, but the explanatory power of Yu's (2009) regressions was lower.

Yu (2009) concluded that the strategy was profitable in the sub-period from 1986-2006 relative to an equally weighted market index, and that it produced positive and significant alphas within the framework of CAPM and FFC4, but that it was increasingly difficult to implement. This is in opposition to this thesis's findings, as the four-screen strategy is still possible to implement in all years up to 2019. However, there is a decline in the number of stocks that meet all four filters, which might make it harder to implement in the future. It is also shown in Section 7.5 that the four-screen strategy no longer produces significant and positive alphas within the framework of either CAPM, FF3, FFC4 or FF5.

8.4 Limitations

This section will address some of the limitations of this thesis, including implications of implementing the portfolios in practice, the thesis' chosen time period and the strings attached to identifying shared characteristics among winners based on the CCM database.

8.4.1 Practical limitations

A final layer of transaction costs associated with creating the portfolios based on the strategy, are costs related to infrastructure required to execute the strategies and potential compensations to the active manager(s). With thousands of investments over several years, the strategy commands advanced tools and skillful manager(s). Whether an investor hires an active manager or adapts the strategy without external help, there is an extra fee not accounted for in transaction costs either as compensation to the active manager or as an alternative cost for the investor. For the end investor to beat the market, the strategy must outperform after all layers of costs associated with adapting the strategy, which is difficult to claim with certainty.

Another limitation to the practical implementation of the strategy is the assumptions that stocks can be bought in fractions. An example is Berkshire Hathaway's stock price which has fluctuated between USD 100,000 and USD 340,000 between 2010 and 2019, which would be impossible to buy. The implication of this assumption gets more problematic the lower the initial investment is, as it is distributed as an equal share in all stocks. A solution to this problem might be to exclude all shares trading above a certain

price. It is, however, problematic to set a limit with confidence, because it would vary greatly with the initial capital invested.

8.4.2 Time period

The time period analyzed in this thesis stretches from 2000 until 2019, which is fully in-line with the research question expressing that the scope of the thesis is to test whether Reinganum's (1988) investment strategy holds in a subsequent time period. To optimize the objectivity of the study these 20 years were chosen partly because the millennium was a natural starting point. An added possible strength of choosing these years, is that one saw a value bull market over the approximately first 10 years, followed by a growth stock bull market the last 10 years (Vanguard, 2020). This could increase the robustness of the strategy in the long run, since the sample of winners should be diversified across both categories. As discussed previously, Reinganum's (1988), time span stretched over a value bull market, which arguably has impacted his investment strategy. However, it should be mentioned that by extending the time period back to for example Reinganum's (1988) period, a more robust alpha estimate could have been achieved. Knowing that the EW six-screen portfolio generates significant alpha over the full period, but not between 2010-2019, it would have been interesting to see if the alpha significance also varied across sub-sample periods after extending the time period back to 1970.

8.4.3 CRSP/Compustat database

The six characteristics common to the winner stocks are a result of an analysis of approximately 40 different fundamental and technical measures. It is important to note that all these measures are based on data available on the CCM database. This impacts the six-screen strategy because it most likely entails that there are other shared characteristics among winner stocks that are not captured in this thesis. The most apparent example of possible missed characteristics are the key figures derived from companies' analytical statements, which are used to analyze value creation in a firm. This is for example free cash flow, liquidity measures and rentability measures (Petersen, Plenborg, & Kinserdal, 2017). However, note that CCM provides sufficient data to test all the filters that Reinganum (1988) addresses in his article, except for the Datagraph rating.

9. Conclusion

The purpose of the thesis has been to investigate if Reinganum's (1988) four-screen strategy yields abnormal returns in the time period 2000-2019, and whether it is possible to create an alpha-generating investment strategy based on analyzing common characteristics among today's stock market winners. To answer the research question, Reinganum's (1988) original four-screen strategy was replicated over the thesis' time period, before the same methodology was followed to create a new investment strategy. Subsequently, Reinganum's (1988) four-screen strategy and the thesis' new strategy was backtested as portfolios to investigate whether they produce abnormal returns.

When replicating Reinganum's (1988) four-screen strategy, the thesis finds that the average cumulative holding period return excess of the S&P 500 from 2000-2019 is 45.9% after two years, which is 8.8 pp higher than Reinganum's (1988) returns between 1970-1983. Thus, presented in like manner to the original paper, Reinganum's (1988) four-screen strategy still outperforms the S&P 500. The equivalent return for this thesis' created six-screen strategy was 9.1%, considerably lower than the four-screen strategy. However, these results are highly influenced by how they are presented, which becomes evident when the strategies are traded as portfolios.

It is impossible to perfectly replicate Reinganum's (1988) method because his winner sample was selected on unknown criteria prior to his analysis. Hence, this thesis slightly modifies the methodology of identifying winner stocks, which might be the reason why the thesis finds less convincing evidence of shared characteristics among the 300 randomly selected winner stocks. Still, six shared attributes are singled out: P/B above 1, D/E below 2, positive three-year annual revenue growth rate, positive EBITDA margin, positive change in the year-over-year EBITDA margin, and positive change in the RSR.

Both the equal-weighted (EW) four-screen and six-screen portfolios yield significantly higher cumulative holding period returns accompanied with superior risk-adjusted returns, relative to the S&P 500 and the market. Among the EW portfolios, the six-screen portfolio stands out as the most attractive investment. The value-weighted (VW) four-screen and six-screen portfolios also outperform the S&P 500 and the market portfolio but underperformed the EW portfolios. The two four-screen portfolios are the riskiest investments, with high unsystematic risk and periods of pronounced negative returns.

Neither the EW nor the VW four-screen portfolios generate abnormal returns after controlling for several risk factors in the complete time-period nor in the individual sub-periods. The EW six-screen portfolio produces significant abnormal returns in the complete time-period, but the estimated alpha coefficient is statistically insignificant in the second sub-period, indicating that the strategy fails to generate consistent abnormal returns. The VW six-screen strategy produces significant abnormal returns after controlling for market, size, value and momentum risk in the complete period, but not in any of the sub-periods.

As a concluding remark, neither Reinganum's (1988) four-screen strategy nor this thesis' created six-screen strategy produces consistent abnormal returns. Thus, based on the analysis in this thesis one cannot conclude whether it is possible to utilize the methodology to construct an alpha-generating strategy. This thesis tests one single combination of filters, but there might be other combinations that will succeed in producing consistent abnormal returns.

10. Further Research

The constructed six-screen portfolios produce risk-adjusted returns above the market and the S&P 500, without any form of risk management. A natural extension of the thesis would therefore be to investigate if the methodology can be combined with risk management, to reduce the downside risk of the portfolio. The thesis is limited to long-only strategies, meaning that the six-screen strategy does not consider the option of shorting stocks. The six-screen portfolios hold thousands of stocks at the same time, yielding significant diversification that eliminates most of the idiosyncratic risk. However, the portfolios are still highly exposed to market risk, with market betas over one for the EW portfolio, and just below one for the VW portfolio. The exposure to market risk could be reduced by allowing shorting of stocks.

If shorting was allowed, the portfolio could be made equity market neutral by being equally long and short, eliminating the overall market risk (Pedersen, 2015). Thus, further research could investigate whether it is possible to identify bad performers that can be shorted, to reduce the market risk of the portfolios. This could for example be done either by creating percentiles for the identified six screens, or by a similar investigation of companies that are experiencing rapid decline in price. This method could be further extended and specified to individual sectors, going long the companies within the industry that are fulfilling the selected screens and shorting companies that are identified as bad performers. Having neutralized both market and industry risk leaves the portfolio exposed to the risks accompanying the risk factors the investor seeks to be exposed to.

Including the possibility of shorting makes the methodology and strategy more complicated, and introduces some new aspects regarding leverage, margin requirements, whether the shares are available for shorting and which investors that are authorized to implement the strategy. However, it can also improve the strategy's performance, and will make the strategy more similar to an actual quant equity portfolio, as investors could be reluctant to implement the strategy without any form of risk management. Hence, further research could investigate using the methodology to identify both winners and losers, creating a long-short strategy.

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Appendices

Appendix A: Downloaded data items from CCM:

This section presents the different data items that are downloaded to perform the analyses in the thesis. The fundamental data is downloaded from CCM, using PERMNO's from the sample of companies downloaded from CRSP.

The following data items have been downloaded to construct the nine-screen and four-screen strategies of Reinganum (1988), and all financial ratios, metrics and technical indicators used to identify shared characteristics among this thesis' winner sample.

Table A.1

Description of data items from CCM used to process data and calculate financial metrics

Name of data item	**Description of data item**
Company Name	Name of the company.
Historical CRSP PERMNO Link to COMPUSTAT Record	PERMNO is a unique stock level identifier. While most of the companies have one class shares, some companies have more than one class shares traded at different prices, and this is the reason why a company can have more than one PERMNO.
GSECTOR – GIC Sectors	This item represents the first level in the hierarchy of the Global Industry Classification Standard (GICS).
CEQQ – Common/Ordinary Equity – Total	Common/Ordinary equity at the end of each quarter.
CSHOQ – Common Shares Outstanding	Common shares presented on a quarterly basis. Not adjusted for stock splits.
PRCCQ – Price Close - Quarter	Closing price last trading day of each quarter. Not adjusted for stock splits.
AJEXQ – Adjustment Factor (Company) – Cumulative by EX-Date	Adjustment factor that represents a ratio that enables you to adjust per-share data as well as share data for

	all stock splits and stock dividends that occur subsequent to the end of a given period (quarterly).
APDEDATEQ – Actual Period End date	Represents the actual date the company closes accounting for the period.
REVTQ – Revenue – Total	Sales/Turnover (Net) plus operating revenues.
NIQ – Net Income (Loss)	Income or loss reported by a company including extraordinary items and discontinued operations.
PIQ – Pretax Income	Operating and nonoperating income before provisions for income taxes and minority interests.
PRCCD – Price – Close - Daily	The close price of the day for the security. Not adjusted for stock splits
Data Date	This item is the reporting date for a data record. For example, for annual company data items this item equals the fiscal period end date. For security level data this item equals the trade date for high, low, close prices. This item is a key field used to retrieve specific data records from the database.
DATAFQTR - Fiscal Data Year and Quarter	This item identifies the fiscal year and quarter with the four fiscal quarters. For example, for a company that ended its 2004 fiscal year in June 2004, the Fiscal Quarter by Year (DATAFQTR) values are: • 2004Q1 represents July - September, 2003 • 2004Q2 represents October - December, 2003 • 2004Q3 represents January - March, 2004 • 2004Q4 represents April - June, 2004

LTQ - Liabilities - Total	This item represents current liabilities plus long-term debt plus other noncurrent liabilities, including deferred taxes and investment tax credit.
CAPXY - Capital Expenditures	This item represents cash outflow or the funds used for additions to the company's property, plant and equipment, excluding amounts arising from acquisitions, reported in the Statement of Cash Flow
OIADPY - Operating Income After Depreciation	This item represents the operating income of a company after deducting expenses for cost of goods sold, selling, general, and administrative expenses, and depreciation.
OIBDPY - Operating Income Before Depreciation	This item includes the effects of adjustments for Cost of Goods Sold and Selling, General, and Administrative Expenses
Dividends - Total	This item represents the total amount of dividends, other than stock dividends, declared on all equity capital of the company, based on the current year's net income
FINCFY - Financing Activities - Net Cash Flow	This item represents cash paid or received for all transactions classified as Financing Activities on a Statement of Cash Flows
IVNCFY - Investing Activities - Net Cash Flow	This item represents net cash received or paid for all transactions classified as investing activities on a Statement of Cash Flows
OANCFY - Operating Activities - Net Cash Flow	This item represents the net change in cash from all items classified in the Operating Activities section on a Statement of Cash Flows

SPIQ – Special Items	This item represents unusual or nonrecurring items presented above taxes by the company
XRDQ - Research and Development Expense	This item represents all costs incurred during the year that relate to the development of new products or services

Table source: *Standard & Poor's Xpressfeed*. Available: Standard & Poor's Global [May 14, 2020]. Retrieved from Wharton Research Data Service.

Appendix B: Formulas for screen calculations

This appendix will present the formulas used for calculating the financial ratios, metrics and technical indicators applied as screens in Reinganum's nine-screen and four-screen strategies, and the thesis' created six-screen strategy. Remember that all data downloaded is unadjusted, which is why an example of the process of adjusting data is presented below.

To illustrate the effect of adjusting data, we look at Frontline Ltd, listed at NYSE. In February 2016, they made a 1:5 stock split, reducing the number of outstanding shares. In the raw quarterly data, Frontline Ltd closes at 2.99 at 31.12.2015, with 781.938 million shares outstanding. In our next data date, 31.03.2016, the share price is 8.37, with 156.387 million shares outstanding. After adjusting the downloaded data for the split, the price and number of outstanding shares from 31.12.2015 is adjusted to 14.95 and 156.387 million. Without adjusting, it looked like the price increased from 2.99 to 8.37 over the quarter, when it actually declined from 14.95 to 8.37 adjusting for the number of shares outstanding. Thus, the price and number of shares outstanding from the time period before the stock split is adjusted to the same level as after the stock split, and the actual price change is available to calculate RSR.

Table B.1

Formulas used to calculate the four and nine-screen filters

1) Price-to-book $< 1^{*}$	$P/B = \frac{Share\ price_q^{**} * Shares\ outstanding_q^{**}}{Book\ value\ of\ \ equity_q}$
2) Five-year quarterly earnings growth > 0	a) Net income (NI) is annualized for each quarter: $Annualized\ NI_q = NI_q + NI_{q-1} + NI_{q-2} + NI_{q-3}$ b) Growth (GR) in NI is calculated as the growth from the same time period last year: $NI_q\ GR = \frac{Annualized\ NI_q}{Annualized\ NI_{q-4}} - 1$ c) Five-year GR is calculated as the arithmetic average of the GR in the last five years: $\frac{NI_q\ GR + NI_{q-4}\ GR + NI_{q-8}\ GR + NI_{q-12}\ GR + NI_{q-16}\ GR}{5}$
3) Quarterly earnings acceleration*	$Earnings\ acceleration_q = \frac{NI_q - NI_{q-1}}{\lvert NI_{q-1}\rvert} - \frac{NI_{q-1} - NI_{q-2}}{\lvert NI_{q-2}\rvert}$
4) Pretax profit margins > 0	$PTP\ margin = \frac{Pretax\ income_q}{Revenue_q}$
5) Shares outstanding < 20 million*	Shares outstanding < 20 million*
6) RSR ≥ 70	a) Relative strength rank based on price** returns $Price\ return_q = \frac{Price_q}{Price_{q-1}} - 1$ b) Price returns for all companies are ranked, with the best company assigned rank 100, and the worst company is assigned rank 0.
7) Change in RSR $> 0^{*}$	$Change\ in\ RSR_q = RSR_q - RSR_{q-1}$

8) Stock is selling within 15% of its maximum price in the last two years	a) Calculated using daily prices** over the last two years.

* The screen is a part of the four-screen strategy. ** Price or number of shares has been adjusted with cumulative adjustment factor provided by CCM

Table B.2

Formulas used to calculate the six-screen filters

1) Price-to-book > 1**	$P/B = \frac{Share\ price_q^{**} * Shares\ outstanding_q^{**}}{Book\ value\ of\ \ equity_q}$
2) Three-year quarterly revenue growth > 0	a) Revenue (Rev) is annualized for each quarter: $Annualized\ Rev_q = Rev_q + Rev_{q-1} + Rev_{q-2} + Rev_{q-3}$ b) Growth (GR) in Rev is calculated as the growth from the same time period last year: $NI_q\ GR = \frac{Annualized\ Rev_q}{Annualized\ Rev_{q-4}} - 1$ c) Three-year GR is calculated as the arithmetic average of the GR in the last five years: $\frac{Rev_q\ GR + Rev_{q-4}\ GR + Rev_{q-8}\ GR + Rev_{q-12}\ GR + Rev_{q-16}\ GR}{5}$
3) Debt-to-equity < 2	$D/E = \frac{Total\ liabilities_q}{Book\ value\ of\ equity_q}$
4) EBITDA margin > 0	$EBITDA\ margin = \frac{EBITDA_q}{Revenue_q}$
5) Change in y/y EBITDA margin > 0	$\Delta EBITDA\ margin = EBITDA\ margin_q - EBITDA\ margin_{q-1}$
6) Change in RSR > 0*	$Change\ in\ RSR_q = RSR_q - RSR_{q-1}$

** Price or number of shares has been adjusted with cumulative adjustment factor provided by CCM

Table B.3

Financial ratios sorted after fundamental, technical, valuation and miscellaneous measures

Fundamental	Technical	Valuation	Miscellaneous
3-year revenue growth	Relative strength rank	Price-to-book	Shares outstanding
Revenue y/y growth	Change in relative strength rank	Price-to-sales	Share price
Accelerating quarterly revenue	Stocks trading within 15%	Price-to-earnings	Market cap
3-year revenue CAGR	maximum price during the previous	Price-to-operating cash flow	
EBITDA	two years		
EBITDA y/y growth			
EBITDA margin			
Change in y/y EBITDA margin			
Accelerating quarterly EBITDA			
EBIT			
EBIT y/y growth			
EBIT margin			
Change in y/y EBIT margin			
Accelerating quarterly EBIT			
Pre-tax profit			
Pre-tax profit y/y growth			
Pre-tax profit margin			
Change in y/y net profit margin			
Accelerating quarterly profits			
Profit			
Profit y/y growth			
Profit margin			
Change in y/y profit margin			
Accelerating quarterly profit			
Debt-to-equity			
Capex-to-sales			
Debt-to-EBITDA			
Operating cash flow-to-EBITDA			
Operating cash flow			
Capex			
Change in Capex			
R&D expenditure			
Change in R&D expenditure			
Dividends			

Appendix C: Quarterly statistics of stocks meeting screens

This appendix presents the quarterly statistics of the stocks meeting the screens in Reinganum's (1988) four-screen strategy and this thesis' six-screen strategy.

Table C.1

Overview of all stocks and number of stocks meeting filter rules of the four-screen strategy

Quarter	Total companies	Price-to-book	Shares outstanding	Change in RSR	Accelerated earnings	All filters
1999Q4	5652	1508	3462	2652	2622	287
2000Q1	5555	1494	3332	2477	2533	225
2000Q2	5542	1647	3291	2921	2979	366
2000Q3	5511	1724	3197	2661	2438	265
2000Q4	5416	2016	3066	3133	2497	418
2001Q1	5400	1887	2986	2561	2335	336
2001Q2	5351	1612	2905	2371	2832	224
2001Q3	5294	1845	2813	2732	2327	332
2001Q4	5273	1529	2723	2170	2463	169
2002Q1	5204	1295	2633	2426	2414	202
2002Q2	5134	1359	2549	2654	2660	264
2002Q3	5044	1808	2493	2381	2298	219
2002Q4	4912	1554	2390	2337	2325	203
2003Q1	4816	1600	2336	2260	2166	210
2003Q2	4754	1123	2290	1986	2608	145
2003Q3	4687	805	2210	2066	2124	115
2003Q4	4603	578	2123	2250	2205	81
2004Q1	4559	478	2050	2086	2144	65
2004Q2	4498	480	1945	2437	2348	80
2004Q3	4450	539	1899	2401	2021	63
2004Q4	4408	427	1846	2026	2091	55
2005Q1	4389	462	1783	2321	1902	61
2005Q2	4379	492	1756	2143	2450	53
2005Q3	4342	432	1694	1966	1940	57
2005Q4	4290	437	1654	2225	2055	53
2006Q1	4295	353	1635	1856	1918	37
2006Q2	4272	405	1611	2191	2301	56
2006Q3	4272	471	1600	2243	1852	62
2006Q4	4232	384	1565	2061	2006	55
2007Q1	4206	353	1530	2062	1843	41
2007Q2	4173	350	1498	1992	2350	44
2007Q3	4139	505	1474	2032	1804	40
2007Q4	4069	751	1442	2121	1837	76
2008Q1	4085	914	1445	1968	1844	114
2008Q2	4064	1140	1436	1912	2118	100
2008Q3	4065	1220	1437	1935	1722	126
2008Q4	4006	1793	1399	1954	1650	175
2009Q1	4030	2053	1398	1662	1870	166
2009Q2	3971	1545	1358	1691	2181	166
2009Q3	3922	1219	1312	1677	1923	95
2009Q4	3860	1159	1266	1865	1737	140
2010Q1	3800	992	1238	1758	1735	108
2010Q2	3750	1121	1213	1966	1994	158
2010Q3	3689	1066	1195	1939	1692	81
2010Q4	3617	844	1152	1728	1604	96
2011Q1	3632	800	1125	1717	1720	93
2011Q2	3580	890	1108	1868	1872	96
2011Q3	3563	1265	1089	1729	1548	160
2011Q4	3520	1090	1064	1720	1528	66
2012Q1	3522	926	1064	1548	1722	104
2012Q2	3496	1015	1037	1802	1838	153
2012Q3	3465	969	1019	1616	1534	70
2012Q4	3432	915	1005	1695	1607	122
2013Q1	3424	768	988	1627	1638	68
2013Q2	3416	708	976	1572	1780	68
2013Q3	3389	621	955	1589	1518	57
2013Q4	3372	535	962	1668	1531	48
2014Q1	3360	509	935	1572	1581	68
2014Q2	3339	540	911	1715	1817	58
2014Q3	3350	606	901	1762	1448	63
2014Q4	3358	610	899	1670	1512	40
2015Q1	3378	611	890	1591	1506	52
2015Q2	3419	615	909	1663	1890	65
2015Q3	3432	768	914	1725	1485	77
2015Q4	3426	773	928	1604	1570	61
2016Q1	3450	832	950	1679	1591	85
2016Q2	3428	792	954	1586	1917	79
2016Q3	3409	683	953	1526	1502	58
2016Q4	3400	589	956	1750	1518	54
2017Q1	3395	568	948	1451	1639	45
2017Q2	3362	571	925	1680	1801	58
2017Q3	3339	595	897	1665	1546	41
2017Q4	3317	561	873	1560	1499	44
2018Q1	3306	572	874	1603	1579	35
2018Q2	3308	544	857	1526	1784	42
2018Q3	3328	547	855	1627	1495	33
2018Q4	3292	831	843	1702	1417	52
2019Q1	3301	676	861	1467	1580	34
2019Q2	3324	720	863	1766	1812	62
2019Q3	3341	769	879	1689	1571	72
2019Q4	3330	704	879	1543	1468	44
Average	4031	912	1527	1945	1915	110
Median	3860	769	1266	1856	1838	72
Max	5652	2053	3462	3133	2979	418
Min	3292	350	843	1451	1417	33

Table C.2

Overview of percentages of stocks meeting filter rules of the four-screen strategy

Quarter	Price-to-book	Shares outstanding	Change in RSI	Accelerated earnings	All filters
1999Q4	26.7%	61.3%	46.9%	46.4%	5.1%
2000Q1	26.9%	60.0%	44.6%	45.6%	4.1%
2000Q2	29.7%	59.4%	52.7%	53.8%	6.6%
2000Q3	31.3%	58.0%	48.3%	44.2%	4.8%
2000Q4	37.2%	56.6%	57.8%	46.1%	7.7%
2001Q1	34.9%	55.3%	47.4%	43.2%	6.2%
2001Q2	30.1%	54.3%	44.3%	52.9%	4.2%
2001Q3	34.9%	53.1%	51.6%	44.0%	6.3%
2001Q4	29.0%	51.6%	41.2%	46.7%	3.2%
2002Q1	24.9%	50.6%	46.6%	46.4%	3.9%
2002Q2	26.5%	49.6%	51.7%	51.8%	5.1%
2002Q3	35.8%	49.4%	47.2%	45.6%	4.3%
2002Q4	31.6%	48.7%	47.6%	47.3%	4.1%
2003Q1	33.2%	48.5%	46.9%	45.0%	4.4%
2003Q2	23.6%	48.2%	41.8%	54.9%	3.1%
2003Q3	17.2%	47.2%	44.1%	45.3%	2.5%
2003Q4	12.6%	46.1%	48.9%	47.9%	1.8%
2004Q1	10.5%	45.0%	45.8%	47.0%	1.4%
2004Q2	10.7%	43.2%	54.2%	52.2%	1.8%
2004Q3	12.1%	42.7%	54.0%	45.4%	1.4%
2004Q4	9.7%	41.9%	46.0%	47.4%	1.2%
2005Q1	10.5%	40.6%	52.9%	43.3%	1.4%
2005Q2	11.2%	40.1%	48.9%	55.9%	1.2%
2005Q3	9.9%	39.0%	45.3%	44.7%	1.3%
2005Q4	10.2%	38.6%	51.9%	47.9%	1.2%
2006Q1	8.2%	38.1%	43.2%	44.7%	0.9%
2006Q2	9.5%	37.7%	51.3%	53.9%	1.3%
2006Q3	11.0%	37.5%	52.5%	43.4%	1.5%
2006Q4	9.1%	37.0%	48.7%	47.4%	1.3%
2007Q1	8.4%	36.4%	49.0%	43.8%	1.0%
2007Q2	8.4%	35.9%	47.7%	56.3%	1.1%
2007Q3	12.2%	35.6%	49.1%	43.6%	1.0%
2007Q4	18.5%	35.4%	52.1%	45.1%	1.9%
2008Q1	22.4%	35.4%	48.2%	45.1%	2.8%
2008Q2	28.1%	35.3%	47.0%	52.1%	2.5%
2008Q3	30.0%	35.4%	47.6%	42.4%	3.1%
2008Q4	44.8%	34.9%	48.8%	41.2%	4.4%
2009Q1	50.9%	34.7%	41.2%	46.4%	4.1%
2009Q2	38.9%	34.2%	42.6%	54.9%	4.2%
2009Q3	31.1%	33.5%	42.8%	49.0%	2.4%
2009Q4	30.0%	32.8%	48.3%	45.0%	3.6%
2010Q1	26.1%	32.6%	46.3%	45.7%	2.8%
2010Q2	29.9%	32.3%	52.4%	53.2%	4.2%
2010Q3	28.9%	32.4%	52.6%	45.9%	2.2%
2010Q4	23.3%	31.8%	47.8%	44.3%	2.7%
2011Q1	22.0%	31.0%	47.3%	47.4%	2.6%
2011Q2	24.9%	30.9%	52.2%	52.3%	2.7%
2011Q3	35.5%	30.6%	48.5%	43.4%	4.5%
2011Q4	31.0%	30.2%	48.9%	43.4%	1.9%
2012Q1	26.3%	30.2%	44.0%	48.9%	3.0%
2012Q2	29.0%	29.7%	51.5%	52.6%	4.4%
2012Q3	28.0%	29.4%	46.6%	44.3%	2.0%
2012Q4	26.7%	29.3%	49.4%	46.8%	3.6%
2013Q1	22.4%	28.9%	47.5%	47.8%	2.0%
2013Q2	20.7%	28.6%	46.0%	52.1%	2.0%
2013Q3	18.3%	28.2%	46.9%	44.8%	1.7%
2013Q4	15.9%	28.5%	49.5%	45.4%	1.4%
2014Q1	15.1%	27.8%	46.8%	47.1%	2.0%
2014Q2	16.2%	27.3%	51.4%	54.4%	1.7%
2014Q3	18.1%	26.9%	52.6%	43.2%	1.9%
2014Q4	18.2%	26.8%	49.7%	45.0%	1.2%
2015Q1	18.1%	26.3%	47.1%	44.6%	1.5%
2015Q2	18.0%	26.6%	48.6%	55.3%	1.9%
2015Q3	22.4%	26.6%	50.3%	43.3%	2.2%
2015Q4	22.6%	27.1%	46.8%	45.8%	1.8%
2016Q1	24.1%	27.5%	48.7%	46.1%	2.5%
2016Q2	23.1%	27.8%	46.3%	55.9%	2.3%
2016Q3	20.0%	28.0%	44.8%	44.1%	1.7%
2016Q4	17.3%	28.1%	51.5%	44.6%	1.6%
2017Q1	16.7%	27.9%	42.7%	48.3%	1.3%
2017Q2	17.0%	27.5%	50.0%	53.6%	1.7%
2017Q3	17.8%	26.9%	49.9%	46.3%	1.2%
2017Q4	16.9%	26.3%	47.0%	45.2%	1.3%
2018Q1	17.3%	26.4%	48.5%	47.8%	1.1%
2018Q2	16.4%	25.9%	46.1%	53.9%	1.3%
2018Q3	16.4%	25.7%	48.9%	44.9%	1.0%
2018Q4	25.2%	25.6%	51.7%	43.0%	1.6%
2019Q1	20.5%	26.1%	44.4%	47.9%	1.0%
2019Q2	21.7%	26.0%	53.1%	54.5%	1.9%
2019Q3	23.0%	26.3%	50.6%	47.0%	2.2%
2019Q4	21.1%	26.4%	46.3%	44.1%	1.3%
Average	22.3%	36.1%	48.3%	47.5%	2.6%
Median	22.4%	32.8%	48.3%	46.3%	2.0%
Max	50.9%	61.3%	57.8%	56.3%	7.7%
Min	8.2%	25.6%	41.2%	41.2%	0.9%

Table C.3

Overview of all stocks and number of stocks meeting filter rules of the six-screen strategy

Quarter	Total companies	Price-to-book	Debt-to-equity	3-year revenue	EBITDA-margin	Change in EBITDA-margin	Change in RSR	All filters
1999Q4	4022	2949	2907	3275	2858	1996	1881	337
2000Q1	3963	2936	2899	3260	2844	1880	1847	339
2000Q2	3950	2819	2868	3241	2824	1835	1960	439
2000Q3	3895	2727	2822	3200	2733	1788	1858	292
2000Q4	3842	2458	2783	3156	2612	1627	2179	351
2001Q1	3778	2486	2776	3041	2575	1473	1678	213
2001Q2	3792	2648	2784	3016	2643	1526	1636	264
2001Q3	3721	2400	2742	2896	2540	1462	1887	245
2001Q4	3631	2533	2689	2749	2448	1577	1499	216
2002Q1	3572	2646	2674	2636	2519	1708	1692	316
2002Q2	3608	2625	2698	2621	2613	1802	1803	308
2002Q3	3610	2280	2717	2588	2564	1909	1635	303
2002Q4	3589	2390	2662	2557	2588	1885	1724	341
2003Q1	3543	2255	2677	2499	2532	1647	1560	269
2003Q2	3572	2635	2700	2407	2637	1672	1610	268
2003Q3	3570	2879	2706	2330	2617	1844	1615	320
2003Q4	3522	3013	2688	2313	2605	1902	1714	378
2004Q1	3484	3060	2713	2334	2622	2017	1672	384
2004Q2	3471	3037	2713	2400	2673	1979	1853	574
2004Q3	3435	2961	2670	2509	2597	1834	1712	472
2004Q4	3403	3033	2665	2640	2573	1701	1644	433
2005Q1	3350	2957	2642	2664	2480	1630	1775	516
2005Q2	3329	2911	2632	2737	2568	1616	1540	405
2005Q3	3251	2899	2555	2703	2487	1575	1605	473
2005Q4	3202	2833	2529	2685	2459	1648	1567	494
2006Q1	3144	2840	2505	2678	2396	1556	1386	414
2006Q2	3098	2766	2455	2665	2407	1508	1543	464
2006Q3	3075	2696	2417	2648	2364	1498	1565	411
2006Q4	3049	2732	2378	2628	2331	1474	1601	425
2007Q1	3022	2744	2381	2593	2289	1483	1530	437
2007Q2	2992	2725	2327	2550	2267	1436	1515	418
2007Q3	2950	2591	2274	2501	2269	1483	1403	414
2007Q4	2931	2445	2245	2441	2216	1450	1546	414
2008Q1	2895	2317	2202	2395	2171	1334	1302	313
2008Q2	2884	2202	2183	2378	2228	1293	1467	350
2008Q3	2881	2136	2199	2358	2210	1269	1337	244
2008Q4	2851	1677	2104	2280	2065	1175	1383	223
2009Q1	2832	1499	2116	2144	1987	1157	1177	173
2009Q2	2825	1846	2140	1970	2149	1310	1228	184
2009Q3	2804	2081	2152	1814	2212	1461	1304	219
2009Q4	2797	2120	2148	1739	2236	1655	1375	335
2010Q1	2782	2211	2146	1701	2201	1762	1252	260
2010Q2	2792	2113	2148	1725	2287	1796	1469	388
2010Q3	2780	2144	2142	1786	2295	1606	1495	405
2010Q4	2761	2261	2137	1817	2281	1533	1256	297
2011Q1	2755	2300	2147	1754	2191	1482	1401	327
2011Q2	2701	2188	2087	1697	2205	1334	1420	302
2011Q3	2679	1905	2047	1750	2207	1339	1225	232
2011Q4	2635	1967	1999	1828	2141	1281	1301	280
2012Q1	2595	2046	1956	1890	2083	1255	1075	232
2012Q2	2576	1964	1947	1968	2113	1298	1297	311
2012Q3	2544	1950	1899	2022	2071	1279	1191	268
2012Q4	2544	1982	1876	2060	2079	1293	1279	312
2013Q1	2527	2046	1862	2061	2038	1221	1211	279
2013Q2	2537	2071	1871	2027	2080	1238	1151	266
2013Q3	2515	2114	1862	1965	2078	1288	1214	329
2013Q4	2511	2171	1873	1944	2051	1281	1219	324
2014Q1	2492	2165	1860	1907	1980	1218	1155	263
2014Q2	2498	2145	1873	1858	2034	1245	1336	313
2014Q3	2483	2095	1844	1830	2063	1316	1262	324
2014Q4	2471	2077	1772	1817	2000	1306	1235	325
2015Q1	2462	2064	1770	1789	1933	1292	1171	270
2015Q2	2465	2046	1789	1772	1982	1311	1089	257
2015Q3	2434	1913	1737	1729	1941	1279	1195	276
2015Q4	2416	1877	1714	1696	1900	1190	1150	233
2016Q1	2397	1863	1694	1657	1837	1184	1264	227
2016Q2	2412	1897	1703	1641	1916	1217	1102	207
2016Q3	2404	1929	1706	1618	1930	1236	1082	200
2016Q4	2396	1964	1693	1610	1894	1279	1147	202
2017Q1	2399	1978	1706	1610	1869	1203	1046	200
2017Q2	2424	1993	1729	1646	1926	1173	1209	235
2017Q3	2409	1959	1713	1620	1914	1181	1192	232
2017Q4	2420	1986	1732	1664	1942	1235	1250	224
2018Q1	2394	1950	1700	1689	1845	1222	1069	217
2018Q2	2418	2000	1731	1756	1903	1291	1123	232
2018Q3	2425	2002	1748	1833	1898	1275	1273	271
2018Q4	2392	1803	1697	1852	1866	1151	1196	238
2019Q1	2350	1865	1601	1838	1807	1148	1076	199
2019Q2	2381	1859	1588	1883	1852	1132	1242	241
2019Q3	2370	1833	1580	1873	1842	1117	1174	209
2019Q4	2369	1850	1568	1855	1824	1148	1044	175
Average	2931	2300	2190	2201	2238	1453	1412	308
Median	2797	2165	2146	2027	2207	1339	1337	297
Max	4022	3060	2907	3275	2858	2017	2179	574
Min	2350	1499	1568	1610	1807	1117	1044	173

Table C.4

Overview of percentages of stocks meeting filter rules of the six-screen strategy

Quarter	Price-to-book	Debt-to-equity	3-year revenue	EBITDA-margin	Change in EBITDA-margin	Change in RSR	All filters
1999Q4	73.3%	72.3%	81.4%	71.1%	49.6%	46.8%	8.4%
2000Q1	74.1%	73.2%	82.3%	71.8%	47.4%	46.6%	8.6%
2000Q2	71.4%	72.6%	82.1%	71.5%	46.5%	49.6%	11.1%
2000Q3	70.0%	72.5%	82.2%	70.2%	45.9%	47.7%	7.5%
2000Q4	64.0%	72.4%	82.1%	68.0%	42.3%	56.7%	9.1%
2001Q1	65.8%	73.5%	80.5%	68.2%	39.0%	44.4%	5.6%
2001Q2	69.8%	73.4%	79.5%	69.7%	40.2%	43.1%	7.0%
2001Q3	64.5%	73.7%	77.8%	68.3%	39.3%	50.7%	6.6%
2001Q4	69.8%	74.1%	75.7%	67.4%	43.4%	41.3%	5.9%
2002Q1	74.1%	74.9%	73.8%	70.5%	47.8%	47.4%	8.8%
2002Q2	72.8%	74.8%	72.6%	72.4%	49.9%	50.0%	8.5%
2002Q3	63.2%	75.3%	71.7%	71.0%	52.9%	45.3%	8.4%
2002Q4	66.6%	74.2%	71.2%	72.1%	52.5%	48.0%	9.5%
2003Q1	63.6%	75.6%	70.5%	71.5%	46.5%	44.0%	7.6%
2003Q2	73.8%	75.6%	67.4%	73.8%	46.8%	45.1%	7.5%
2003Q3	80.6%	75.8%	65.3%	73.3%	51.7%	45.2%	9.0%
2003Q4	85.5%	76.3%	65.7%	74.0%	54.0%	48.7%	10.7%
2004Q1	87.8%	77.9%	67.0%	75.3%	57.9%	48.0%	11.0%
2004Q2	87.5%	78.2%	69.1%	77.0%	57.0%	53.4%	16.5%
2004Q3	86.2%	77.7%	73.0%	75.6%	53.4%	49.8%	13.7%
2004Q4	89.1%	78.3%	77.6%	75.6%	50.0%	48.3%	12.7%
2005Q1	88.3%	78.9%	79.5%	74.0%	48.7%	53.0%	15.4%
2005Q2	87.4%	79.1%	82.2%	77.1%	48.5%	46.3%	12.2%
2005Q3	89.2%	78.6%	83.1%	76.5%	48.4%	49.4%	14.5%
2005Q4	88.5%	79.0%	83.9%	76.8%	51.5%	48.9%	15.4%
2006Q1	90.3%	79.7%	85.2%	76.2%	49.5%	44.1%	13.2%
2006Q2	89.3%	79.2%	86.0%	77.7%	48.7%	49.8%	15.0%
2006Q3	87.7%	78.6%	86.1%	76.9%	48.7%	50.9%	13.4%
2006Q4	89.6%	78.0%	86.2%	76.5%	48.3%	52.5%	13.9%
2007Q1	90.8%	78.8%	85.8%	75.7%	49.1%	50.6%	14.5%
2007Q2	91.1%	77.8%	85.2%	75.8%	48.0%	50.6%	14.0%
2007Q3	87.8%	77.1%	84.8%	76.9%	50.3%	47.6%	14.0%
2007Q4	83.4%	76.6%	83.3%	75.6%	49.5%	52.7%	14.1%
2008Q1	80.0%	76.1%	82.7%	75.0%	46.1%	45.0%	10.8%
2008Q2	76.4%	75.7%	82.5%	77.3%	44.8%	50.9%	12.1%
2008Q3	74.1%	76.3%	81.8%	76.7%	44.0%	46.4%	8.5%
2008Q4	58.8%	73.8%	80.0%	72.4%	41.2%	48.5%	7.8%
2009Q1	52.9%	74.7%	75.7%	70.2%	40.9%	41.6%	6.1%
2009Q2	65.3%	75.8%	69.7%	76.1%	46.4%	43.5%	6.5%
2009Q3	74.2%	76.7%	64.7%	78.9%	52.1%	46.5%	7.8%
2009Q4	75.8%	76.8%	62.2%	79.9%	59.2%	49.2%	12.0%
2010Q1	79.5%	77.1%	61.1%	79.1%	63.3%	45.0%	9.3%
2010Q2	75.7%	76.9%	61.8%	81.9%	64.3%	52.6%	13.9%
2010Q3	77.1%	77.1%	64.2%	82.6%	57.8%	53.8%	14.6%
2010Q4	81.9%	77.4%	65.8%	82.6%	55.5%	45.5%	10.8%
2011Q1	83.5%	77.9%	63.7%	79.5%	53.8%	50.9%	11.9%
2011Q2	81.0%	77.3%	62.8%	81.6%	49.4%	52.6%	11.2%
2011Q3	71.1%	76.4%	65.3%	82.4%	50.0%	45.7%	8.7%
2011Q4	74.6%	75.9%	69.4%	81.3%	48.6%	49.4%	10.6%
2012Q1	78.8%	75.4%	72.8%	80.3%	48.4%	41.4%	8.9%
2012Q2	76.2%	75.6%	76.4%	82.0%	50.4%	50.3%	12.1%
2012Q3	76.7%	74.6%	79.5%	81.4%	50.3%	46.8%	10.5%
2012Q4	77.9%	73.7%	81.0%	81.7%	50.8%	50.3%	12.3%
2013Q1	81.0%	73.7%	81.6%	80.6%	48.3%	47.9%	11.0%
2013Q2	81.6%	73.7%	79.9%	82.0%	48.8%	45.4%	10.5%
2013Q3	84.1%	74.0%	78.1%	82.6%	51.2%	48.3%	13.1%
2013Q4	86.5%	74.6%	77.4%	81.7%	51.0%	48.5%	12.9%
2014Q1	86.9%	74.6%	76.5%	79.5%	48.9%	46.3%	10.6%
2014Q2	85.9%	75.0%	74.4%	81.4%	49.8%	53.5%	12.5%
2014Q3	84.4%	74.3%	73.7%	83.1%	53.0%	50.8%	13.0%
2014Q4	84.1%	71.7%	73.5%	80.9%	52.9%	50.0%	13.2%
2015Q1	83.8%	71.9%	72.7%	78.5%	52.5%	47.6%	11.0%
2015Q2	83.0%	72.6%	71.9%	80.4%	53.2%	44.2%	10.4%
2015Q3	78.6%	71.4%	71.0%	79.7%	52.5%	49.1%	11.3%
2015Q4	77.7%	70.9%	70.2%	78.6%	49.3%	47.6%	9.6%
2016Q1	77.7%	70.7%	69.1%	76.6%	49.4%	52.7%	9.5%
2016Q2	78.6%	70.6%	68.0%	79.4%	50.5%	45.7%	8.6%
2016Q3	80.2%	71.0%	67.3%	80.3%	51.4%	45.0%	8.3%
2016Q4	82.0%	70.7%	67.2%	79.0%	53.4%	47.9%	8.4%
2017Q1	82.5%	71.1%	67.1%	77.9%	50.1%	43.6%	8.3%
2017Q2	82.2%	71.3%	67.9%	79.5%	48.4%	49.9%	9.7%
2017Q3	81.3%	71.1%	67.2%	79.5%	49.0%	49.5%	9.6%
2017Q4	82.1%	71.6%	68.8%	80.2%	51.0%	51.7%	9.3%
2018Q1	81.5%	71.0%	70.6%	77.1%	51.0%	44.7%	9.1%
2018Q2	82.7%	71.6%	72.6%	78.7%	53.4%	46.4%	9.6%
2018Q3	82.6%	72.1%	75.6%	78.3%	52.6%	52.5%	11.2%
2018Q4	75.4%	70.9%	77.4%	78.0%	48.1%	50.0%	9.9%
2019Q1	79.4%	68.1%	78.2%	76.9%	48.9%	45.8%	8.5%
2019Q2	78.1%	66.7%	79.1%	77.8%	47.5%	52.2%	10.1%
2019Q3	77.3%	66.7%	79.0%	77.7%	47.1%	49.5%	8.8%
2019Q4	78.1%	66.2%	78.3%	77.0%	48.5%	44.1%	7.4%
Average	78.9%	74.5%	74.8%	76.9%	49.8%	48.2%	10.6%
Median	80.0%	74.7%	75.6%	77.1%	49.5%	48.3%	10.5%
Max	91.1%	79.7%	86.2%	83.1%	64.3%	56.7%	16.5%
Min	52.9%	66.2%	61.1%	67.4%	39.0%	41.3%	5.6%

Appendix D: Nine-screen strategy statistics

This appendix presents the overview of total stocks and the number of stocks meeting the filter rules of the nine-screen strategy. It is important to note that the tables below only include eight filters, while the Datagraph rating is missing. The Datagraph rating is based on a proprietary formula that assigns weights to "reported earnings, capitalization, sponsorship, relative strength of stock, price/volume characteristics, group rank and other factors" (William O'Neil+CO, 2021). This formula is not publicly known, which is why the factor is excluded when replicating the nine-screen strategy.

Table D.1

Overview of all stocks and number of stocks meeting filter rules of the nine-screen strategy

Year	Total companies	Price-to-book	Shares outstanding	RSR > 70	Change in RSR	Accelerated earnings	PTP-margin	5-year growth rate	Price compared to max	All filters
2000	3196	966	1710	1049	1642	1510	2211	1895	759	3
2001	3195	992	1641	971	1421	1473	1948	1813	800	6
2002	3217	958	1553	942	1534	1546	2069	1745	847	6
2003	3189	766	1451	933	1450	1532	2171	1760	1116	5
2004	3191	393	1287	1042	1611	1526	2322	1848	1604	3
2005	3255	377	1156	1085	1617	1568	2339	1896	1399	2
2006	3122	329	1033	1030	1531	1481	2275	1857	1322	1
2007	2918	333	907	1014	1483	1394	2096	1785	1234	2
2008	2746	743	843	890	1307	1246	1787	1688	403	1
2009	2677	869	791	833	1211	1297	1706	1495	312	1
2010	2640	549	744	859	1298	1254	1939	1456	994	1
2011	2596	558	696	855	1286	1196	1912	1454	1058	1
2012	2571	562	656	768	1212	1229	1853	1418	1044	3
2013	2509	398	611	769	1198	1187	1796	1406	1479	2
2014	2404	333	567	765	1209	1138	1740	1428	1253	1
2015	2378	451	552	705	1115	1119	1629	1512	904	1
2016	2307	472	554	714	1110	1096	1576	1406	849	3
2017	2241	390	527	642	1087	1098	1549	1377	1133	2
2018	2214	429	490	706	1073	1057	1539	1377	818	2
2019	2252	483	488	742	1082	1093	1502	1451	742	1
Average	2741	567	913	866	1324	1302	1898	1603	1003	2
Median	2658	477	767	857	1292	1250	1883	1503	1019	2
Max	3255	992	1710	1085	1642	1568	2339	1896	1604	6
Min	2214	329	488	642	1073	1057	1502	1377	312	1

Table D.2

Overview of percentages of stocks meeting filter rules of the nine-screen strategy

Year	Price-to-book	Shares outstanding	RSR > 70	Change in RSR	Accelerated earnings	PTP-margin	5-year growth rate	Price compared to max	All filters
2000	30%	54%	33%	51%	47%	69%	59%	24%	0.1%
2001	31%	51%	30%	44%	46%	61%	57%	25%	0.1%
2002	30%	48%	29%	48%	48%	64%	54%	26%	0.2%
2003	24%	46%	29%	45%	48%	68%	55%	35%	0.2%
2004	12%	40%	33%	50%	48%	73%	58%	50%	0.2%
2005	12%	35%	33%	50%	48%	72%	58%	43%	0.2%
2006	11%	33%	33%	49%	47%	73%	59%	42%	0.2%
2007	11%	31%	35%	51%	48%	72%	61%	42%	0.2%
2008	27%	31%	32%	48%	45%	65%	61%	15%	0.2%
2009	32%	30%	31%	45%	48%	64%	56%	12%	0.2%
2010	21%	28%	33%	49%	47%	73%	55%	38%	0.1%
2011	21%	27%	33%	50%	46%	74%	56%	41%	0.2%
2012	22%	25%	30%	47%	48%	72%	55%	41%	0.1%
2013	16%	24%	31%	48%	47%	72%	56%	59%	0.1%
2014	14%	24%	32%	50%	47%	72%	59%	52%	0.1%
2015	19%	23%	30%	47%	47%	69%	64%	38%	0.1%
2016	20%	24%	31%	48%	47%	68%	61%	37%	0.1%
2017	17%	24%	29%	49%	49%	69%	61%	51%	0.1%
2018	19%	22%	32%	48%	48%	69%	62%	37%	0.1%
2019	21%	22%	33%	48%	49%	67%	64%	33%	0.0%
Average	21%	32%	32%	48%	48%	69%	59%	37%	0.1%
Median	21%	29%	32%	48%	48%	69%	59%	38%	0.1%
Max	32%	54%	35%	51%	49%	74%	64%	59%	0.2%
Min	11%	22%	29%	44%	45%	61%	54%	12%	0.0%

Appendix E: Monthly and quarterly rebalancing of the equal-weighted portfolios

Both the equal-weighted and the value-weighted portfolios have to be rebalanced every quarter at a minimum, as this is when new stocks enter or exit the portfolio. The value-weighted portfolios are rebalanced quarterly, meaning that the stocks are bought at the beginning of the quarter, and no changes are made until new stocks enter or exit the portfolio. The reason for this is that there is no need to rebalance before the quarter ends, because the stocks are value-weighted in the beginning and will therefore remain value-weighted when the companies' values are changing.

The equal-weighted portfolios can be rebalanced monthly or quarterly. The results presented in Section 7.5 shows the performance of the monthly rebalanced portfolios, meaning that every stock makes up the same weight of the portfolio at the beginning of every month (except from stocks with multiple buy signals that are weighted in proportion to their number of buy signals at this time). Figure E.1 presents the cumulative holding period return of the four-screen portfolio with both monthly and quarterly rebalancing, where quarterly rebalancing means that the portfolios are only rebalanced to equal weights every time new stocks enter or exit the portfolio.

Figure E.1

EW four-screen portfolio indexed cumulative holding period returns with monthly and quarterly rebalancing

The plot of the two EW four-screen portfolios shows that the difference between the two portfolios is minimal for most of the time. The two portfolios move closely, and the average difference in monthly portfolio returns is 0.017%, in favor of the monthly rebalanced portfolio. The maximum difference in monthly returns occur in September of 2009, where the quarterly rebalanced portfolio delivers returns of 6.3%, which is 2.4 pp higher than the monthly rebalanced portfolio. This happens in a quarter with 735 investments and three consecutive months of positive returns for both portfolios, indicating that the quarterly rebalanced portfolio gains additional returns due to the cumulative effect. The monthly rebalanced portfolio finish with cumulative returns that are 19 pp above the quarterly rebalanced portfolio.

Figure E.2 presents the same figure for the six-screen EW portfolio.

Figure E.2

EW six-screen portfolio indexed cumulative holding period returns with monthly and quarterly rebalancing

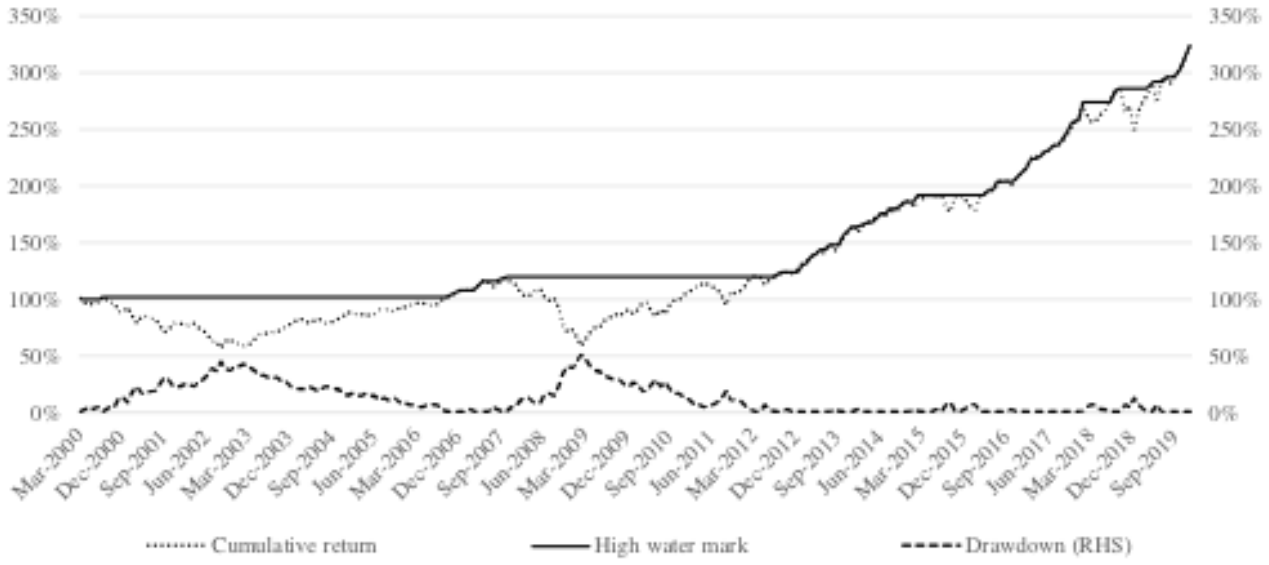
The plot of the two six-screen portfolios shows that they are even closer connected than the four-screen portfolios, and there are only minor differences in how the portfolio performs. The average difference in monthly returns between the two is 0.006% in favor of the monthly rebalanced portfolio. Both the largest difference of 1.53% in favor of the monthly rebalanced portfolio and 0.98% in favor of the quarterly rebalanced portfolio happen within the first two-year holding period, where the number of stocks in the portfolio is below the average of the overall period. Thus, it seems like the increased number of stocks in the six-screen portfolio reduces the impact of rebalancing on the two portfolios. Another interesting finding is that the month with the largest difference in favor of the quarterly rebalanced portfolio occurs at the end of a quarter of successive losses, in opposition to the four-screen portfolio. The reason for this is that the returns are the same in both portfolios, but the base that negative returns are calculated from is lower for the quarterly rebalanced portfolio, resulting in lower losses.

Appendix F: Drawdown of S&P 500

Figure K. presents the cumulative return, HWM and drawdown for the S&P 500. Note that the maximum possible value for drawdown (right axis) is 100%, but the axis is extended for illustrative purposes.

Figure F.1

EW six-screen portfolio indexed cumulative holding period returns with monthly and quarterly rebalancing



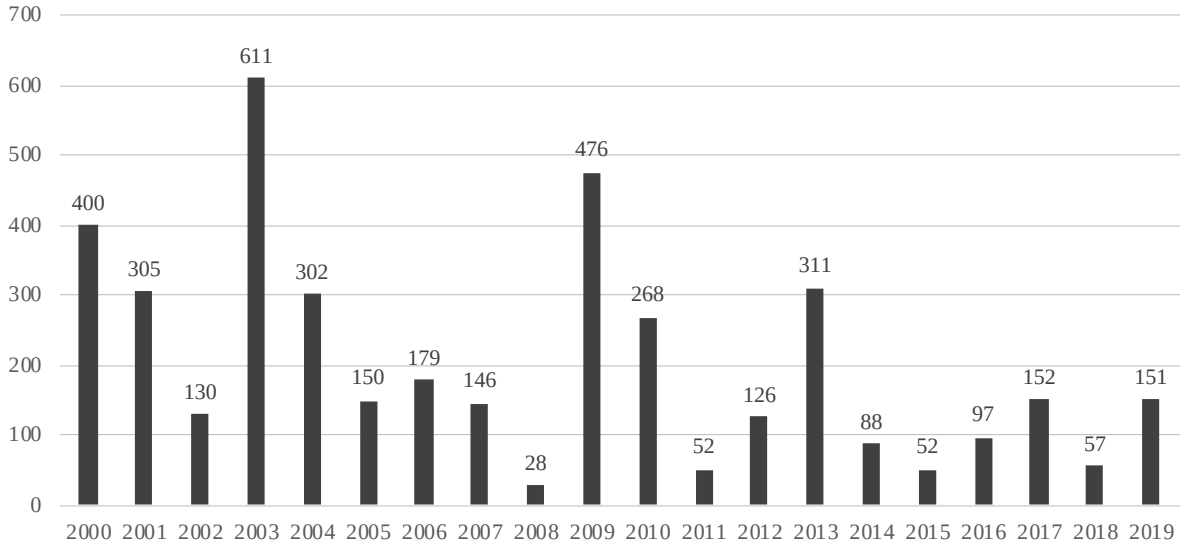
The performance of the S&P 500 over the same time differs significantly from the two constructed portfolios in the first seven years of the time period. After a slight increase in HMW after five months, the S&P 500 enters a period of six years of drawdown, with a maximum drawdown of 44.4% in September 2002. This is in sharp contrast to the constructed portfolios, that experiences maximum drawdowns of 17.4% and 26.8%. These portfolios have both reached their previous HWM in less than a year, but it takes the S&P 500 more than four years to accomplish the same. Approximately one year later, the S&P 500 encounter another long period of drawdown. The financial crisis leaves S&P 500 with a maximum drawdown of 50.2%, and it takes more than four years before the S&P 500 once again reaches its previous HWM. For the remaining time period, S&P 500 suffers only one significant

drawdown of 13.6% in December 2018, before it finishes 2019 with a cumulative return at all time high of 323.1%.

Appendix G: Stocks at least doubling in price

Table G.1

Number of stocks at least doubling per year over the time period



Appendix H: Characteristics of winners the thesis' winner sample

Table H.1

Accelerated revenue in the buy and eight preceding quarters

			Percentile								
Quarter	**Mean**	**Median**	**1st**	**5th**	**10th**	**25th**	**50th**	**75th**	**90th**	**95th**	**99th**
Buy	0.69	0.03	-1.38	-0.51	-0.29	-0.09	0.03	0.13	0.38	0.63	2.99
Buy-1	-0.04	-0.03	-1.33	-0.58	-0.37	-0.13	-0.03	0.08	0.33	0.53	1.58
Buy-2	0.07	0.05	-1.42	-0.47	-0.31	-0.07	0.05	0.23	0.48	0.66	1.09
Buy-3	-0.09	-0.03	-2.04	-0.81	-0.43	-0.19	-0.03	0.09	0.24	0.36	1.74
Buy-4	0.07	0.01	-0.93	-0.56	-0.27	-0.10	0.01	0.15	0.42	0.66	1.61
Buy-5	-0.04	-0.02	-1.92	-0.65	-0.38	-0.15	-0.02	0.09	0.34	0.54	1.05
Buy-6	-0.26	0.03	-1.60	-0.71	-0.46	-0.13	0.03	0.22	0.49	0.80	1.79
Buy-7	0.20	-0.05	-2.75	-0.79	-0.62	-0.27	-0.05	0.10	0.40	0.66	1.95
Buy-8	0.05	0.02	-1.10	-0.38	-0.29	-0.08	0.02	0.17	0.41	0.64	2.08

Table H.2

Accelerated EBIT in the buy and eight preceding quarters

			Percentile								
Quarter	**Mean**	**Median**	**1st**	**5th**	**10th**	**25th**	**50th**	**75th**	**90th**	**95th**	**99th**
Buy	1.15	-0.06	-14.11	-4.66	-2.27	-0.77	-0.06	0.52	2.22	4.70	51.72
Buy - 1	-1.33	-0.10	-65.58	-4.43	-2.05	-0.75	-0.10	0.38	1.96	5.31	21.09
Buy - 2	0.88	0.02	-17.87	-4.66	-2.15	-0.63	0.02	0.64	2.86	9.51	30.62
Buy - 3	0.54	-0.03	-24.18	-7.14	-2.48	-0.71	-0.03	0.72	2.99	10.11	29.91
Buy - 4	-0.83	-0.13	-36.64	-7.49	-2.33	-0.90	-0.13	0.38	1.56	4.86	23.87
Buy - 5	0.25	-0.06	-15.91	-3.78	-2.43	-0.64	-0.06	0.62	2.72	7.58	24.62
Buy - 6	0.04	-0.06	-40.93	-6.89	-3.09	-0.75	-0.06	0.69	2.86	6.24	36.14
Buy - 7	-0.32	-0.07	-76.37	-9.38	-2.62	-0.95	-0.07	0.69	3.20	5.58	48.30
Buy - 8	1.44	0.00	-17.41	-4.09	-2.05	-0.62	0.00	0.71	2.79	7.88	73.42

Table H.3

Accelerated earnings in the buy and eight preceding quarters

			Percentile								
Quarter	**Mean**	**Median**	**1st**	**5th**	**10th**	**25th**	**50th**	**75th**	**90th**	**95th**	**99th**
Buy	-0.41	-0.01	-34.49	-9.26	-4.79	-1.28	-0.01	1.19	4.41	8.34	18.10
Buy-1	-5.50	-0.11	-39.52	-6.01	-3.30	-1.10	-0.11	1.15	3.83	9.21	42.86
Buy-2	13.85	0.11	-63.27	-5.96	-2.98	-0.68	0.11	1.23	4.15	7.85	107.47
Buy-3	-6.21	-0.05	-22.67	-9.08	-5.75	-1.46	-0.05	0.94	3.77	13.95	99.07
Buy-4	-4.91	-0.14	-104.10	-18.57	-4.13	-1.42	-0.14	1.00	5.26	9.45	28.02
Buy-5	8.92	-0.01	-42.39	-8.97	-3.97	-0.98	-0.01	1.37	6.50	14.88	72.43
Buy-6	-7.11	0.01	-47.04	-10.36	-5.13	-0.99	0.01	1.03	4.85	8.64	43.82
Buy-7	1.89	-0.06	-24.46	-7.37	-5.42	-1.40	-0.06	1.03	4.91	8.64	46.14
Buy-8	-0.58	0.02	-40.70	-9.67	-5.24	-1.17	0.02	0.99	4.81	7.65	15.85

Table H.4

Number of shares outstanding in the buy and eight preceding quarters

			Percentile								
Quarter	**Mean**	**Median**	**1st**	**5th**	**10th**	**25th**	**50th**	**75th**	**90th**	**95th**	**99th**
Buy	52.60	24.35	1.75	5.39	7.82	13.54	24.35	56.34	109.18	180.96	456.04
Buy-1	52.24	23.42	1.68	5.35	7.64	13.20	23.42	55.39	108.21	181.65	461.64
Buy-2	52.41	23.37	1.68	5.37	7.58	13.06	23.37	55.56	106.60	181.21	462.48
Buy-3	52.97	21.90	1.67	5.28	7.30	12.41	21.90	54.75	107.11	185.98	464.37
Buy-4	52.96	22.49	1.65	4.95	7.10	12.29	22.49	54.65	107.65	199.54	465.04
Buy-5	54.51	22.04	1.73	4.83	6.85	12.16	22.04	54.40	117.61	206.43	496.59
Buy-6	53.53	21.86	1.71	4.79	6.41	12.16	21.86	53.12	111.71	202.65	492.58
Buy-7	53.70	21.85	1.69	4.71	6.37	12.10	21.85	54.27	109.58	200.42	494.64
Buy-8	48.38	21.51	1.68	4.31	6.36	11.89	21.51	53.95	97.81	185.03	395.39

Table H.5

Pretax margin in the buy and eight preceding quarters

			Percentile								
Quarter	**Mean**	**Median**	**1st**	**5th**	**10th**	**25th**	**50th**	**75th**	**90th**	**95th**	**99th**
Buy	52.60	24.35	1.75	5.39	7.82	13.54	24.35	56.34	109.18	180.96	456.04
Buy-1	52.24	23.42	1.68	5.35	7.64	13.20	23.42	55.39	108.21	181.65	461.64
Buy-2	52.41	23.37	1.68	5.37	7.58	13.06	23.37	55.56	106.60	181.21	462.48
Buy-3	52.97	21.90	1.67	5.28	7.30	12.41	21.90	54.75	107.11	185.98	464.37
Buy-4	52.96	22.49	1.65	4.95	7.10	12.29	22.49	54.65	107.65	199.54	465.04
Buy-5	54.51	22.04	1.73	4.83	6.85	12.16	22.04	54.40	117.61	206.43	496.59
Buy-6	53.53	21.86	1.71	4.79	6.41	12.16	21.86	53.12	111.71	202.65	492.58
Buy-7	53.70	21.85	1.69	4.71	6.37	12.10	21.85	54.27	109.58	200.42	494.64
Buy-8	48.38	21.51	1.68	4.31	6.36	11.89	21.51	53.95	97.81	185.03	395.39

Appendix I: Characteristics of winners from random sample of 200 companies

Table I.1

Price-to-book ratio in the buy and eight preceding quarters

			Percentile								
Quarter	**Mean**	**% > 1**	**1st**	**5th**	**10th**	**25th**	**50th**	**75th**	**90th**	**95th**	**99th**
Buy	2.23	63.9%	-2.27	-0.16	0.28	0.75	1.32	2.94	5.85	7.60	14.88
Buy - 1	2.65	64.4%	-1.61	-0.12	0.39	0.71	1.36	3.01	5.82	9.83	22.49
Buy - 2	2.70	64.6%	-1.06	-0.08	0.45	0.76	1.44	2.96	4.95	7.11	16.40
Buy - 3	2.52	65.6%	-1.10	-0.03	0.36	0.72	1.44	3.00	5.55	8.16	18.69
Buy - 4	3.11	65.4%	-1.37	0.16	0.42	0.76	1.38	2.83	6.08	11.47	25.37
Buy - 5	3.14	65.6%	-0.70	0.24	0.45	0.81	1.50	2.92	6.22	10.47	36.02
Buy - 6	3.45	71.3%	-1.12	0.40	0.51	0.95	1.65	3.27	7.15	9.75	36.41
Buy - 7	3.09	75.3%	-2.70	0.38	0.53	1.01	1.68	3.11	6.21	8.69	25.09
Buy - 8	3.01	73.5%	-5.02	0.33	0.51	0.97	1.66	3.09	6.12	10.68	25.59

Table I.2

Debt-to-equity in the buy and eight preceding quarters

			Percentile								
Quarter	**Mean**	**% < 2**	**1st**	**5th**	**10th**	**25th**	**50th**	**75th**	**90th**	**95th**	**99th**
Buy	2.35	80.5%	-8.32	-2.21	-0.87	-0.73	-0.26	1.23	4.82	9.58	36.34
Buy-1	3.89	82.1%	-9.77	-1.89	-0.88	-0.73	-0.11	1.05	4.96	12.38	164.00
Buy-2	1.55	85.3%	-15.53	-3.06	-0.92	-0.75	-0.27	0.78	3.53	8.66	34.07
Buy-3	2.11	84.7%	-10.41	-2.84	-0.91	-0.73	-0.25	0.83	3.65	7.95	26.43
Buy-4	2.18	83.7%	-17.25	-0.99	-0.89	-0.73	-0.24	0.94	3.92	11.62	34.59
Buy-5	1.99	85.2%	-7.45	-0.94	-0.88	-0.74	-0.26	0.84	2.85	8.94	33.14
Buy-6	2.42	82.8%	-6.67	-0.93	-0.87	-0.72	-0.22	0.99	3.28	9.55	65.97
Buy-7	2.11	83.5%	-12.95	-0.93	-0.84	-0.72	-0.06	0.88	3.65	10.88	46.28
Buy-8	2.47	84.1%	-4.51	-0.89	-0.84	-0.68	-0.02	0.90	3.83	12.27	62.59

Table I.3

Three-year revenue growth rate in the buy and eight preceding quarters

			Percentile								
Quarter	**Mean**	**% > 0**	**1st**	**5th**	**10th**	**25th**	**50th**	**75th**	**90th**	**95th**	**99th**
Buy	30.2%	77.4%	-37.8%	-15.7%	-10.7%	1.0%	10.2%	27.9%	74.6%	132.3%	294.2%
Buy - 1	30.7%	79.3%	-33.5%	-11.7%	-9.5%	1.3%	9.2%	38.8%	71.2%	135.9%	301.3%
Buy - 2	28.5%	75.9%	-33.9%	-20.3%	-12.6%	1.6%	11.6%	45.1%	75.7%	143.8%	296.3%
Buy - 3	29.4%	79.2%	-36.8%	-14.5%	-9.1%	0.3%	10.8%	36.3%	72.3%	143.9%	299.6%
Buy - 4	25.6%	80.6%	-32.2%	-16.7%	-9.5%	0.2%	12.3%	42.3%	76.2%	137.5%	283.3%
Buy - 5	26.7%	81.2%	-31.9%	-14.6%	-11.8%	0.9%	15.1%	44.9%	80.7%	149.6%	291.6%
Buy - 6	37.6%	78.9%	-30.1%	-13.2%	-9.0%	0.5%	13.7%	50.8%	95.2%	165.3%	327.3%
Buy - 7	27.8%	78.3%	-31.9%	-18.8%	-4.7%	1.7%	12.3%	53.2%	101.4%	168.2%	311.2%
Buy - 8	35.2%	77.3%	-29.9%	-14.9%	-7.8%	2.4%	11.7%	51.0%	96.8%	165.5%	309.2%

Table I.4

EBITDA margin in the buy and eight preceding quarters

			Percentile								
Quarter	**Mean**	**% > 0**	**1st**	**5th**	**10th**	**25th**	**50th**	**75th**	**90th**	**95th**	**99th**
Buy	-8.6%	71.2%	-268.0%	-132.3%	-42.4%	-1.5%	6.2%	16.4%	24.0%	28.6%	34.4%
Buy-1	-3.9%	75.0%	-240.6%	-93.7%	-24.8%	0.3%	7.8%	15.6%	23.4%	27.1%	36.3%
Buy-2	-6.8%	76.2%	-245.9%	-103.9%	-40.8%	0.9%	7.0%	14.9%	23.9%	26.6%	36.6%
Buy-3	-13.9%	68.2%	-295.4%	-185.2%	-51.3%	-3.6%	5.6%	14.1%	22.3%	25.1%	36.4%
Buy-4	-7.8%	71.1%	-308.8%	-126.8%	-31.2%	-6.7%	7.1%	15.4%	25.3%	32.4%	47.1%
Buy-5	-9.1%	75.7%	-258.9%	-120.2%	-49.5%	0.7%	8.2%	15.0%	23.6%	31.2%	33.9%
Buy-6	-9.0%	73.9%	-233.3%	-121.4%	-68.3%	-0.6%	5.3%	13.3%	21.0%	28.8%	47.6%
Buy-7	-10.9%	67.9%	-261.8%	-153.1%	-28.5%	-4.5%	4.6%	13.9%	22.0%	25.4%	35.9%
Buy-8	-7.0%	69.7%	-334.9%	-70.0%	-34.5%	-3.9%	6.0%	14.9%	26.0%	28.8%	46.7%

Table I.5

Change in year-over-year EBITDA margins in the buy and eight preceding quarters

			Percentile								
Quarter	**Mean**	**% > 0**	**1st**	**5th**	**10th**	**25th**	**50th**	**75th**	**90th**	**95th**	**99th**
Buy	0.01	59.6%	-1.94	-1.98	-0.54	-0.13	-0.02	0.09	0.51	2.46	3.71
Buy-1	0.05	59.9%	-1.14	-1.40	-0.83	-0.20	0.01	0.12	0.42	2.31	2.58
Buy-2	0.12	61.2%	-0.64	-0.95	-0.76	-0.15	0.05	0.22	0.67	3.40	4.31
Buy-3	-0.08	62.0%	-0.91	-1.32	-0.92	-0.08	0.01	0.16	0.32	2.21	2.84
Buy-4	0.09	53.6%	-2.08	-1.20	-0.43	-0.08	-0.03	0.12	0.32	2.75	3.59
Buy-5	-0.19	44.5%	-3.01	-1.32	-0.56	-0.16	-0.04	0.03	0.29	2.35	2.50
Buy-6	-0.13	47.3%	-3.40	-1.31	-0.65	-0.43	0.02	0.08	0.41	2.67	2.67
Buy-7	0.05	49.5%	-3.12	-0.89	-0.43	-0.12	0.02	0.13	0.56	3.01	3.21
Buy-8	0.12	53.2%	-2.50	-0.99	-0.56	-0.09	0.04	0.19	0.73	3.06	3.56

Table I.6

Relative strength rank

			Percentile								
Quarter	**Mean**	**Median**	**1st**	**5th**	**10th**	**25th**	**50th**	**75th**	**90th**	**95th**	**99th**
Buy	52.80	52.75	1.85	6.24	7.60	20.65	52.75	83.80	96.23	97.70	99.24
Buy - 1	51.81	53.10	2.39	5.99	9.50	19.85	53.10	85.00	94.52	97.00	98.74
Buy - 2	50.28	50.35	1.48	3.81	6.72	19.45	50.35	81.98	94.38	97.69	99.22
Buy - 3	48.32	43.00	1.23	5.56	7.75	17.38	43.00	80.35	94.13	97.16	99.45
Buy - 4	47.23	43.70	1.27	4.62	8.08	16.05	43.70	73.88	92.25	96.06	98.96
Buy - 5	46.16	39.50	1.63	3.48	6.76	17.40	39.50	73.95	92.49	97.54	99.32
Buy - 6	45.40	39.10	2.00	3.62	6.06	19.80	39.10	71.30	90.62	97.36	99.40
Buy - 7	44.86	39.90	3.09	5.13	9.32	19.20	39.90	72.05	90.58	95.59	98.78
Buy - 8	47.02	44.20	3.00	5.50	8.08	20.20	44.20	78.80	90.92	96.02	98.29

Appendix J: Characteristics of winners from random sample of 300 companies

Table J.1

Price-to-book ratio in the buy and eight preceding quarters

			Percentile								
Quarter	**Mean**	**% > 1**	**1st**	**5th**	**10th**	**25th**	**50th**	**75th**	**90th**	**95th**	**99th**
Buy	2.81	64.5%	-15.58	-1.85	0.16	0.61	1.47	3.04	7.15	9.91	38.77
Buy - 1	4.34	68.2%	-5.44	-0.86	0.32	0.71	1.58	2.95	6.82	11.59	39.37
Buy - 2	3.08	65.2%	-18.70	-1.01	0.27	0.74	1.57	3.16	6.18	11.95	21.70
Buy - 3	4.17	64.6%	-23.20	-0.80	0.20	0.77	1.45	3.16	6.78	11.97	26.05
Buy - 4	1.12	65.5%	-24.89	-1.12	0.20	0.78	1.33	3.09	6.22	12.74	35.83
Buy - 5	2.48	69.7%	-5.38	-0.40	0.39	0.88	1.45	3.02	7.97	11.87	28.08
Buy - 6	1.12	72.6%	-45.64	-1.11	0.39	0.93	1.74	3.29	7.21	11.37	21.15
Buy - 7	2.99	70.7%	-4.81	0.21	0.44	0.93	1.83	3.65	8.36	14.59	46.02
Buy - 8	4.88	73.1%	-4.34	0.16	0.47	0.94	1.92	3.78	7.80	15.59	67.04

Table J.2

Debt-to-equity in the buy and eight preceding quarters

			Percentile								
Quarter	**Mean**	**% < 2**	**1st**	**5th**	**10th**	**25th**	**50th**	**75th**	**90th**	**95th**	**99th**
Buy	0.83	80.3%	-27.13	-2.04	0.02	0.26	0.69	1.69	3.86	6.02	17.82
Buy - 1	1.37	78.5%	-10.92	-1.57	0.07	0.26	0.77	1.72	3.89	6.52	17.20
Buy - 2	0.90	80.1%	-18.34	-1.73	0.05	0.28	0.72	1.67	3.70	6.59	21.01
Buy - 3	1.81	80.0%	-29.99	-2.52	0.06	0.29	0.78	1.73	3.32	6.52	23.48
Buy - 4	0.38	82.2%	-31.63	-3.53	0.07	0.26	0.74	1.59	3.03	5.93	16.35
Buy - 5	4.40	81.4%	-21.23	-2.07	0.10	0.30	0.74	1.73	3.02	5.78	59.00
Buy - 6	0.12	81.0%	-18.08	-2.98	0.07	0.26	0.72	1.63	3.01	4.52	27.46
Buy - 7	1.57	78.2%	-5.43	0.05	0.10	0.29	0.77	1.70	3.82	7.19	40.19
Buy - 8	1.58	78.0%	-7.86	0.03	0.14	0.30	0.78	1.78	3.61	7.42	31.40

Table J.3

Three-year revenue growth rate in the buy and eight preceding quarters

			Percentile								
Quarter	**Mean**	**% > 0**	**1st**	**5th**	**10th**	**25th**	**50th**	**75th**	**90th**	**95th**	**99th**
Buy	22.3%	65.3%	-61.2%	-24.4%	-11.6%	-2.6%	8.7%	21.8%	60.4%	116.4%	346.9%
Buy - 1	27.5%	64.5%	-65.0%	-23.5%	-12.1%	-1.7%	11.2%	26.7%	74.1%	132.2%	398.0%
Buy - 2	34.2%	68.3%	-68.2%	-21.3%	-11.7%	-1.3%	12.2%	24.5%	71.5%	115.6%	393.7%
Buy - 3	26.5%	64.8%	65.2%	-20.3%	-14.3%	-1.6%	11.9%	28.2%	68.2%	119.9%	270.0%
Buy - 4	27.1%	65.1%	64.6%	-23.2%	-12.6%	-2.4%	9.4%	25.6%	67.5%	127.4%	358.2%
Buy - 5	32.4%	69.3%	-69.7%	-24.8%	-11.8%	-2.3%	9.9%	25.9%	62.2%	118.6%	420.6%
Buy - 6	31.0%	71.8%	-62.4%	-22.9%	-9.2%	-1.7%	10.3%	26.1%	79.7%	145.9%	390.5%
Buy - 7	29.6%	70.3%	-59.2%	-19.6%	-9.9%	-1.6%	8.9%	24.9%	78.0%	120.5%	421.6%
Buy - 8	33.6%	69.2%	-63.2%	-21.3%	-12.1%	-1.6%	10.8%	25.4%	75.4%	130.8%	387.7%

Table J.4

EBITDA margin in the buy and eight preceding quarters

			Percentile								
Quarter	**Mean**	**% > 0**	**1st**	**5th**	**10th**	**25th**	**50th**	**75th**	**90th**	**95th**	**99th**
Buy	-19.2%	68.6%	-542.2%	-154.1%	-48.2%	0.0%	6.4%	14.9%	26.0%	38.1%	72.2%
Buy - 1	-23.3%	65.7%	-606.7%	-201.7%	-70.8%	-1.2%	5.8%	13.9%	25.5%	35.1%	60.5%
Buy - 2	-30.9%	62.7%	-723.0%	-190.7%	-62.6%	-6.7%	5.0%	13.1%	23.5%	34.4%	67.9%
Buy - 3	-26.6%	61.2%	-694.3%	-159.5%	-64.3%	-5.9%	4.6%	12.7%	25.7%	35.3%	58.4%
Buy - 4	-34.4%	57.6%	-584.0%	-256.4%	-98.1%	-6.3%	3.8%	12.8%	25.9%	37.9%	69.1%
Buy - 5	-43.8%	62.0%	-655.1%	-199.7%	-100.6%	-4.3%	4.9%	14.2%	26.3%	38.9%	59.3%
Buy - 6	-25.7%	62.2%	-611.8%	-214.5%	-80.2%	-4.0%	5.0%	13.9%	27.1%	44.4%	67.2%
Buy - 7	-32.3%	59.8%	-384.7%	-203.9%	-66.1%	-4.7%	4.0%	14.0%	25.8%	43.0%	75.9%
Buy - 8	-25.5%	59.3%	-536.5%	-202.4%	-62.0%	-4.5%	4.2%	15.1%	25.5%	40.7%	70.1%

Table J.5

Change in year-over-year EBITDA margins in the buy and eight preceding quarters

			Percentile								
Quarter	**Mean**	**% > 0**	**1st**	**5th**	**10th**	**25th**	**50th**	**75th**	**90th**	**95th**	**99th**
Buy	20.69	59.8%	-79.52	-0.59	-0.19	-0.03	0.02	0.12	0.54	1.77	21.22
Buy - 1	14.35	54.4%	-14.80	-0.65	-0.22	-0.05	0.01	0.08	0.32	1.12	24.51
Buy - 2	16.94	50.6%	-12.13	-0.61	-0.19	-0.05	0.00	0.08	0.35	1.76	46.55
Buy - 3	-0.38	50.4%	-8.75	-0.66	-0.25	-0.06	0.00	0.07	0.41	1.12	20.25
Buy - 4	-6.86	49.2%	-20.86	-1.58	-0.34	-0.10	0.00	0.07	0.44	1.91	22.04
Buy - 5	-2.06	52.2%	-12.13	-1.08	-0.31	-0.06	0.00	0.07	0.45	1.30	62.97
Buy - 6	-16.76	51.0%	-12.24	-1.14	-0.25	-0.05	0.00	0.08	0.56	2.21	61.16
Buy - 7	-16.81	55.9%	-35.62	-1.22	-0.28	-0.06	0.01	0.09	0.44	1.64	30.16
Buy - 8	-17.58	46.6%	-26.49	-1.68	-0.34	-0.10	-0.01	0.07	0.35	1.99	22.93

Table J.6

Relative strength rank

			Percentile								
Quarter	**Mean**	**Median**	**1st**	**5th**	**10th**	**25th**	**50th**	**75th**	**90th**	**95th**	**99th**
Buy	51.22	48.80	2.87	5.61	8.40	18.70	48.80	84.65	94.56	97.40	99.10
Buy - 1	45.97	39.80	2.30	4.30	7.05	16.10	39.80	76.83	92.05	95.68	97.77
Buy - 2	46.31	41.20	1.93	4.55	7.80	16.93	41.20	77.45	92.75	95.88	98.87
Buy - 3	43.30	33.35	3.50	6.22	9.32	16.75	33.35	71.70	89.24	95.86	98.77
Buy - 4	46.34	42.55	1.74	4.80	9.37	19.75	42.55	72.53	92.33	97.41	99.04
Buy - 5	51.72	50.50	3.31	6.40	10.75	21.88	50.50	81.53	93.50	97.33	99.65
Buy - 6	46.90	42.60	2.41	4.33	8.46	17.48	42.60	73.88	89.14	94.74	99.19
Buy - 7	48.12	46.30	2.07	5.80	8.67	20.53	46.30	75.60	91.59	98.17	99.66
Buy - 8	49.00	46.75	2.04	5.03	9.00	21.75	46.75	77.55	94.05	96.90	99.76

Appendix K: Data and construction of factor portfolios

All factor portfolios are downloaded from Kenneth French Data Library (French, 2021a). The construction and calculations behind the factor portfolios are presented below, to increase the understanding of how this thesis' constructed portfolios are exposed to the different risk factors.

Capital asset pricing model:

Capital asset pricing model (CAPM) states that portfolio returns are dependent on the exposure to the market risk, thus the factor used is the excess return on the market portfolio. The market portfolio is the value-weighted return of all CRSP firms with share code 10 or 11, listed on the NYSE, AMEX and Nasdaq stock exchanges. The market risk factor applied is in excess of the risk-free rate, proxied by the Treasury bill rate (from Ibbotson Associates) (French, 2021d).

Fama and French three-factor model:

In Fama and French three-factor model (FF3), the excess return on the market is calculated in the same way as aforementioned. Thus, the factor model introduces two additional factors, SMB and HML (Fama & French, 1993). SMB captures the historic excess returns of small-cap companies over large-cap companies, and HML captures the historic excess returns of value stocks over growth stocks. The two factors are calculated using value-weighted portfolios based on the two factors. The portfolios are labeled with two letters, where the first describes the *Size* group, and the second describes the *B/M* group.

Size is divided into two groups, small (S) or big (B). The breakpoint is the NYSE median, which means that companies with a market cap below the NYSE median are characterized as small, and companies with a market capitalization above the NYSE median are characterized as big. B/M is divided into three groups, high (H), neutral (N) or low (L). The breakpoints applied are the 30^{th} and 70^{th} NYSE percentiles. Thus, a company with B/M in the bottom 30% of NYSE will be characterized as low (L), the middle 40% as neutral (N), and companies in the top 30% are characterized as high (H) (Fama & French, 2015).

The SMB portfolio is constructed by 2x3 sorts of the size and value portfolios (Fama & French, 2015, s. 6):

$$SMB = \frac{SH + SN + SL}{3} - \frac{BH + BN + BL}{3}$$

The HML portfolio is constructed by 2x2 sorts of the value and size portfolios (Fama & French, 2015, s. 6)::

$$HML = \frac{SH + BH}{2} - \frac{SL + BL}{2}$$

Fama, French and Carhart four-factor model:

Fama, French and Carhart four-factor model is an extension of the original FF3 model, adding a momentum factor (Bali et al., 2016). The three original factors are calculated in the same way as aforementioned.

Momentum, "Up minus down" (UMD) are formed using six value-weighted portfolios on size and prior (2-12 months) returns. Size is the same, while the prior return breakpoints are the 30th and 70th NYSE percentiles. Thus, a company with t-13 to t-2 returns in the bottom 30% of NYSE will be characterized as low returns (D), the middle 40% as neutral and the top 30% as high returns (U) (French, 2021b).

The UMD portfolio is constructed by 2x3 sorts of the size and momentum portfolios (French, 2021b):

$$UMD = \frac{SH + SN + SL}{2} - \frac{BH + BN + BL}{2}$$

Fama and French five-factor model:

The final factor model applied in this paper is the Fama and French five-factor model (Fama & French, 2015). The factors are constructed using six value-weight portfolios formed on size and book-to-market, six value-weight portfolios formed on size and operating profitability, and six value-weight portfolios formed on size and investments. The additional factors are RMW, the difference between the returns on diversified portfolios of stocks with robust and weak profitability, and CMA, the difference between the returns on diversified portfolios of the stocks of low and high investment firms.

RMW include all NYSE, AMEX and Nasdaq stocks with market equity data, positive book equity data, non-missing revenues and at least one of the following: cost of goods sold, selling, general and administrative expenses, or interest expenses (French, 2021c). The breakpoints are the 30th and 70th NYSE percentiles. Thus, a company with operating profitability in the bottom 30% of NYSE will be characterized as weak (W), the middle 40% as neutral (N) and the top 30% as robust (R).

CMA include all NYSE, AMEX and Nasdaq stocks with market equity data and total assets data. The breakpoints are the 30th and 70th NYSE percentiles. Thus, a company with investments in the bottom 30% of NYSE will be characterized as conservative (C), the middle 40% as neutral (N) and the top 30% as aggressive (A) (French, 2021c).

In this model, the SMB portfolios are calculated different from the FF3, and the returns of the two portfolios are therefore not similar. Thus, formulas for construction of all portfolios are presented (French, 2021c):

$$SMB_{B/M} = \frac{SH + SN + SL}{3} - \frac{BH + BN + BL}{3}$$

$$SMB_{OP} = \frac{SR + SN + SW}{3} + \frac{BR + BN + BW}{3}$$

$$SMB_{Inv} = \frac{SC + SN + SA}{3} - \frac{BC + BN + BA}{3}$$

$$\boldsymbol{SMB = \frac{SMB_{B/M} + SMB_{OP} + SMB_{Inv}}{3}}$$

$$\boldsymbol{HML = \frac{SH + BH}{2} - \frac{SL + BL}{2}}$$

$$\boldsymbol{RMW = \frac{SR + BR}{2} - \frac{SW + BW}{2}}$$

$$\boldsymbol{CMA = \frac{SC + BC}{2} - \frac{SA + BA}{2}}$$

Appendix L: Stationarity and diagnostic checks

L.1 Stationarity

The results for the stationarity tests on all variables over the overall period and the individual sub-periods are displayed in tables K.1, K.2 and K.3. The results are output from the Augmented Dickey-Fuller tests conducted in R, which checks for stationarity in the variables (Enders, 2015). As seen, the test statistics for all variables are larger than the critical values, meaning that one can reject the null hypothesis of a unit root process in the time series. Therefore, the time series are assumed to be stationary.

Table L.1

Test statistic and critical value for ADF-test, overall period of 2000-2019

Time series	Test statistic	Critical Value
EW four-screen excess return	-8.6937	-1.95
EW six-screen excess return	-10.6985	-2.88
VW four-screen excess return	-9.4969	-1.95
VW six-screen excess return	-11.1182	-3.43
Market excess return	-10.5042	-1.95
SMB3	-12.4241	-3.43
HML	-10.5932	-3.43
UMD	-12.1415	-1.95
SMB5	-11.9817	-3.43
RMW	-11.3277	-3.43
CMA	-10.3752	-3.43

Table L.2

Test statistic and critical value for ADF-test, sub-period of 2000-2009

Time series	Test statistic	Critical Value
EW four-screen excess return	-5.805	-1.95
EW six-screen excess return	-7.4345	-1.95
VW four-screen excess return	-6.3004	-1.95
VW six-screen excess return	-7.4012	-1.95
Market excess return	-7.3863	-1.95
SMB3	-8.8863	-2.88
HML	-7.7425	-3.43
UMD	-8.5954	-1.95
SMB5	-8.4784	-3.43
RMW	-7.8214	-2.88
CMA	-7.597	-3.43

Table L.3

Test statistic and critical value for ADF-test, sub-period of 2010-2019

Time series	Test statistic	Critical Value
EW four-screen excess return	-7.0204	-1.95
EW six-screen excess return	-7.891	-2.88
VW four-screen excess return	-7.764	-1.95
VW six-screen excess return	-8.6373	-2.88
Market excess return	-8.5797	-2.88
SMB3	-8.0966	-1.95
HML	-7.2993	-1.95
UMD	-8.0494	-1.95
SMB5	-8.2453	-1.95
RMW	-8.0984	-1.95
CMA	-7.279	-1.95

L.2 Linearity

Firstly, the linearity assumption for all 48 regression models is checked. This is done by plotting the dependent variable against the respective explanatory variables. The tests are structured by presenting linearity plots for the EW four-screen and VW four-screen factor model regressions for the full time period, followed by the same tests for the two sub-samples. The same structure for the six-screen portfolio is performed.

Figure L.1

Equal-weighted four-screen portfolio linearity assumption 2000-2019

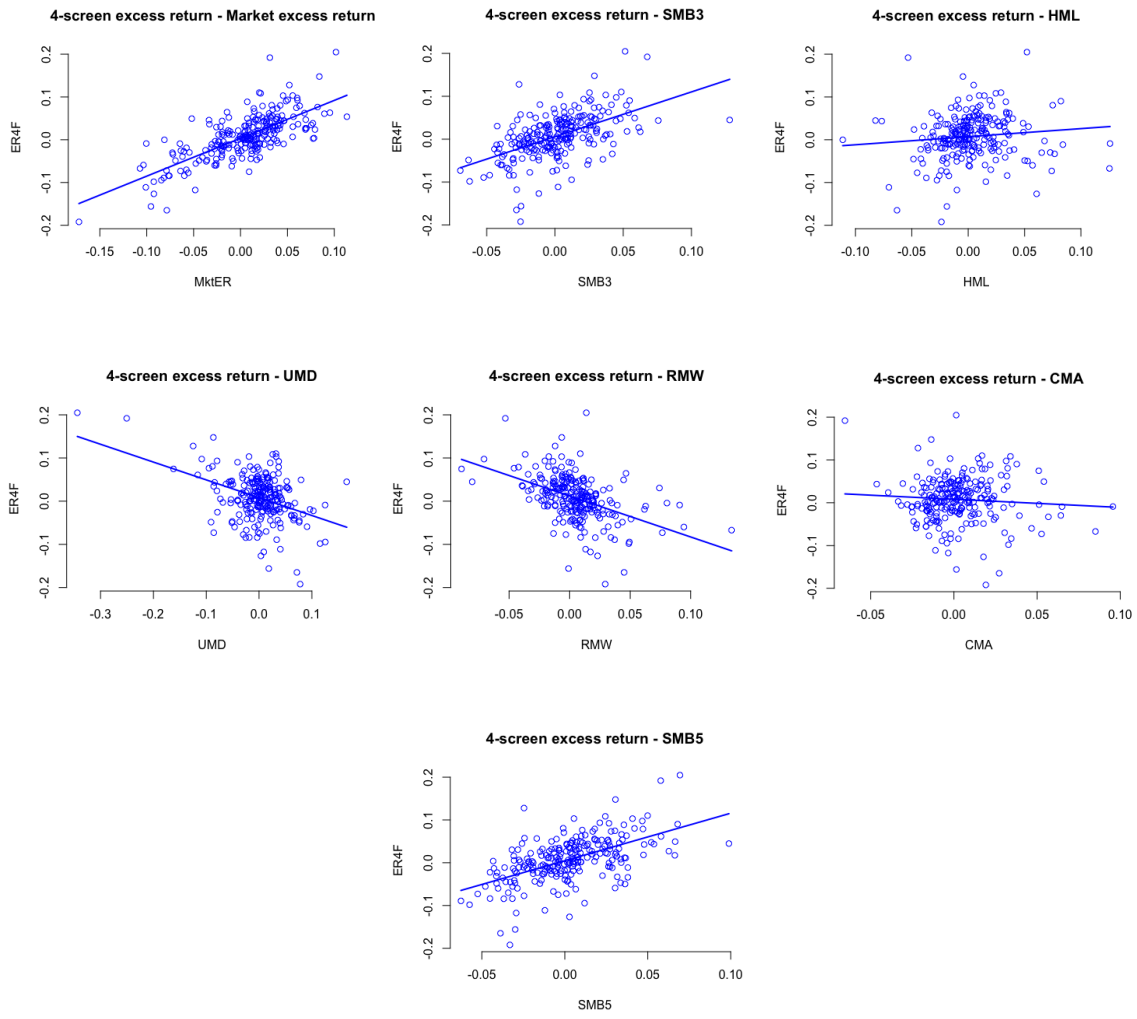


Figure L.2

Equal weighted four-screen portfolio linearity assumption 2000-2009

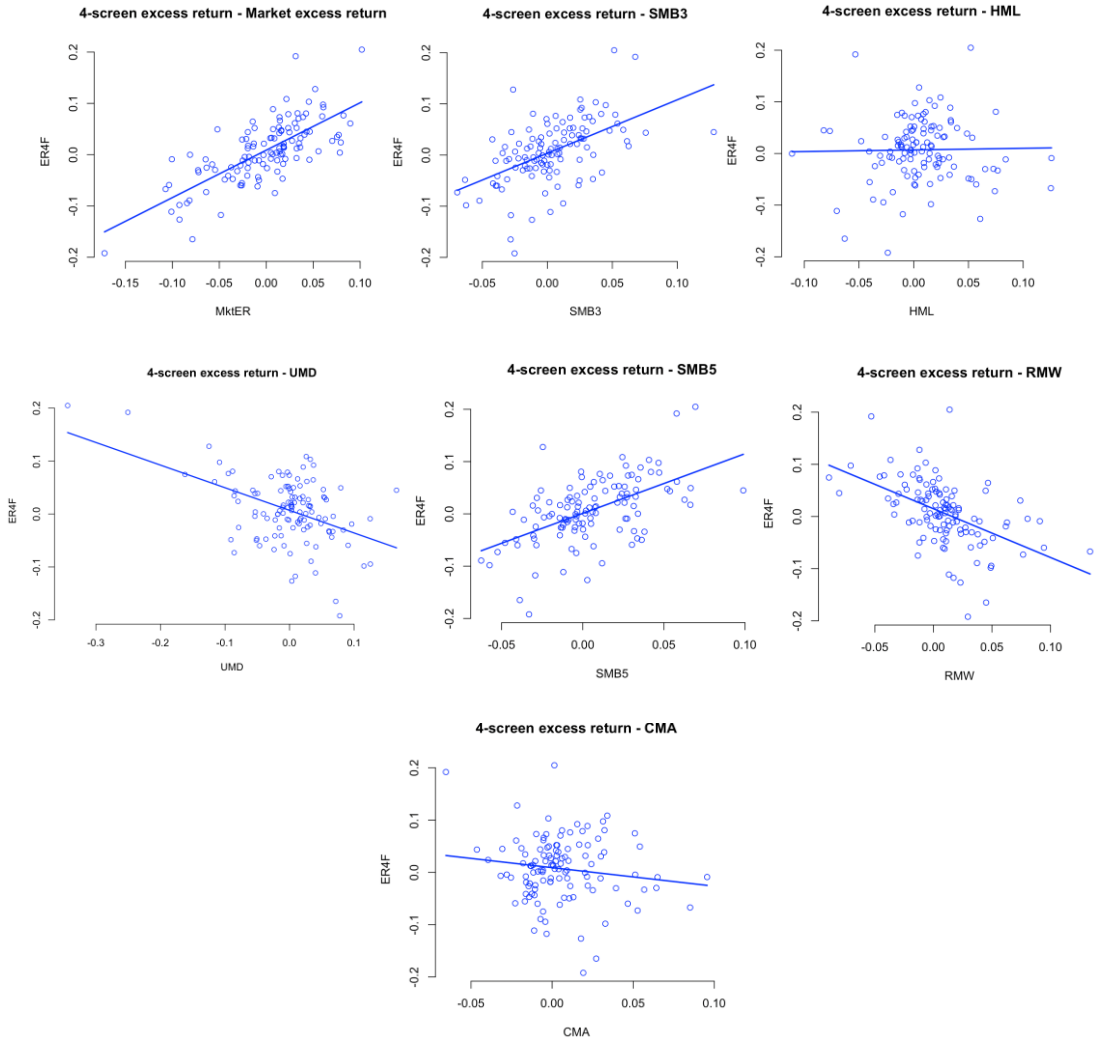


Figure L.3

Equal weighted four-screen portfolio linearity assumption 2010-2019

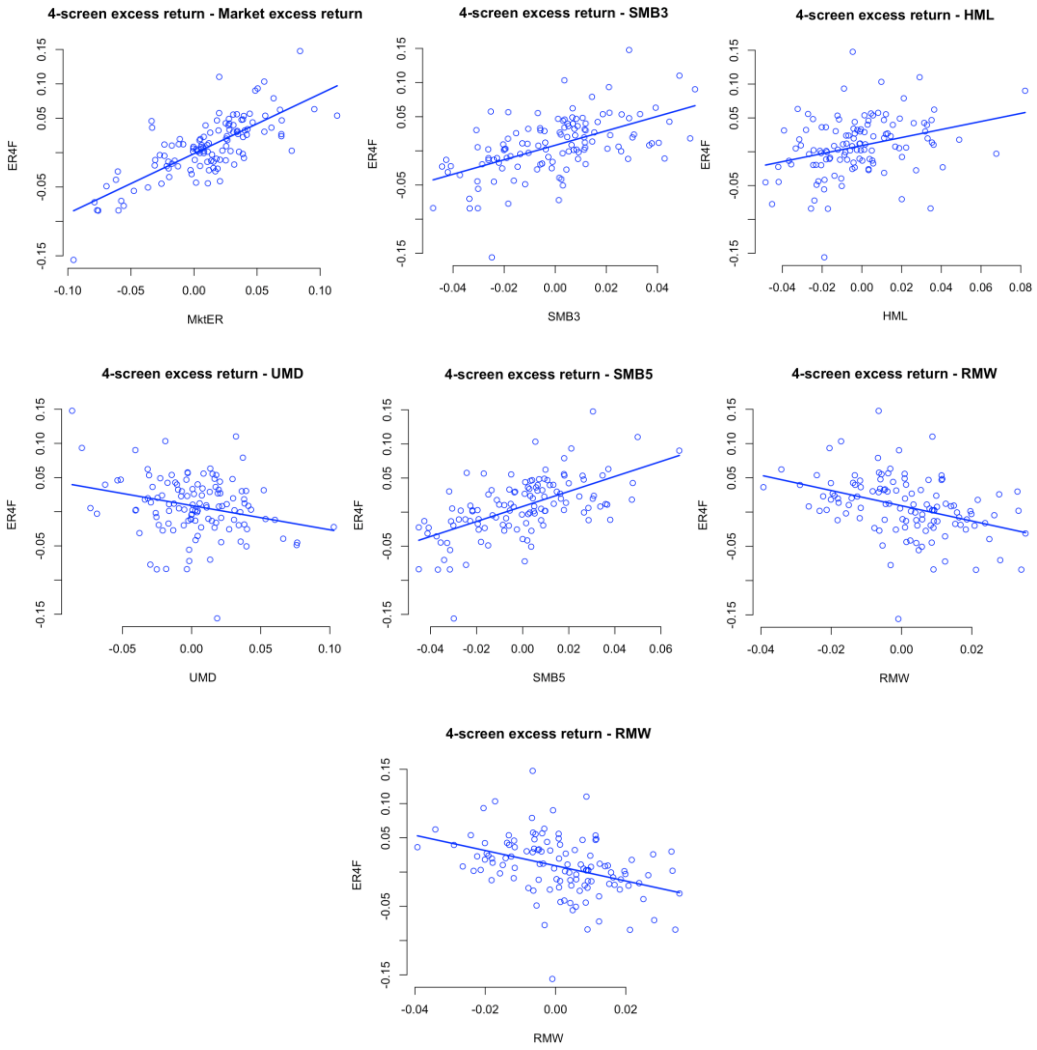


Figure L.4

Equal weighted six-screen portfolio linearity assumption 2000-2019

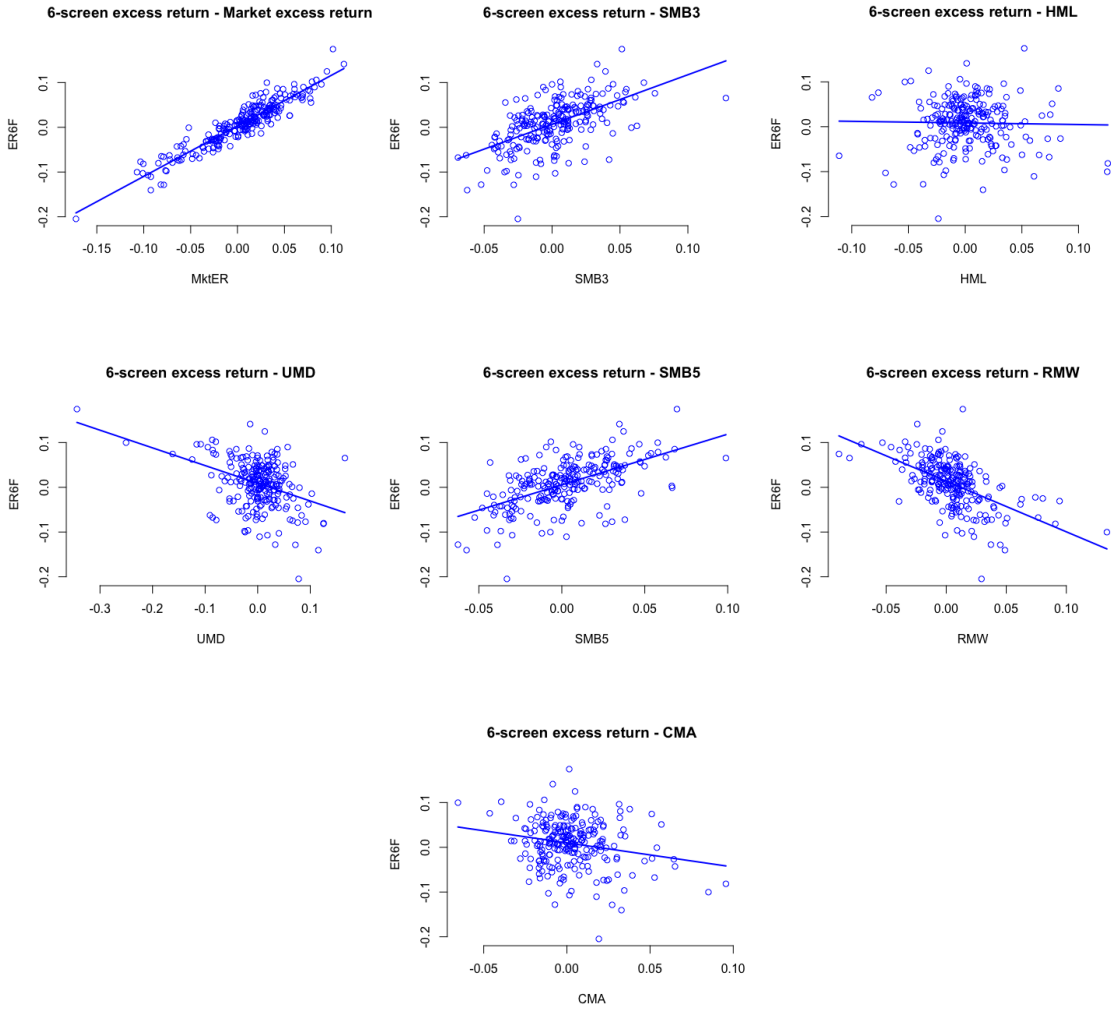


Figure L.5

Equal weighted six-screen portfolio linearity assumption 2000-2009

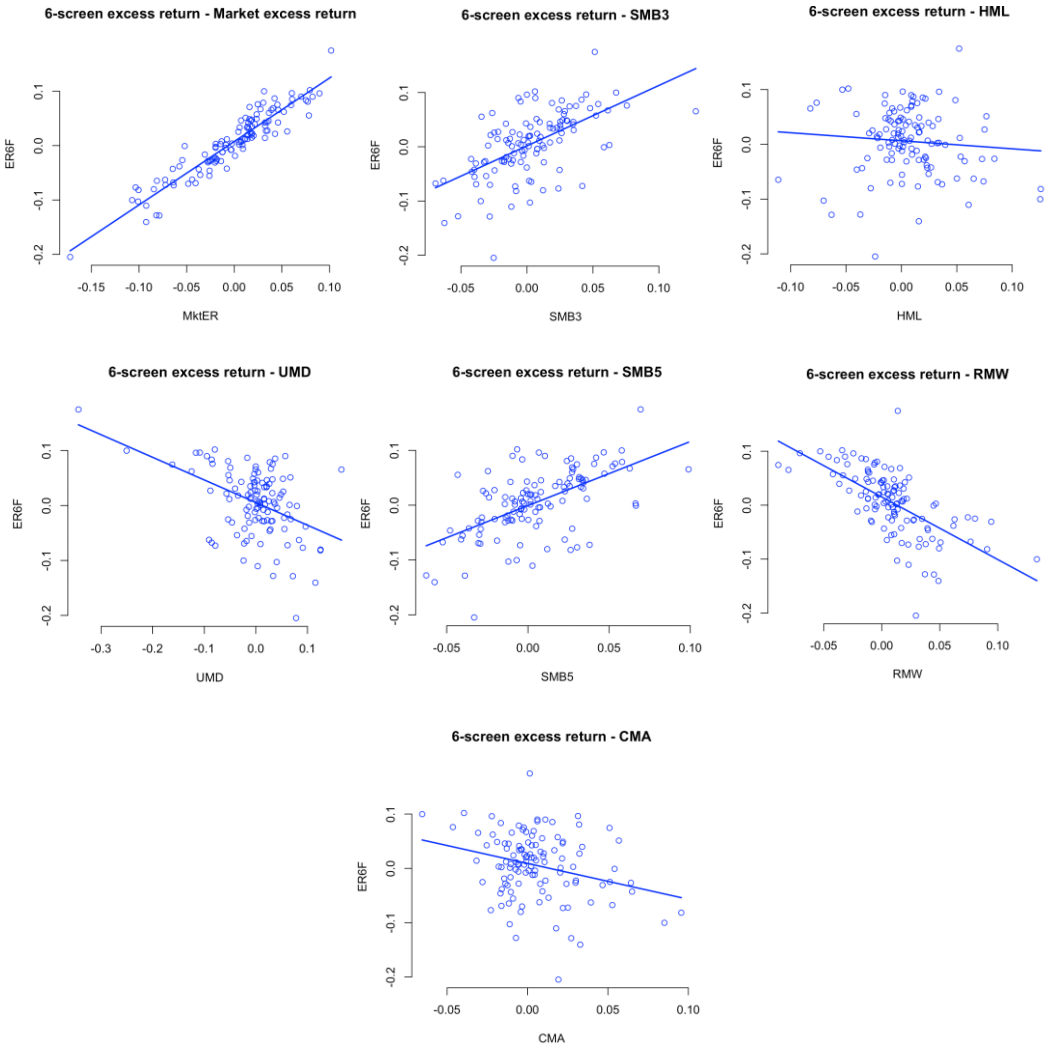


Figure L.6

Equal weighted six-screen portfolio linearity assumption 2010-2019

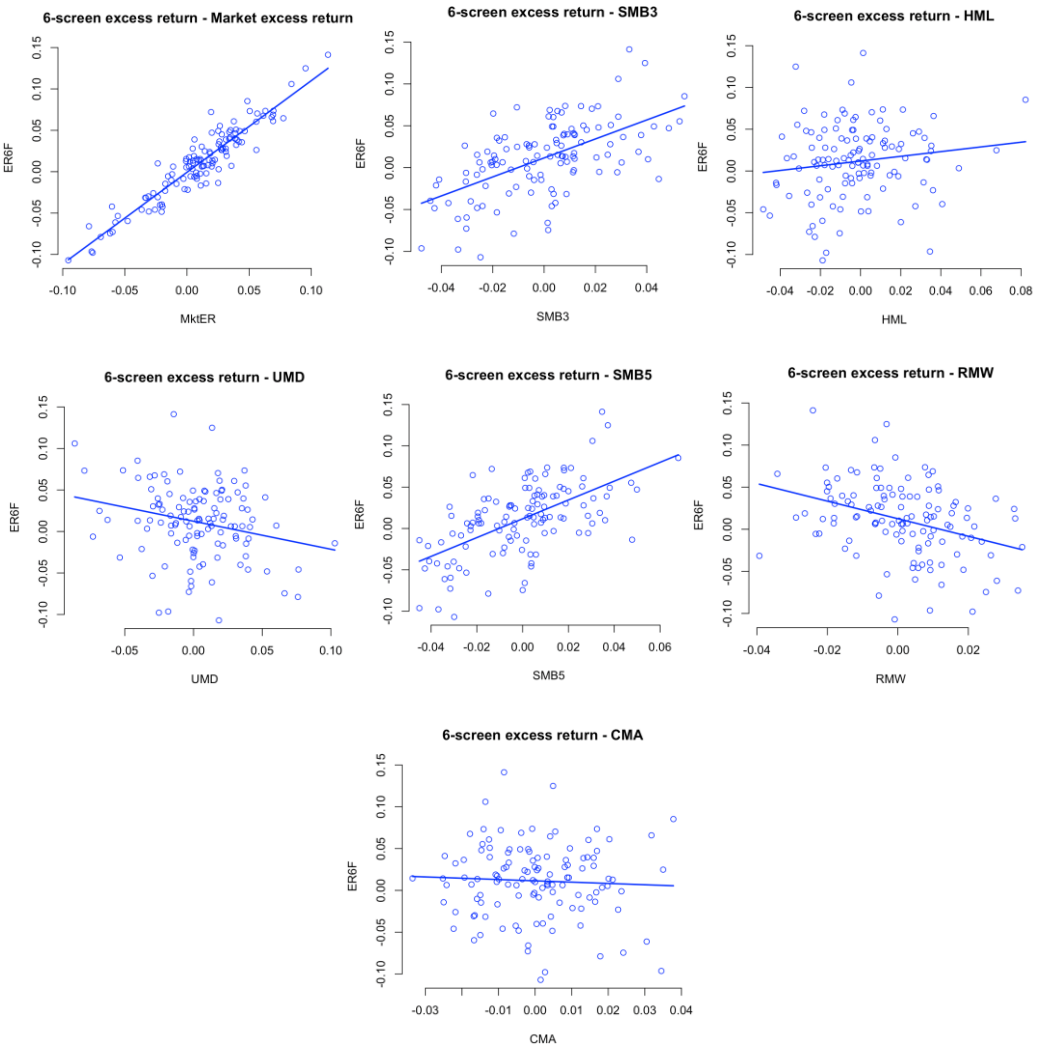


Figure L.7

Equal-weighted six-screen portfolio linearity assumption 2000-2019

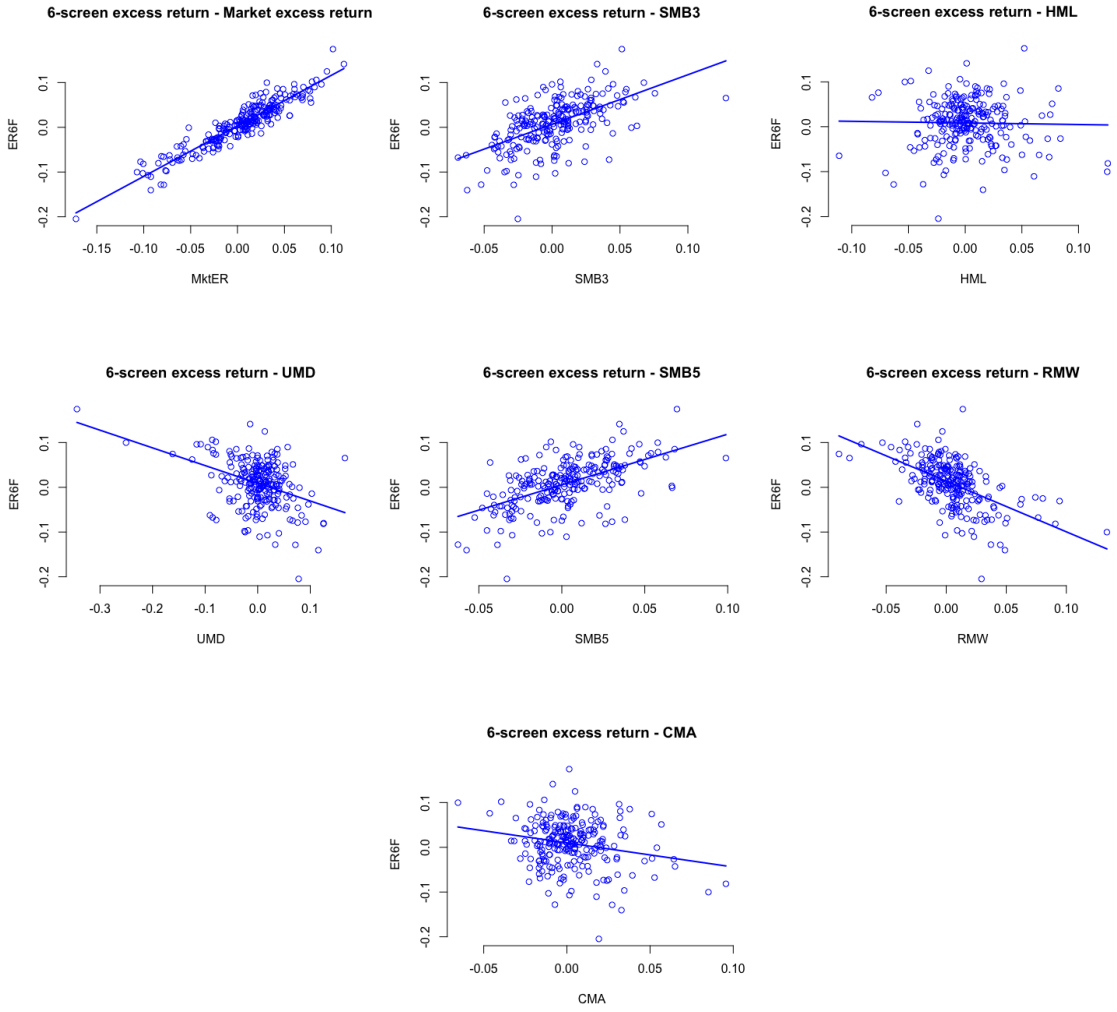


Figure L.8

Value-weighted four-screen portfolio linearity assumption 2000-2019

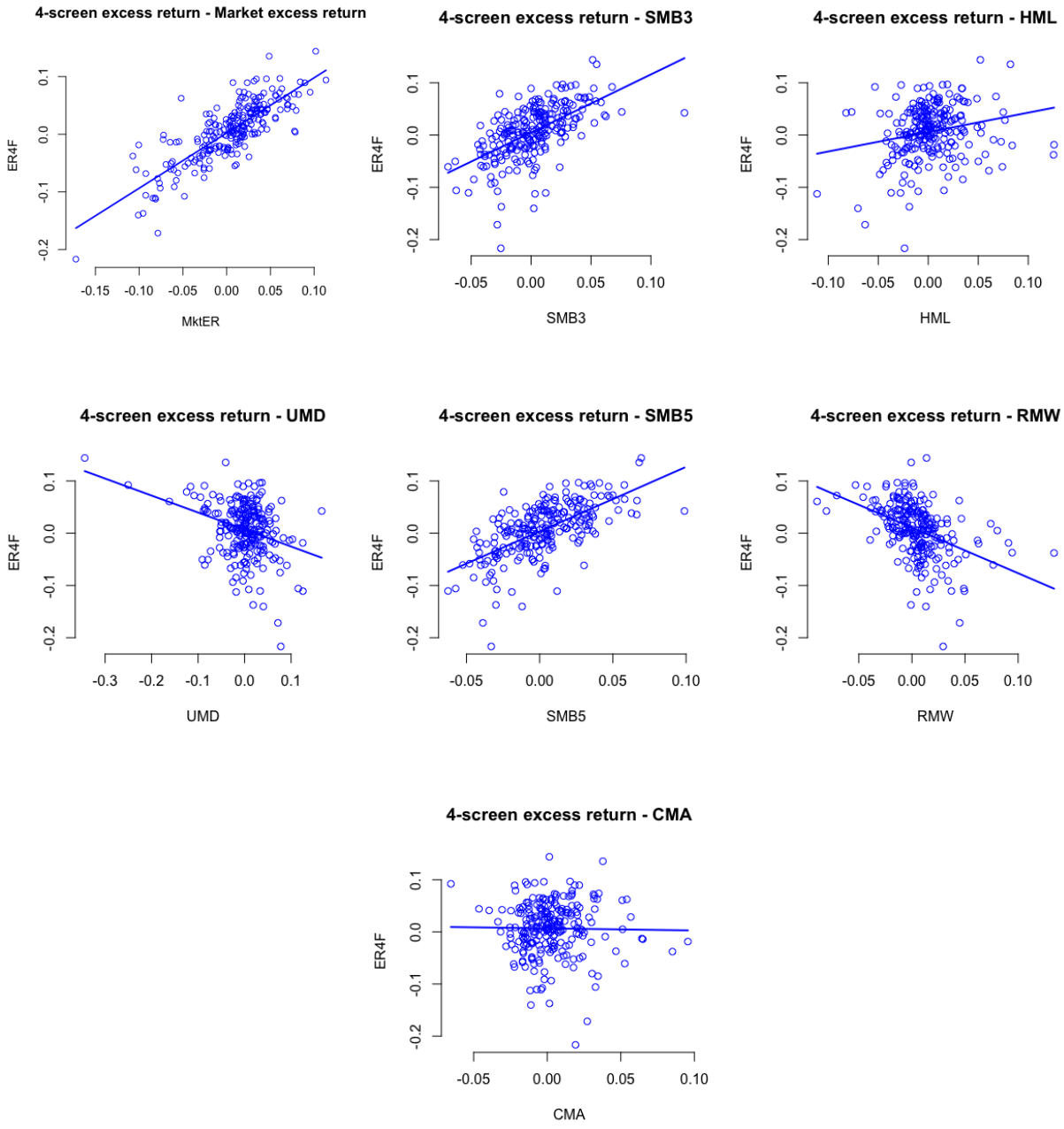


Figure L.9

Value-weighted four-screen portfolio linearity assumption 2000-2009

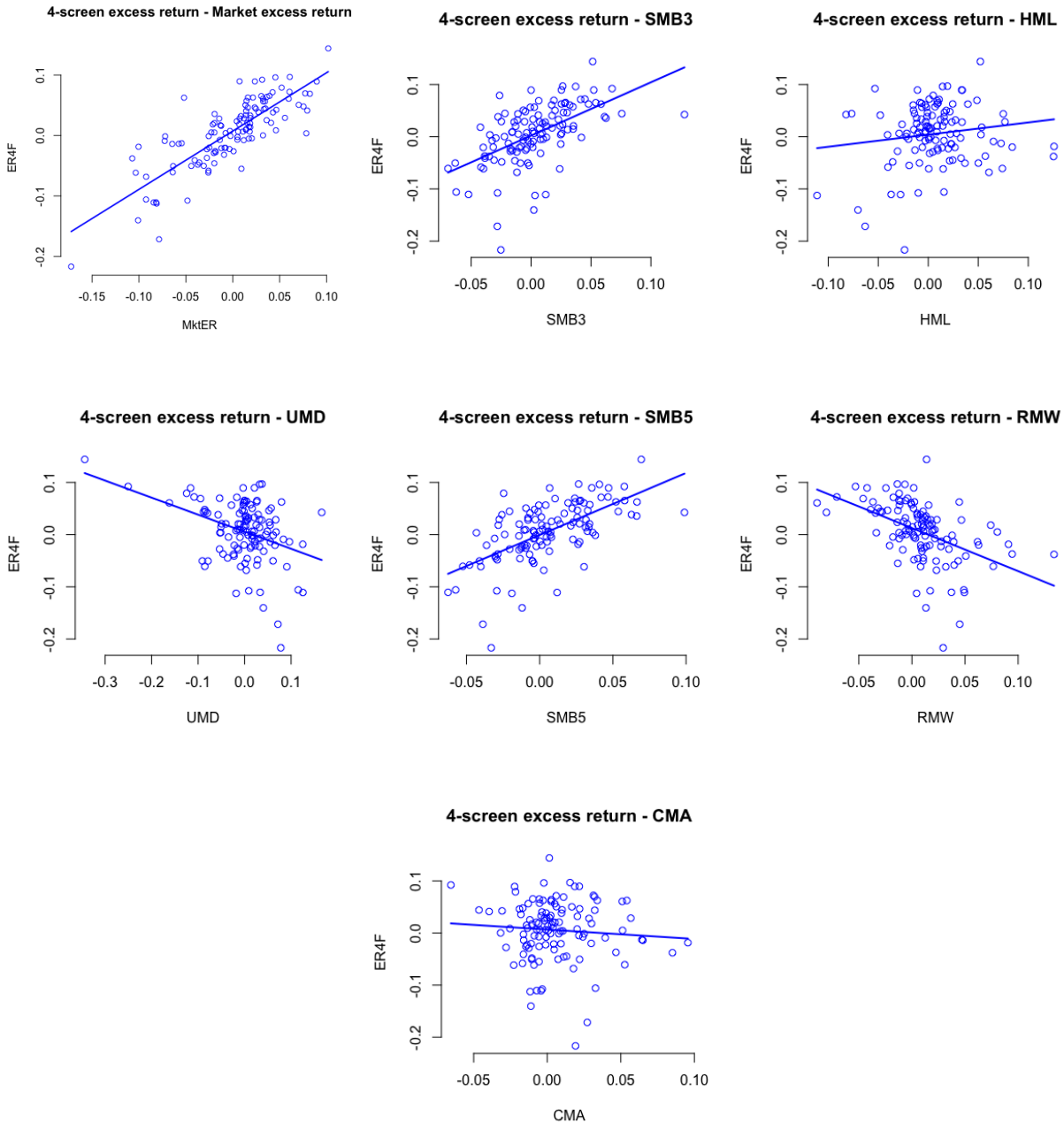


Figure L.10

Value-weighted four-screen portfolio linearity assumption 2010-2019

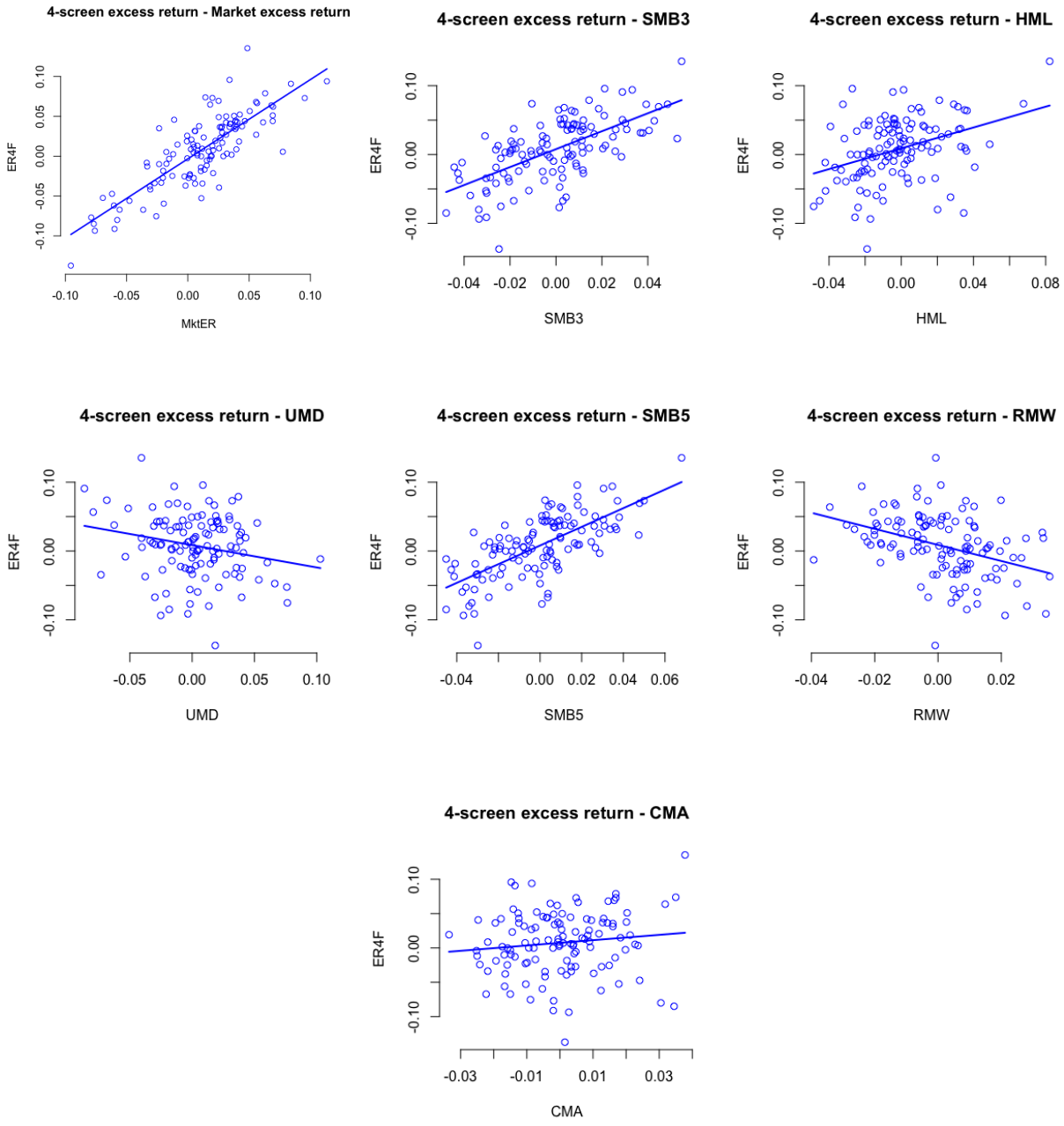


Figure L.11

Value-weighted six-screen portfolio linearity assumption 2000-2019

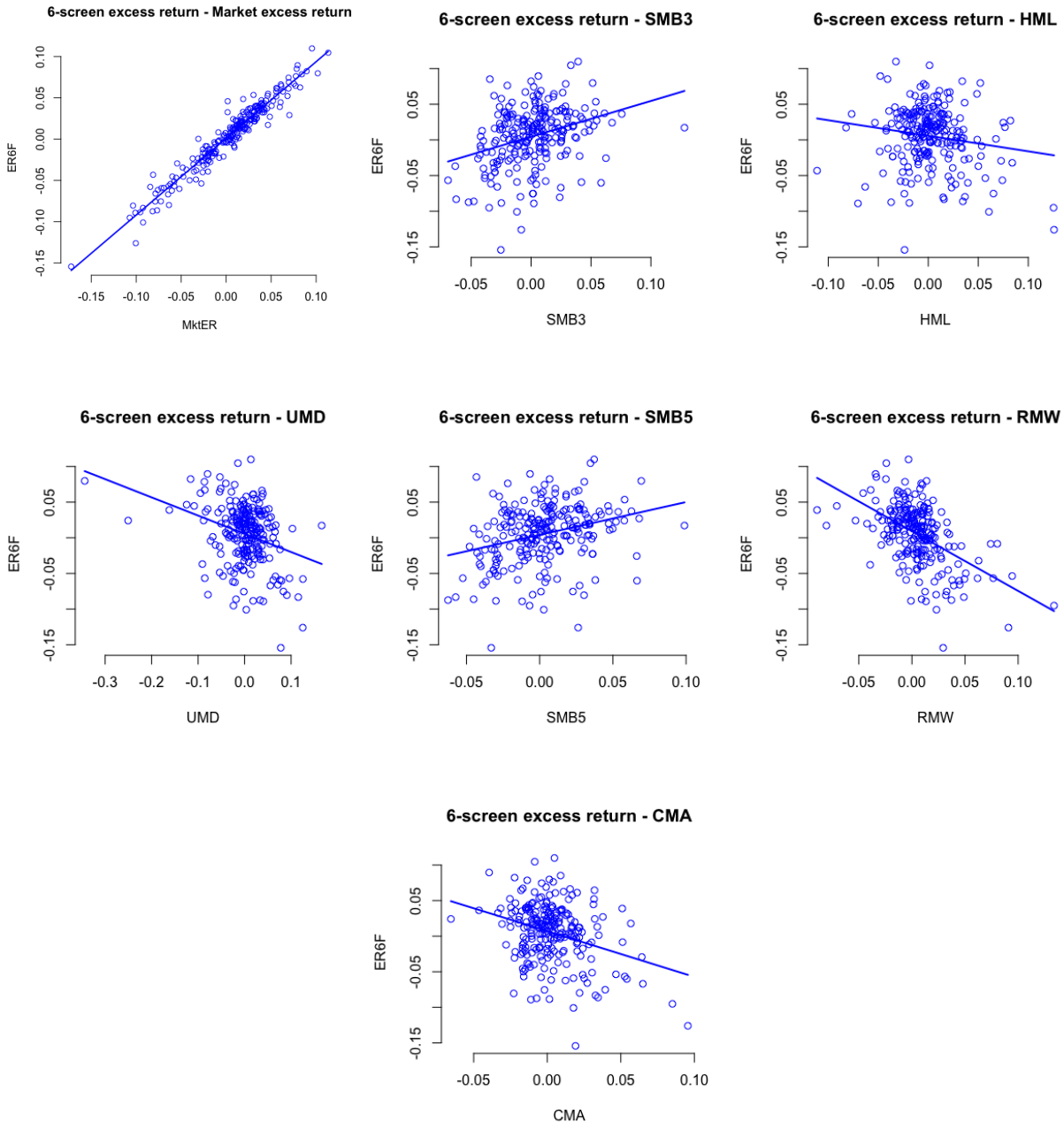


Figure L.12

Value-weighted six-screen portfolio linearity assumption 2000-2009

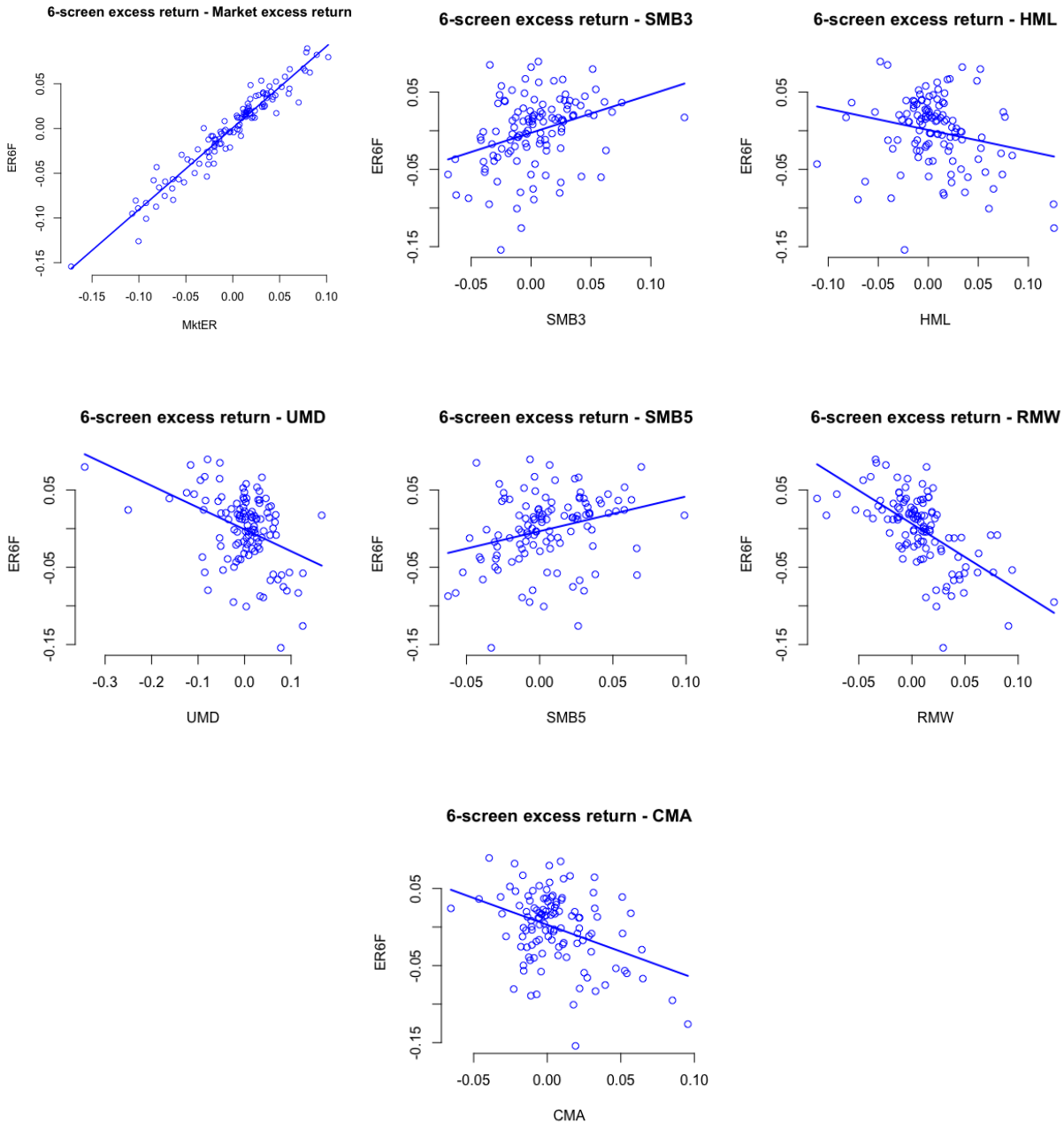
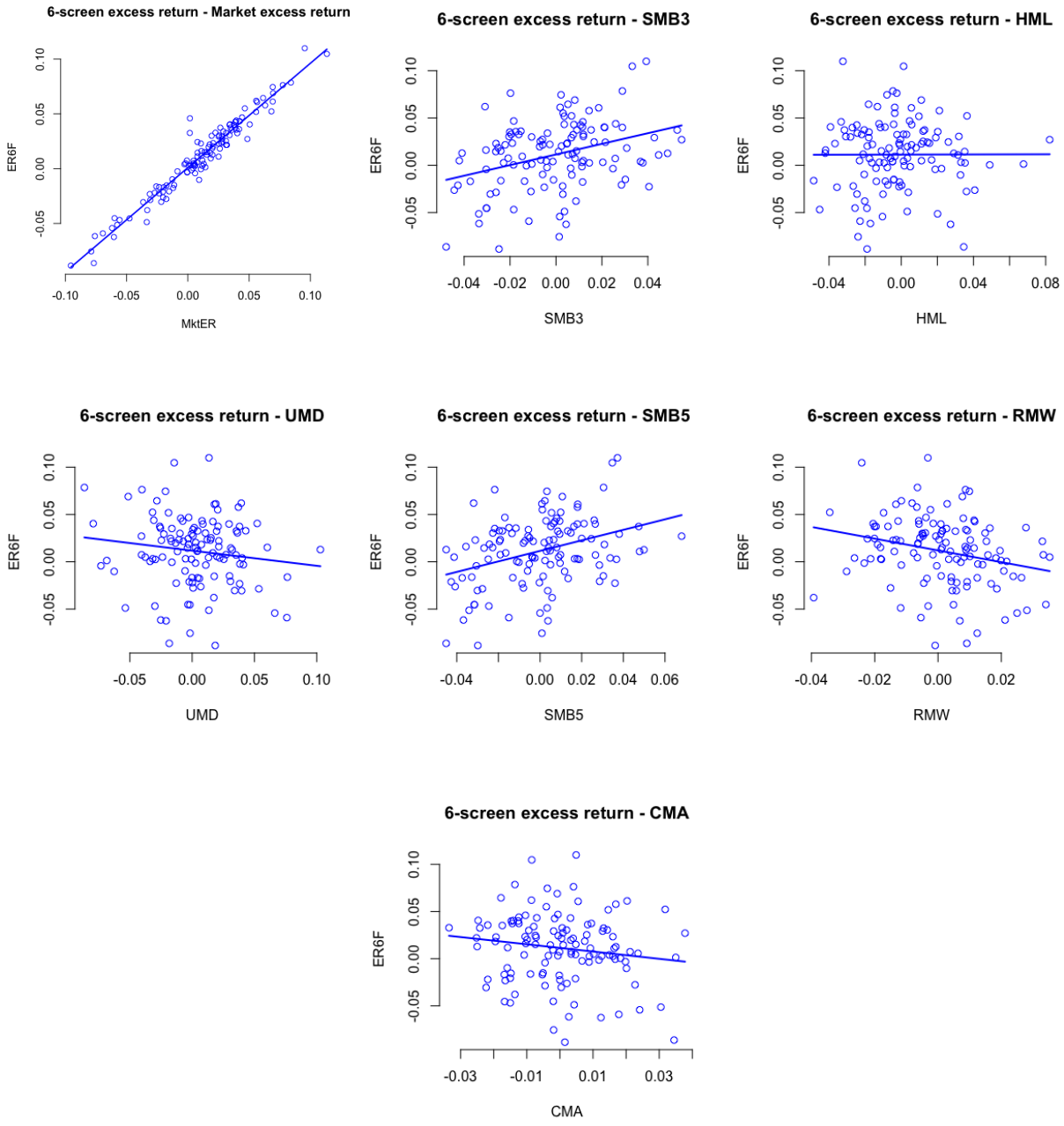


Figure L.13

Value-weighted six-screen portfolio linearity assumption 2010-2019



L.3 Constant variance, autocorrelation and normality

Further, diagnostics checks for the homoskedasticity, autocorrelation and normality are checked. The p-values for each tested is reported in the tables below, which is sorted on each portfolio and presented separately for the full sample period and the two sub-sample periods.

Table L.4

Equal-weighted four-screen portfolio linearity assumption 2000-2019

	CAPM	**FF3**	**FFC4**	**FF5**
Studentized Breusch-Pagan test for heteroskedasticity				
P-value	*0.6362*	*0.0352*	*0.0016*	*0.0413*
Breusch-Godfrey test for serial correlation				
P-value	*0.0002*	*0.0411*	*0.0078*	*0.0343*
Jarque-Bera test for normality				
P-value	*0.0250*	*0.0149*	*0.0542*	*0.0390*

Table L.5

Equal-weighted four-screen portfolio linearity assumption 2000-2009

	CAPM	**FF3**	**FFC4**	**FF5**
Studentized Breusch-Pagan test for heteroskedasticity				
P-value	*0.5013*	*0.1361*	*0.0968*	*0.2159*
Breusch-Godfrey test for serial correlation				
P-value	*0.0083*	*0.1209*	*0.0277*	*0.1091*
Jarque-Bera test for normality				
P-value	*0.0427*	*0.0018*	*0.4591*	*0.0038*

Table L.6

Equal-weighted four-screen portfolio linearity assumption 2010-2019

	CAPM	**FF3**	**FFC4**	**FF5**
Studentized Breusch-Pagan test for heteroskedasticity				
P-value	*0.4702*	*0.6817*	*0.1202*	*0.3945*
Breusch-Godfrey test for serial correlation				
P-value	*0.0926*	*0.2842*	*0.2310*	*0.2906*
Jarque-Bera test for normality				
P-value	*0.0250*	*0.0149*	*0.0542*	*0.0390*

Table L.7

Equal-weighted six-screen portfolio linearity assumption 2000-2019

	CAPM	FF3	FFC4	FF5
Studentized Breusch-Pagan test for heteroskedasticity				
P-value	*0.9692*	*0.0376*	*0.2640*	*0.2231*
Breusch-Godfrey test for serial correlation				
P-value	*0.9585*	*0.4745*	*0.9103*	*0.6753*
Jarque-Bera test for normality				
P-value	*0.0123*	*0.0000*	*0.0000*	*0.0000*

Table L.8

Equal-weighted six-screen portfolio linearity assumption 2000-2009

	CAPM	FF3	FFC4	FF5
Studentized Breusch-Pagan test for heteroskedasticity				
P-value	*0.9384*	*0.0012*	*0.0402*	*0.0064*
Breusch-Godfrey test for serial correlation				
P-value	*0.9488*	*0.0677*	*0.1132*	*0.0799*
Jarque-Bera test for normality				
P-value	*0.6967*	*0.0000*	*0.1057*	*0.0000*

Table L.9

Equal-weighted six-screen portfolio linearity assumption 2010-2019

	CAPM	FF3	FFC4	FF5
Studentized Breusch-Pagan test for heteroskedasticity				
P-value	*0.5111*	*0.6619*	*0.7350*	*0.8307*
Breusch-Godfrey test for serial correlation				
P-value	*0.0645*	*0.0256*	*0.0125*	*0.0269*
Jarque-Bera test for normality				
P-value	*0.2320*	*0.0000*	*0.0000*	*0.0000*

Table L.10

Value-weighted four-screen portfolio linearity assumption 2000-2019

	CAPM	**FF3**	**FFC4**	**FF5**
Studentized Breusch-Pagan test for heteroskedasticity				
P-value	0.0045	0.0508	0.1115	0.1102
Breusch-Godfrey test for serial correlation				
P-value	0.0265	0.0894	0.0546	0.0864
Jarque-Bera Test for normality				
P-value	0.0073	0.6323	0.6548	0.7813

Table L.11

Value-weighted four-screen portfolio linearity assumption 2000-2009

	CAPM	FF3	FFC4	FF5
Studentized Breusch-Pagan test for heteroskedasticity				
p-value	0.0025	0.0873	0.2110	0.1788
Breusch-Godfrey test for serial correlation				
p-value	0.0075	0.0045	0.0033	0.0084
Jarque-Bera Test for normality				
p-value	0.3554	0.5341	0.4848	0.5515

Table L.12

Value-weighted four-screen portfolio linearity assumption 2010-2019

	CAPM	**FF3**	**FFC4**	**FF5**
Studentized Breusch-Pagan test for heteroskedasticity				
p-value	0.5173	0.9548	0.9733	0.8362
Breusch-Godfrey test for serial correlation				
p-value	0.3123	0.1630	0.2080	0.1326
Jarque-Bera Test for normality				
p-value	0.0117	0.0307	0.0209	0.0362

Table L.13

Value-weighted six-screen portfolio linearity assumption 2000-2019

	CAPM	FF3	FFC4	FF5
Studentized Breusch-Pagan test for heteroskedasticity				
p-value	0.2579	0.3888	0.0517	0.6817
Breusch-Godfrey test for serial correlation				
p-value	0.0799	0.0002	0.0005	0.0000
Jarque-Bera Test for normality				
p-value	0.0000	0.0000	0.0000	0.0000

Table L.14

Value-weighted six-screen portfolio linearity assumption 2000-2009

	CAPM	FF3	FFC4	FF5
Studentized Breusch-Pagan test for heteroskedasticity				
p-value	0.3067	0.7909	0.0747	0.8878
Breusch-Godfrey test for serial correlation				
p-value	0.2291	0.0086	0.0089	0.0034
Jarque-Bera Test for normality				
p-value	0.0638	0.0038	0.0000	0.0000

Table L.15

Value-weighted six-screen portfolio linearity assumption 2010-2019

	CAPM	FF3	FFC4	FF5
Studentized Breusch-Pagan test for heteroskedasticity				
p-value	0.9038	0.4971	0.5247	0.6839
Breusch-Godfrey test for serial correlation				
p-value	0.3215	0.0670	0.0968	0.0291
Jarque-Bera Test for normality				
p-value	0.0000	0.0000	0.0000	0.0000

L.4 Multicollinearity

Multicollinearity in the independent variables is checked by plotting each model's variation inflation factor (VIF). If the VIF is estimated below the five, marked as the dotted line in the figures, multicollinearity is assumed to not be a problem. Note that the independent variables are identical in the value-weighted and equal-weighted portfolios, thus 15 VIF-plots are presented, sorted on the full sample period and the two sub-periods.

Figure L.14

Multicollinearity assumption 2000-2019

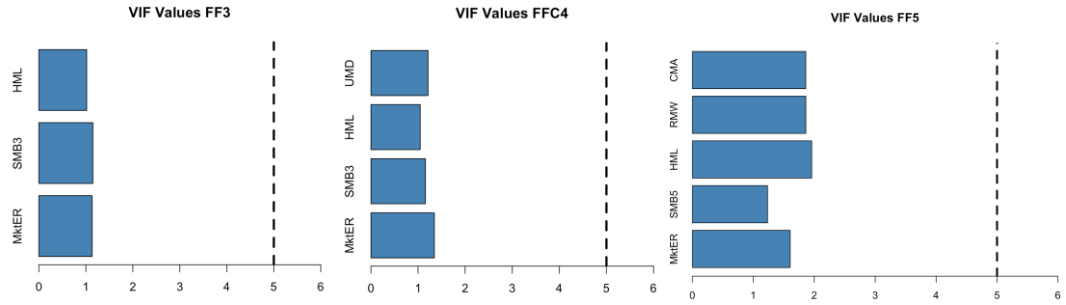


Figure L.15

Multicollinearity assumption 2000-2009

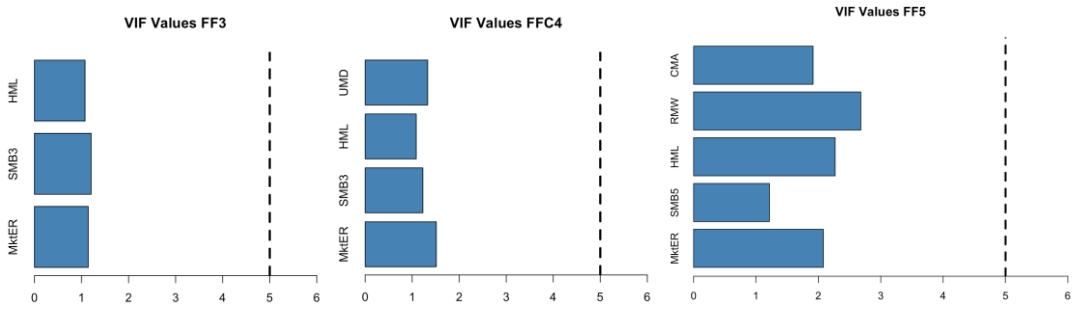


Figure L.15

Multicollinearity assumption 2009-2010