ZHAW School of Management and Law

The Relation Between Short Interest and Future Returns of NASDAQ Listed Stocks

Bachelor's Thesis

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Author:
Nenad Dinic
16-571-382

Supervisor:
Dr. Dominik Boos

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Management Summary

The short interest of a stock refers to the total amount of shares shorted by traders, professional investors and hedge funds, who profit from a decline in the stock price. Market participants can gain an informational advantage if the short interest level of a stock contains relevant information about the future share price development. Although prior research has shown that stocks with high short interest levels are more likely to experience negative abnormal returns in the following months, the relation has not been widely investigated for NASDAQ listed securities during the rising equity market from 2012 to 2019.

The aim of this Bachelor's thesis is to analyse the one-month abnormal return of NASDAQ listed stocks with either a very low or a very high short interest level during the period 2012 to 2019. Both the short interest as a percentage of float (SIPF) and the short interest ratio (SIR) are applied to determine which metric provides higher and more significant abnormal returns. Stocks are ranked each month to form equal-weighted portfolios based on either the SIPF or the SIR level retrieved from Bloomberg. The lightly shorted portfolios include securities below the 1st and 10th percentiles, while the heavily shorted portfolios contain stocks above the 90th and 99th percentiles. To evaluate the absolute performance, the total return over the entire period, as well as the geometric average return, is determined. Abnormal returns are estimated through ordinary least squares regressions and by applying two different multi-factor asset pricing models.

The empirical results indicate that portfolio formations based on the metric SIPF deliver higher and more significant returns than ones sorted by SIR, regardless of the asset pricing model. Lightly shorted portfolios generate significant excess returns when containing stocks below the 1st percentile (1.1% per month) and below the 10th percentile (1.0% per month). In contrast, the heavily shorted portfolios experience a significant negative abnormal return if they comprise stocks above the 90th percentile (-0.9% per month) and above the 99th percentile (-1.4% per month).

In conclusion, short interest as a percentage of float can be a valuable sentiment indicator for forecasting the future share price development of NASDAQ listed securities. The findings of this study confirm prior research suggesting that buying stocks with a very low short interest level potentially leads to higher returns for investors, while stocks with a very high short interest level should be avoided or sold due to the high probability of underperforming considerably.

Further studies could investigate the relation between short interest and the subsequent stock return for non-U.S. markets. It would be desirable to implement short interest estimations from financial data providers covering shorter time periods – for example, on a day-to-day or week-to-week basis.

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List of Abbreviations

AMEX .... *American Stock Exchange*
B/M .... *Book-to-market ratio*
C4F .... *Carhart four-factor*
CAPM .... *Capital asset pricing model*
CCMP .... *NASDAQ Composite Index*
EMH .... *Efficient market hypothesis*
FF3F .... *Fama-French three-factor*
GMR .... *Geometric mean return*
HML .... *High Minus Low*
IPO .... *Initial public offering*
MOM .... *Momentum*
NYSE .... *New York Stock Exchange*
OLS .... *Ordinary least squares*
SIPF .... *Short interest as a percentage of float*
SIR .... *Short interest ratio*
SMB .... *Small Minus Big*
XCMP .... *NASDAQ Composite Total Return Index*

1 Introduction

1.1 Background and Problem Definition

Shorting a stock, also known as short selling, is a controversial strategy widely used by traders, professional investors and hedge funds. It involves selling borrowed shares with the aim of repurchasing them at lower prices to return to the lender. Since profits can only be realised in the event of a falling share price, short sellers focus primarily on overvalued stocks and avoid undervalued or fairly valued securities.

The total amount of shares shorted by market participants but not yet bought back is called short interest. If a particular security has a high short interest, it signals that many well-informed and knowledgeable financial experts currently consider the shares to be overvalued and thus expect a falling share price. This gives rise to the question of whether the current short interest level of a stock contains relevant information about the future share price development – information that could be systematically used to earn higher returns. This would, however, contradict the theory of efficient markets, which states that the current price of a security reflects all information, including historical market trading data such as short interest. It would therefore not be possible to generate a significant positive or negative abnormal return that is not captured by a multi-factor asset pricing model, for example the Fama-French three-factor model or the Carhart four-factor model.

Moreover, the global stock market mostly moved upwards and regularly reached new all-time highs between 2012 and 2019, making it challenging for short sellers to bet on falling share prices. The trend may have also influenced the informative value of short interest. The NASDAQ Composite Index, which contains all stocks traded on the NASDAQ Stock Market, performed particularly well over this eight-year period due to the sharp rise in equity prices of information technology companies.

Although several studies have confirmed that heavily and lightly shorted stocks generated abnormal returns after consideration of multi-factor asset pricing models, the predictive power of short interest on the subsequent return of NASDAQ listed stocks during the rising equity market over the last eight years has not been widely investigated. To address the knowledge gap concerning that particular time frame, this study focuses on the relationship between short interest and future returns of NASDAQ stocks during the months January 2012 to December 2019.

The NASDAQ Stock Market is divided into three different market tiers. Listed companies must meet certain financial, liquidity and corporate governance requirements in order to remain listed on the stock exchange and the corresponding market level (Nasdaq, Inc., 2020a):

1) NASDAQ Global Select Market (most stringent requirements)
2) NASDAQ Global Market
3) NASDAQ Capital Market (least stringent requirements)

The average short interest as a percentage of daily trading volume across all NASDAQ listed securities between 2011 and 2019 ranged from three to five days and was mostly constant over time, as shown in figure 1. In contrast, the average short interest of less capitalised firm listings, reflected by the NASDAQ Capital Market, was more inconsistent and volatile. It is therefore essential to include small-capitalised companies in the dataset to prevent a size bias.

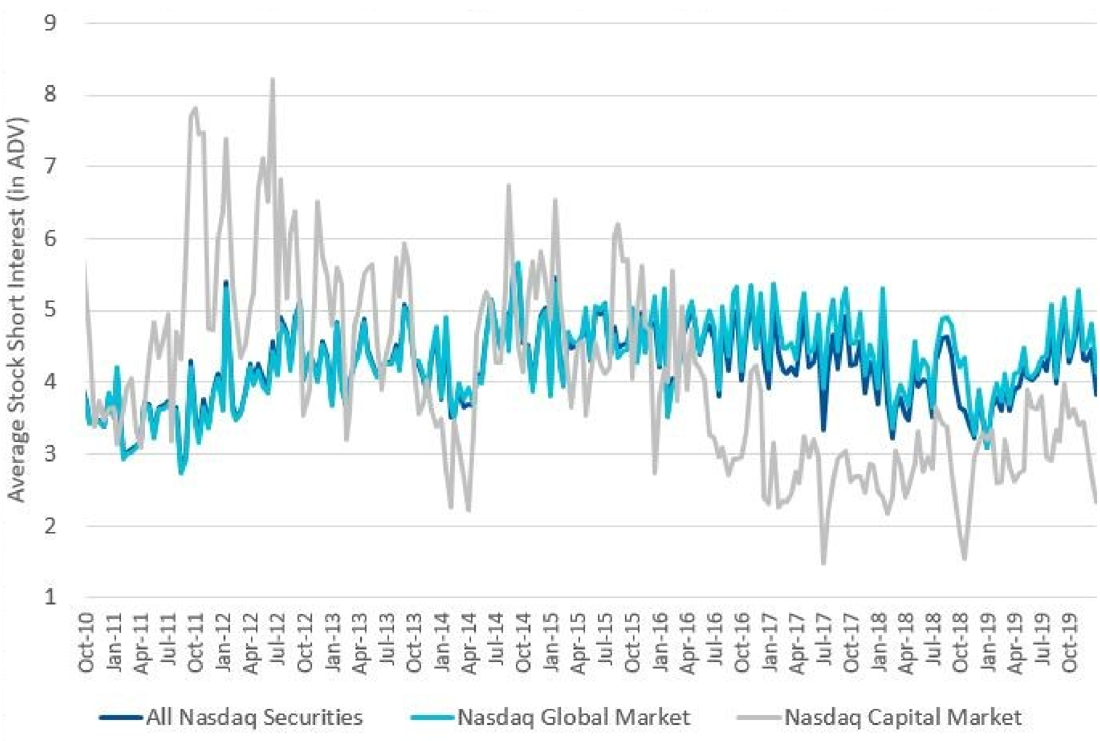

Figure 1: Short Interest of NASDAQ Stocks 2011–2019 (Nasdaq, Inc., 2020b)

1.2 Research Question and Objective

This paper analyses one-month returns of portfolios, containing NASDAQ stocks with either a very high or a very low short interest, during the period January 2012 to December 2019. The aim is to provide answers to the following research question:

1) How did NASDAQ listed stocks with a very low or a very high short interest level perform in the following month, and did these securities generate significant abnormal one-month returns based on multi-factor asset pricing models?

Although most existing literature has used short interest as a percentage of shares outstanding as an indicator for future returns, this paper considers the short interest as a percentage of float (SIPF) and the short interest ratio (SIR) to determine which of the two metrics provides better and more consistent results. The second research question is therefore:

2) Are both the short interest as a percentage of float and the short interest ratio reliable indicators of subsequent one-month stock returns, and which metric provides higher and more significant abnormal one-month stock returns?

A brief relative sector analysis is then performed by comparing the sector exposure of the individual short interest portfolios with the sector weightings of the NASDAQ Composite Index. The aim is to explore which sectors are more exposed to short selling activity. For this reason, the final research question is:

3) How do sector weightings differ between the constructed short interest portfolios and the market index?

1.3 Overview

The remainder of this paper is structured as follows. Chapter 2 introduces the concept of short selling, the publication of short interest information in different countries, the most relevant short selling metrics, the efficient market hypothesis and asset pricing models. Chapter 3 presents the current state of knowledge on short interest levels, and chapter 4 describes the dataset, the portfolio formation and the method of analysis. Chapter 5 discusses the empirical results, and in chapter 6 the conclusions are briefly summarised.

2 Theoretical Framework

The purpose of this chapter is to present the theoretical background of short selling, market efficiency and asset pricing models for the measurement of risk-adjusted returns.

2.1 The Concept of Short Selling

In order to short a security, an investor must first find an existing owner (lender) who is willing to lend the security, typically from a broker-dealer or an institutional investor. The short seller (borrower) needs to leave an initial collateral with the broker-dealer, which is at least the market value of the borrowed share and typically 102% of the market value for U.S. securities. Under Regulation T, the Federal Reserve Board requires short sellers to deposit a higher initial margin of at least 150% of the value, if the lender is a U.S. broker-dealer. Cash is the most common form of collateral (D'Avolio, 2002, p. 275). In case the share price declines, the short seller is obliged to hold the cash collateral, even if they have sufficient assets available in the margin account. However, if the price rises, they are required to increase their collateral. The short seller must pay a stock loan fee as well as any dividend they receive from the borrowed security to the lender. As the short seller lends their cash collateral, the lender pays them a rebate rate, which consists of the current market interest rate minus the stock loan fee (Werner, 2010, p. 8).

Changes of the rebate rate for every stock occur daily. Hence, this rebate rate acts as an equilibrium in the securities lending market, balancing supply and demand. The majority of large-capitalised stocks are usually cheap and easy to borrow, meaning the rebate rate is high and short sellers can quickly find a stock lender. In contrast, stocks that are expensive and hard to borrow undergo short sales constraints and may even have a negative rebate rate. A negative rebate rate means that short sellers need to make a daily payment to the lender for the right to borrow the shares, instead of receiving a regular payment from the lender as interest on the short sale proceeds. Illiquid small-capitalised stocks with low institutional ownership and securities that are in high demand for borrowing are the items most affected by these short sale constraints (Jones & Lamont, 2002, pp. 211–212).

At some point, short sellers need to close their position by returning the borrowed stock to the lender. The resulting profit or loss of the transaction consists of the difference between the initial short sale price and the current repurchase price. If the security is being traded lower in the meantime, the borrower can cover their short position and obtain the securities cheaper on the market, which results in a profit. On the other hand, if the share price has risen since the inception of the loan, the short seller generates a loss.

The lender has the right to request the return of his shares at any time. Once the lender terminates the equity loan, and if the stock price has increased in the meantime, short sellers are forced to close their position at a loss if they are not able to find other shares to borrow within a period of three days (Geczy, Musto, & Reed, 2002, p. 244).

2.2 Publication of Short Interest Data

The regulations on the publication of short interest data is treated differently depending on the country of the stock exchange. As shown in the left column of table 1, markets in Japan and in countries from the European Union (EU) only publish the short interest data by position holder. The European Securities and Markets Authority (ESMA) requires short sellers to report to the relevant National Competent Authority (NCA), if the shares are traded on an EU regulated market and the position reaches or exceeds a certain threshold level of the issued share capital (European Securities and Markets Authority, 2013). The information, however, is difficult to interpret from an investor's point of view, as not all short positions are published, and a manual calculation is required to determine the total shares shorted for a specific stock.

For that reason, empirical studies on short selling activity more often investigate securities from countries listed in the right column of table 1. In these countries, stock exchanges publish short interest data by traded volume and position and thus increase market transparency. Moreover, the stock exchanges offer a comprehensive and clearly arranged overview of current short interest levels on their websites free of charge.

Countries with Short Interest Data by **Position Holder**			Countries with Short Interest Data by **Traded Volume and Position**		
Austria	Greece	Poland	Australia	Israel	Singapore
Belgium	Hungary	Portugal	Brazil	Malaysia	South Korea
Denmark	Ireland	Spain	Canada	Mexico	Taiwan
Finland	Italy	Sweden	China	New Zealand	Thailand
France	Japan	United Kingdom	Chile	Norway	Turkey
Germany	Netherlands		Hong Kong	Peru	United States

Table 1: Short Interest Reporting by Country (Exchange Data International, n.d.)

Short interest data is published every two weeks for NASDAQ listed securities. Every broker-dealer regulated by the Financial Industry Regulatory Authority (FINRA) in the U.S. is responsible for reporting the total short interest position in all customer and proprietary accounts bi-weekly. The reports are filed on the 15th and the last business day of each month and then published by the stock exchange eight business days later (Nasdaq Trader, n.d.).

However, there is a high demand for short interest data that is less delayed, or for markets with no regulatory requirements such as Switzerland. Therefore, in order to estimate the approximate level of short interest on a daily basis, or even in real time, financial information providers such as S3 Partners (2018) and IHS Markit (n.d.) collate securities lending data, including rebate rates, directly from broker-dealers and custodians, as explained in section 2.1. The providers then extrapolate the obtained lending and borrowing information in order to offer an estimated short interest of many global stocks. The estimates are considered very accurate, as this process requires large amounts of data and an in-depth analysis of trends in the securities lending market.

2.3 Short Selling Metrics

In the following section, three commonly applied short selling metrics that serve as a market sentiment indicator are explained. Since the literature presents various definitions, the ratios are defined according to the Bloomberg Terminal.

- Short interest as a percentage of shares outstanding is defined as the total number of shares shorted in relation to the total shares outstanding. The vast majority of empirical studies have used this indicator to measure the level of short interest.

$$Short\ Interest\ as\ \%\ of\ Shares\ Outstanding\ = \frac{Short\ Interest}{Total\ Shares\ Outstanding}\ x\ 100$$

- Short interest as a percentage of float (SIPF) is defined as the total number of shares shorted in relation to the equity float. The float corresponds to the number of shares that are available to the public and is calculated by subtracting the shares held by insiders, and those deemed to be stagnant shareholders, from the shares outstanding. A major advantage of this indicator is the improved reflection of short interest level for newly listed companies. After an initial public offering (IPO), the participation of insiders, such as executives and directors of the firm, is usually high, which can skew the amount of shares outstanding. For example, a newly listed company may have a total of 100 million shares outstanding. However, due to the high level of insider ownership, 60 million shares belong to employees within the firm who are not allowed to legally trade the security on a stock exchange until the lock-up period expires. As a result, the float only amounts to 40 million shares.

$$Short\ Interest\ as\ \%\ of\ Float\ (SIPF)\ = \frac{Short\ Interest}{Equity\ Float}\ x\ 100$$

- Short interest ratio (SIR) is defined as the short interest divided by the average daily trading volume for a specific time period, in this case over the last 30 trading days. The metric is also called the days-to-cover ratio, because it indicates how many days it would take short sellers to cover their positions.

$$Short\ Interest\ Ratio\ (SIR)\ = \frac{Short\ Interest}{Average\ Daily\ Trading\ Volume}$$

2.4 Efficient Market Hypothesis

A concept by Fama (1965) suggests that stock market prices follow a random walk, and that their short-term movements are unpredictable. Based on this mechanism of the financial market, which consists of hundreds of thousands of participants, all available information is always correctly taken into account when determining stock prices. In other words, the market is driven by rational expectations and behaves efficiently.

Assuming that market participants as a whole behave rationally on average, the efficient market hypothesis (EMH) describes three forms of informational efficiencies in financial markets: weak, semi-strong and strong (Fama, 1970).

- The weak form of efficiency asserts that stock prices reflect all historical information contained in market trading data. Any kind of data regarding past share prices, trading volume or numbers of shorted shares are not related to future price movements, because everything known has already been priced in. Therefore, an investment strategy based on technical analysis or short interest cannot consistently result in higher returns than the market and generate excess returns.

- The semi-strong form of efficiency states that in addition to historical information, all publicly available information, such as fundamental data or earnings forecast, is included in the share prices. Equities react immediately to news, and investors do not have the time to buy or sell shares after the news is published.

- The strong form of efficiency is the most rigorous and involves the assumption that in addition to historical market data and publicly known information, all private information is reflected in share prices too. The markets are completely efficient, and as a result it is impossible to beat the market, even with insider information.

This paper tests the EMH in its weakest form. If the weak form of market efficiency holds, the monthly published short interest data of NASDAQ listed stocks would not have any impact on the subsequent development of share prices. The price of a stock is always properly valued and already reflects any information regarding the published numbers of shorted shares.

2.5 Single and Multi-Factor Asset Pricing Models

This section describes three asset pricing models that aim to explain the return of a stock or a portfolio. The difference between the actual return and the expected return according to these models is called excess return, abnormal return or alpha.

The Capital Asset Pricing Model (CAPM) developed by Sharpe (1964), Lintner (1965) and Mossin (1966) is a widely used market equilibrium model that establishes a linear relationship between the price of a security or portfolio and its risk. The required variables to calculate the expected return of a stock or portfolio according to the CAPM are the current risk-free rate, which usually refers to the Treasury bill rate or the government bond yield; the expected return of the market; and the beta of the security or portfolio being analysed. The difference between the risk-free rate and the expected return of the market is called the risk premium and compensates for being exposed to systematic, non-diversifiable risk. The beta serves as a coefficient to measure the volatility of a security or a portfolio relative to the overall market. Stocks that move in the same direction as the market have a positive beta, whereas stocks that move in the opposite direction of the market have a negative beta. Assets with a high beta are riskier and must therefore offer a higher return on average to compensate for the risk. Consequently, investors can only achieve a higher expected return at higher market risk.

Jensen (1968) developed the risk-adjusted performance measure Jensen's Alpha which results directly from the CAPM. The abnormal return represents the difference between the actual return realised and the expected return according to the CAPM.

The CAPM corresponds to a one-factor model when realised returns are analysed over several periods, such as months or years. In the decades following Jensen's work, economists thoroughly revised the CAPM and developed multi-factor models to improve the explanatory variability in the cross section of stock returns, since beta was not the only risk measure considered.

Using linear cross-sectional regressions, Fama and French (1992) examined a number of different potential factors, such as the price-earnings ratio or the debt-equity ratio, in terms of their effect on average returns. They concluded that the estimated beta factor of the CAPM had only a weak influence on the U.S. stock market for the years 1963 to 1990.

However, the factors market capitalisation and book-to-market ratio (B/M)[1] improve the explanatory power considerably. Consequently, shares with a low market capitalisation achieve higher returns than those with a high market capitalisation, while shares with a high B/M achieve a better performance than those with a low B/M.

Using this foundation, Fama and French (1993) developed the three-factor (FF3F) model by extending the CAPM with the additional factors Small Minus Big (SMB) and High Minus Low (HML), which capture returns related to company size and the B/M as follows:

- SMB measures the historic excess returns of small-capitalised companies over large-capitalised companies. The return equals a long position in small sized firms, financed with a short position in the large sized firms.

- HML measures the historic excess returns of stocks with a high B/M over stocks with a low B/M. The return equals a long position in stocks with a high B/M, financed with a short position in stocks with a low B/M.

While the CAPM can only explain approximately 70% of U.S. stock returns, the FF3F model can determine approximately 90% (Fama & French, 1993, pp. 20–25).

Based on the work of Fama and French (1993) and Jegadeesh and Titman (1993), Carhart (1997) proposed the four-factor (C4F) model by adding a further component to the FF3F model – momentum.

Jegadeesh and Titman (1993) examined the effect of momentum (MOM) by applying an investment strategy for NYSE (New York Stock Exchange) and AMEX (American Stock Exchange) listed stocks between 1965 and 1989. They documented significant quarterly and annual positive returns when buying securities that had performed relatively well in the past and selling securities that had performed relatively poorly in the past. Their conclusion was that rising prices tend to rise further, while falling prices tend to fall further.

[1] The B/M of a company is calculated by dividing the equity capital by the market capitalisation.

PR1YR is the prior-one-year return momentum factor as defined by Carhart (1997), and it can be obtained as follows. First, the monthly return of all NYSE, AMEX and NASDAQ stocks over the previous eleven months is calculated. Second, the returns are sorted and divided into three equal-weighted portfolios according to their ranking. The top 30%, the medium 40% and the bottom 30% of portfolios are formed on a monthly basis. Finally, PR1YR is determined by the difference between the average return of the top and bottom portfolios.

The investigation of U.S. equity mutual funds in the period 1963 to 1993 has shown that the returns are strongly correlated with the PR1YR, SMB and HML coefficients (Carhart, 1997, p. 63). For this reason, general consensus suggests that the C4F model has a stronger explanatory power of returns compared to FF3F model, and the potential of risk-adjusted abnormal returns under the restrictions of the C4F model is expected to decrease even further.

3 Literature Review

This chapter discusses previous research on how short interest affects future stock price movements and the extent to which investors are able to achieve excess returns. Due to the transparent publication of short interest data in the U.S., as described in section 2.2, most academic studies have focused on U.S. markets. If not described otherwise, the authors of all studies in this chapter have defined the level of short interest as the total number of shares divided by total shares outstanding.

3.1 Theoretical Models

Miller (1977), as well as Diamond and Verrecchia (1987), argued against the efficient market hypothesis in their examination of the influence of short selling constraints on the speed of price adjustments to bad news. Their results indicate that the high costs of short selling make it more difficult to reflect bad information on a stock price rapidly. Furthermore, equities are expected to be overvalued by market participants, when short selling constraints prevent investors to sell short (as explained in section 2.1). Short sellers trade only if they expect that the price will significantly decrease as a reward for the high transaction costs and risks. Therefore, the only counterparties that benefit from short selling are the well-informed traders who are strongly convinced of future negative price development. The uninformed or less-informed investors are unwilling to sell short.

Despite the supposed success of short sellers identifying overpriced stocks, Jones and Lamont (2002, p. 211) emphasised that using short interest as a proxy for shorting demand is problematic, because the amount of short interest solely represents the matching amount of supply and demand. In addition, stocks that cannot be shortened due to limited supply have an infinite cost of shortening, and yet the level of short interest is zero.

3.2 The Relation Between Short Interest and Stock Returns in the U.S.

The first researchers to empirically investigate short sales and equity returns came to different conclusions. Seneca (1967) employed a multiple regression analysis on the Standard and Poor’s 500 Index (S&P 500), and found that high short interest leads to lower returns. In contrast, Mayor (1968) additionally included samples of 14 randomly selected firms from the most frequently shorted stocks in the U.S. and could not find a significant relationship between short interest levels and stock prices. Based on a large number of regressions, he suggested that the findings were consistent with the random walk hypothesis, as short sellers are unable to predict future price movements and outperform the market.

Figlewski (1981) tried a different approach. For the period 1973 to 1979, all S&P 500 stocks were sorted annually into ten portfolios according to their average six-month short interest level. Each security in the portfolio was weighted in relation to its relative market value in order to calculate monthly returns. The study verified a negative relationship between a high short interest and future excess returns using the CAPM. Although all ten portfolios showed positive returns, Figlewski advised investors to purchase securities with a low short interest in order to improve portfolio returns.

The authors of more recent studies have proposed similar results using different methodological analyses, including regression analysis, the calendar time portfolio approach and time-series studies.

Dechow, Hutton, Meulbroek and Sloan (2001) analysed monthly short interest data from all NYSE and AMEX listed firms from 1976 to 1993 and compared it with the fundamentals of each security, such as cash-flow-to-price, earnings-to-price and book-to-market. The authors showed that short sellers predominantly use these ratios to identify overpriced stocks, which have relatively low short sale transaction costs. As a result, companies with low fundamental metrics have increased short interest. When the ratios had improved, it was found that short sellers covered their positions to generate a profit. Moreover, the empirical results showed a negative correlation between short interest and stock return.

Several academic studies have examined short interest data in connection with the cross section of stock returns after controlling for the associated risk exposures according to the FF3F or the C4F model. Desai, Ramesh, Thiagarajan and Balachandran (2002) reported negative abnormal returns for highly shorted NASDAQ stocks between June 1988 and December 1994 using the calendar time portfolio approach after controlling for the C4F sensitivities (market beta, size, B/M, and momentum). In a similar manner to Figlewski (1981), the authors formed portfolios based on the short interest level of a stock. In particular, they constructed portfolios of highly shorted stocks that had at least 2.5%, 5%, 7% and 10% short interest as of shares outstanding. Instead of value-weighting each stock, they chose to equal-weight the securities in their portfolios. The portfolios were rebalanced monthly to replace all securities that did not meet the threshold with firms that did. Their findings were consistent with Dechow et al. (2001), as highly shorted companies generated significant negative abnormal returns. Furthermore, heavily shorted stocks experienced liquidation or forced delisting within 36 months far more often than companies with high values of the fundamentals.

Asquith, Pathak and Ritter (2005) documented similar results based on short interest data for AMEX stocks from 1980 to 2002, as well as for NASDAQ stocks from June 1988 to December 2002. Using the same research design as Desai et al. (2002), they calculated the abnormal returns using the FF3F and C4F regression model on five different high short interest portfolios. Furthermore, after forming equally weighted portfolios of highly shorted stocks, they divided each portfolio into thirds by institutional ownership. This additional segmentation enabled them to not only prove that highly shorted stocks underperform the market significantly, but also that the relationship becomes even stronger when the institutional ownership is low. However, after constructing portfolios using a value-weighted approach, the authors did not find a statistically significant underperformance or a relationship between institutional ownership and subsequent returns.

The consideration of both weighting methods in the construction of portfolios was also applied in a study conducted by Boehmer, Huszar and Jordan (2010), who analysed the monthly abnormal returns of NYSE, AMEX and NASDAQ listed stocks during the period 1988 to 2005. As suggested by Asquith et al. (2005), the calendar time portfolio approach was adopted, and the portfolios were both value-weighted and equal-weighted. The highly shorted portfolios included securities from the 99th, 95th and 90th percentiles of the short interest level distribution as of the previous month, whereas the lightly shorted portfolios included securities from the 1st, 5th and 10th percentiles. The study supported the argument that securities with low short interest experience both statistically and economically significant positive abnormal returns, whereas heavily shorted stocks underperform the market. These positive returns among stocks with an extreme lack of short interest are often larger (in absolute value) than negative returns for highly shorted stocks. Securities with greater short interest are therefore priced more accurately, and short selling promotes market efficiency.

One of the most recent studies related to short interest was conducted by Guo and Wu (2019), who investigated the predictive power of short interest for future returns of stocks under consideration of the credit rating of a company. The authors also propose the monthly change in short interest as an additional return predictor for future stock performance, as it improves the sentiment of short sellers. Although they covered all listed securities on the NYSE, NASDAQ and AMEX from January 1986 to February 2017, they dropped observations with stock prices below $5 per share and companies with a market value below the 5^{th} percentile of the NYSE market capitalisation. Thus, the results are not determined by small and illiquid stocks. For each month, the authors sorted the securities into decile portfolios according to either the current short interest level or the monthly change in short interest level, resulting in 20 portfolios for each month. For the analysis, the average credit rating was assigned to the portfolio. After running multiple regression to estimate the excess return, they obtained a slightly different result to Boehmer et al. (2010).

First, the findings of Guo and Wu (2019) showed that the return predictability, when considering the short interest level and credit rating of a stock, is mainly significant for firms with a speculative credit rating but insignificant for investment-grade companies. Second, the abnormal return is larger in the highly shorted portfolios (regardless of the sorting criteria, short interest level or monthly change in short interest level), whereas Boehmer et al. (2010) observed larger abnormal returns in the lightly shorted portfolios. One possible explanation is that Guo and Wu (2019) excluded stocks with share prices below $5, which means that the results of Boehmer et al. (2010) could have been mainly influenced by stocks priced below $5.

3.3 The Relation Between Short Interest and Stock Returns in Other Countries

One of the first studies outside the U.S. was conducted by Aitken, Frino, McCorry and Swan (1998), who researched the intraday reactions to short sales on the Australian Stock Exchange (ASX). The event study included a thorough analysis of all short sales that were placed either in the form of market orders or limit orders between 1994 and 1996. Abnormal returns were calculated based on four different performance indicators for either a period of 15 minutes after the short sale transactions occurred or on a transaction-by-transaction basis for 30 trades before and after the short sale. The authors found significant negative abnormal returns after a short sale has been executed.

Chien, Wang and Hsu (2016) analysed short sales by institutions and individuals on the Taiwan Stock Exchange (TWSE) between 2006 and 2012. Their findings generally supported the results of previous studies, documenting a negative relationship between the level of short interest and future stock returns. For their regression analysis, the authors considered four fundamental-to-price ratios at the end of each fiscal year, as well as institutional holdings of each stock.

Mohamad (2017) examined daily short interest data from the London Stock Exchange (LSE) over the period 2003 to 2010 and compared the abnormal returns of the constructed portfolios considering many different criteria and research methods. The author formed the portfolios according to the top and bottom percentile rank using a 120- and 60-day estimation period, used different models of event studies, compared equal and value-based weightings and applied different models of the calendar time portfolio approach. He found significant negative abnormal returns associated with heavily shorted stocks throughout all methodologies. The author emphasised that the chosen weighting method for the calendar time portfolio approach has a large impact on the final result and can lead to conflicting results. It is therefore important to disclose both results.

3.4 Research on Short Interest Indicators and Sectoral Breakdown

As mentioned at the beginning of chapter 3, nearly all the investigations have measured shorting activity based on the metric short interest as a percentage of shares outstanding. By contrast, Hong, Li, Ni, Scheinkman and Yan (2015) have shown that using SIR as a proxy for overvalued stocks results in even higher monthly abnormal returns and higher statistical significance. They analysed all shares listed on the NYSE, AMEX and NASDAQ over the years 1988 to 2008. The researchers argued that SIR is inversely correlated to trading volume and therefore reflects the marginal shorting costs per share. If the SIR of a share is already at a high level, additional short sellers would only bet on falling prices and accept the high costs of short selling if they firmly believe that the share is overvalued. Apart from these findings, little research has been conducted comparing different short interest indicators.

There is also a lack of literature focusing on whether individual stock sectors are more affected by short sales than others, particularly on the NASDAQ stock exchange. Nevertheless, Linnertová (2015) analysed the short selling activity of NASDAQ listed stocks from 2000 to 2014 and found that the sectors technology (4.6), utilities (6.3), construction & materials (7.5) and oil & gas (7.5) had the lowest average level of SIR. In contrast, the sectors travel (28.4), food & beverage (24.5), health care (23.1) and chemicals (22.1) reported the highest SIR during this period.

4 Data and Methodology

This chapter provides information on the stocks examined, the time frame and the methodology applied to answer the research questions. The corresponding Microsoft Excel workbooks used for data processing are provided in appendices A to D.

4.1 Dataset and Selection Criteria

Previous authors examining the influence of short interest on the U.S. stock market have incorporated delisted securities using the bias-free database of the Center for Research in Security Prices (CRSP) or COMPUSTAT. Access to these two databases is restricted, which is why the relevant information has been retrieved from the Bloomberg Terminal. Multiple aspects are taken into account to ensure that the applied backtesting methodology is bias-free of delistings, mergers and acquisitions, stock splits or dividend payments.

The dataset includes the SIPF and SIR as described in section 2.3, as well as the total return price for all stocks included in the NASDAQ Composite Index[2]. The examined period is from January 2012 to December 2019.

First, the historical index constituents[3] of the NASDAQ as of every year-end from 31 December 2011 to 31 December 2018 were exported to multiple spreadsheets in Microsoft Excel. In addition to the ticker and name, the Bloomberg Industry Classification Systems (BICS) of each security were also retrieved. This resulted in eight different index groups, each containing between 2,442 and 2,633 securities. The procedure ensured that firms which were delisted in the course of the year were also taken into account. IPOs listed on the NASDAQ Stock Market between 2012 and 2018 were automatically included in the following year, whereas IPOs of 2019 were not covered.

Second, with the assistance of the Bloomberg Excel Add-In, the following monthly financial data for each security in the corresponding year were retrieved[4]:

- Short Interest as % of Float (SIPF)
- Short Interest Ratio (SIR)
- Total Return Gross Index (TR)

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[2] Bloomberg ticker: CCMP:IND
[3] Bloomberg function: <MEMB>
[4] Bloomberg functions: <SI_PERCENT_EQUITY_FLOAT>; <SHORT_INT_RATIO>; and <TOT_RETURN_INDEX_GROSS_DVDS>

TR specifies the adjusted historical price of a security reflecting capital gains, cash dividends, spin-offs, stock splits and other corporate actions. The collected data was cross-checked to ensure correctness by examining additional Bloomberg functions.[5]

The Excel spreadsheets allow a clear overview of the large amount of data and enable further processing of the data. Missing data from the Bloomberg Terminal are indicated with the error value #N/A N/A.

All cells with a SIPF or SIR of zero have been replaced by the error term #N/A N/A, as it cannot be verified whether the figure was correct and representative or simply an error. Boehmer et al. (2010), in contrast, included non-reported short positions in their examination. However, the replacement in this dataset is negligible, since only 0.2% of all SIPF and SIR values are zero. Missing TR values result in the inability to calculate the monthly returns. As a result, for securities that do not have a TR in a given month but contain SIPF and SIR figures, the SIPF and SIR cells of the corresponding month have been manually replaced with the error value #N/A N/A.

4.2 Data Description

The original dataset covers 4,404 unique ticker symbols, of which 4,370 provide a short interest metric for at least one month. After the adjustments as described in section 4.1, the final dataset consists of 230,791 monthly observations for the SIPF and 241,761 monthly observations for the SIR. Brief summaries of the SIPF and SIR data are shown in tables 2 and 3, respectively.

The median for both metrics is highest in 2012 but remains more or less constant for the following years, which is in line with figure 1 in section 1.1. The mean is higher than the median for both ratios, and indicates that the distribution is skewed to the right. In five out of eight years, the maximum values of the SIPF are above 100%, which is very unusual but can occur in certain situations. One possible explanation is that offshore short seller or foreign broker-dealers are involved in the transactions. A second reason could be that transactions involved one party borrowing the shorted security and passing it on to a third party as a new transaction (Ashraf, 2020). Furthermore, the maximum value of the variable SIR is disproportionally high in every year. A review of the individual incidents shows that extraordinarily high SIR values are primarily found in securities with

[5] Bloomberg functions: <SHORT_INT>; <EQY_FLOAT>; and <PX_LAST>

low trading volumes, particularly in stocks of small-capitalised firms or companies that have issued multiple share classes. Occurrences with a high SIR or SIPF of over 100% are subject to short sale constraints, as explained in section 2.1, and result in higher costs of borrowing the specific stock.

Year	Ticker	Observations	Mean	Median	Min	Max
2012	2,421	28,863	5.19	3.1249	0.000100	110.8056
2013	2,313	27,602	4.87	2.3065	0.000045	68.7051
2014	2,337	27,917	5.53	2.7751	0.000100	122.7883
2015	2,445	29,210	5.56	2.7886	0.000100	84.6201
2016	2,482	29,668	5.59	2.9754	0.000001	72.0377
2017	2,420	28,890	5.75	2.8491	0.000100	227.2843
2018	2,420	28,876	5.80	2.9237	0.000020	131.1491
2019	2,489	29,765	5.78	2.9071	0.000095	100.6904

Table 2: Descriptive Statistics of SIPF Entries in the Dataset

Year	Ticker	Observations	Mean	Median	Min	Max
2012	2,521	30,171	8.82	5.4170	0.0010	1,121
2013	2,412	28,912	6.88	4.1360	0.0010	501.7
2014	2,438	29,238	6.88	4.2720	0.0010	2,717
2015	2,542	30,455	7.30	4.4300	0.0010	2,686
2016	2,590	31,020	8.32	4.8005	0.0010	2,788
2017	2,524	30,215	7.49	4.2210	0.0010	10,351
2018	2,536	30,347	7.24	4.0020	0.0010	3,079
2019	2,622	31,403	7.28	4.2170	0.0010	1,322

Table 3: Descriptive Statistics of SIR Entries in the Dataset

4.3 Portfolio Formation and Rebalancing Method

The chosen method to assemble the portfolios and measure their abnormal returns was the calendar time portfolio approach, as applied by other researchers in their investigations (Asquith et al., 2005; Boehmer et al., 2010; Desai et al., 2002). In each calendar month over the period 31 December 2011 until 30 November 2019, portfolios were formed based on the 1st, 10th, 90th and 99th percentile of either the SIPF or the SIR level. As a first step, the percentile rank for each security based on the SIPF and SIR at the end of the month was identified using Microsoft Excel.[6] Cells with the error value #N/A N/A were excluded from the calculation. This ranking process was repeated for every month to obtain different percentile rankings for each security in a specific month

[6] Microsoft Excel function: QUANTILSRANG.INKL()

over a period of eight years. The described process ensured that different portfolio formations could be constructed every month.

Four SIPF and four SIR portfolios were then formed according to the percentile threshold. Stocks that were below the 1st or 10th percentile in the respective month, as well as stocks that were above the 90th or 99th percentile, met the criteria for inclusion in the specified portfolio:

- SIPF 1% = includes securities below the 1st percentile
- SIPF 10% = includes securities below the 10th percentile
- SIPF 90% = includes securities above the 90th percentile
- SIPF 99% = includes securities above the 99th percentile

- SIR 1% = includes securities below the 1st percentile
- SIR 10% = includes securities below the 10th percentile
- SIR 90% = includes securities above the 90th percentile
- SIR 99% = includes securities above the 99th percentile

As illustrated in table 4, the annual number of securities within the monthly formed portfolios fluctuates. This variation is explained by missing values, yearly index adjustments, but also as a consequence of multiple securities sharing the same percentile rank in a given month.

Year	SIPF 1%	SIPF 10%	SIPF 90%	SIPF 99%	SIR 1%	SIR 10%	SIR 90%	SIR 99%
2012	300	2,890	2,890	297	316	3,024	3,022	312
2013	283	2,765	2,765	279	304	2,897	2,894	299
2014	290	2,798	2,797	288	303	2,930	2,927	300
2015	300	2,927	2,926	300	312	3,050	3,047	312
2016	302	2,972	2,972	300	312	3,108	3,106	312
2017	301	2,893	2,892	300	312	3,025	3,024	312
2018	301	2,892	2,892	300	316	3,041	3,040	312
2019	304	2,979	2,979	300	330	3,147	3,144	324
Total	2,381	23,116	23,113	2,364	2,505	24,222	24,204	2,483

Table 4: Number of Securities in the SIPF and SIR Portfolios

The selected shares are weighted equally within the portfolio. It is unclear whether the equally weighted method is inferior to the value-weighted method when analysing the performance of shorted stocks in a portfolio (Boehmer et al., 2010, p. 84). The two weighting methods could lead to conflicting results, which is why it is generally recommended to present the outcome for both methods (Mohamad, 2017, p. 1489). However, for reasons of feasibility, this paper only presents the results for equally weighted portfolios.

The TR price in the dataset allows the monthly returns of each security to be calculated by using the following formula:

$$r = \frac{P_t}{P_{t-1}} - 1$$

where:

r = One-month return of the security

P_t = Price of the security at month t

P_{t-1} = Price of the security at month t-1

After determining the one-month return for all securities, the corresponding portfolio returns was computed based on the following equation:

$$R_p = \sum_{i=1}^{n} w_i \, r_i$$

where:

R_p = Portfolio return

w_i = Weight of security i

r_i = Return of the security i

n = Number of different securities in the portfolio

4.4 Method of Analysis

A total of 96 monthly portfolio returns for eight different strategies were derived. For an initial comparison of the absolute return, the total return after eight years for every strategy was determined as follows:

$$R_{Total} = \prod_{t=1}^{T}(1 + R_{pt}) - 1$$

where:

R_{Total} = Return of the portfolio for the full period

R_{pt} = Portfolio return at month t

T = Number of monthly portfolio returns

For a second performance comparison, the geometric mean return (GMR) of every portfolio was calculated. The GMR is considered an adequate method of increasing the comparability of annual returns over multiple periods, as the compounding of returns is factored into the equation:

$$GMR = \sqrt[T]{1 + R_{Total}} - 1$$

where:

GMR = Geometric mean return

R_{Total} = Return of the portfolio for the full period

T = Number of years

To determine whether abnormal portfolio returns were generated, a multiple linear regression analysis for all eight portfolio formations[7] based on the FF3F and C4F model was performed in Microsoft Excel with the Analysis ToolPak Add-in. Thus, a total of 16 regressions were conducted, each containing a sample size of n=96.

[7] The results of a long-short strategy by combining two portfolio formations are not presented in this thesis, because the findings are of little relevance to answering the research questions. However, the results can be accessed upon request.

The FF3F regression equation as defined by Fama and French (1993) was applied as follows:

$$R_{pt} - Rf_t = \alpha_p + \beta_1 [RM_t - Rf_t] + \beta_2 SMB_t + \beta_3 HML_t + e_{pt}$$

where:

R_{pt} = Return of the portfolio at month t

Rf_t = Return of the risk-free asset at month t

α_p = Intercept (average monthly abnormal return)

$\beta_{1,2,3}$ = Factor coefficients

RM_t = Return of the market at month t

SMB_t = Historic excess return of SMB portfolio at month t

HML_t = Historic excess return of HML portfolio at month t

e_{pt} = Error term

The C4F regression equation (Carhart, 1997) was formed by the inclusion of the momentum factor:

$$R_{pt} - Rf_t = \alpha_p + \beta_1 [RM_t - Rf_t] + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 MOM_t + e_{pt}$$

where:

R_{pt} = Return of the portfolio at month t

Rf_t = Return of the risk-free asset at month t

α_p = Intercept (average monthly abnormal return)

$\beta_{1,2,3,4}$ = Factor coefficients

RM_t = Return of the market at month t

SMB_t = Historic excess return of SMB portfolio at month t

HML_t = Historic excess return of HML portfolio at month t

MOM_t = Historic excess return of MOM portfolio at month t

e_{pt} = Error term

The relationship between the dependent variable and the explanatory variables was measured by using the ordinary least squares (OLS) method, which estimates the intercept and β-coefficients. In both equations, the dependent variable is given as the portfolio return minus the risk-free asset return $(R_{pt} - Rf_t)$. The monthly return of the market (RM_t) corresponds to the NASDAQ Composite Total Return Index and was retrieved from Refinitiv Eikon. The monthly risk-free asset return (Rf_t) refers to the yield on the one-month Treasury bills and was obtained, along with the SMB, HML and MOM factors, from Kenneth French's website.[8] Although these factor loadings are not exclusively derived for NASDAQ listed shares, but for all NYSE, AMEX and NASDAQ listed securities, the factors are generally considered to be representative for the entire U.S. stock market and were therefore applied in this paper.

The F-test was performed for all 16 portfolio regressions, to assess the overall significance of the regression coefficients. A null hypothesis H_0 was established, which suggests that all beta coefficients are zero and thus the FF3F and C4F model have no explanatory power, whereas the alternative hypothesis H_1 suggests that at least one beta coefficient is considered a significant predictive parameter. The hypotheses for the FF3F and C4F regressions are as follows:

FF3F

H_0 : $\beta_1 = \beta_2 = \beta_3 = 0$

H_1 : at least one $\beta \neq 0$

C4F

H_0 : $\beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$

H_1 : at least one $\beta \neq 0$

The null hypothesis was tested according to the following F-statistic formula (Newbold, Carlson, & Thorne, 2013, p. 505):

$$F = \frac{SSR \,/\, K}{SSE \,/\, (n - K - 1)}$$

where:

SSR = Amount variability explained by the regression

SSE = Amount variability unexplained by the regression

K = Degrees of freedom for the numerator

n – K – 1 = Degrees of freedom for the denominator

[8] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

If the derived F-value was higher than the critical F-value at a significance level of 0.05, the null hypothesis was rejected.

Once the statistically significant explanatory power of at least one of the regression coefficients was found, a further null hypothesis was examined with the student's t-test. The t-statistic measures the significance of the estimated individual regression parameters. The intercept α_p is of particular interest when verifying whether the SIPF and SIR portfolios generate abnormal returns, both positive and negative. The null hypothesis supports the EMH and states that the average monthly abnormal return, denoted as $\alpha_{p,}$ is equal to zero under consideration of the FF3F and C4F model. Hence, the null hypothesis H_0 and the alternative hypothesis H_1 are noted as follows:

H_0 : $\alpha_p = 0$ $\qquad$ H_1 : $\alpha_p \neq 0$

The following formula calculates the required t-value for a one-sample t-test (Kent State University, 2020):

$$t = \frac{\bar{x} - \mu}{s_{\bar{x}}}$$

where:

$$s_{\bar{x}} = \frac{s}{\sqrt{n}}$$

where:

$\bar{x}$ = Sample mean

μ = Proposed constant for the population mean

$s_{\bar{x}}$ = Estimated standard error of the mean

s = Sample standard deviation

As the FF3F and C4F model imply an abnormal return of zero, nothing is subtracted from the mean of monthly abnormal in the numerator, thus the t-value of the intercept is solely determined as the monthly abnormal return divided by the estimated standard error. The obtained t-value of the intercept and of each regression coefficient was reviewed for statistical significance based on the p-value at a significance level of 0.05. As a result, H_0 is rejected in favour of H_1 if the p-value of the intercept is less than 0.05.

In a last step, a brief sector analysis was conducted by comparing the sector exposure of the equally weighted market index and the eight portfolio formations.

5 Empirical Results

This chapter contains the empirical results for all statistical analyses described in chapter 4. First, descriptive statistics on the resulting portfolio returns are presented. Second, the returns are measured on an absolute level, and on a risk-adjusted level based on the FF3F and C4F model. Finally, the industry sector exposure within the portfolios is analysed.

5.1 Descriptive Statistics

The monthly returns (n=96) for the SIPF and SIR portfolios, as well as for the benchmark, measured by the NASDAQ Composite Total Return Index (XCMP), are summarised in tables 5 and 6.

For both metrics, the lightly shorted portfolios show a right skewed distribution and a higher mean than the heavily shorted portfolios, which have a left skewed distribution. Each created portfolio exhibits a smaller median and a higher maximum return than the market index XCMP. While the SIPF 10% portfolio is the only one that has a lower standard deviation (0.0292) than the XCMP (0.0388), it is also the portfolio with the highest median, lowest monthly loss and the lowest maximum return among all eight formations constructed by the level of SIPF or SIR. Under consideration of all displayed returns, the SIR 1% portfolio has the highest mean (0.0191), the highest maximum value (0.8398) and the largest standard deviation (0.1101), and it is also the only one with a negative median (-0.0057). Among all observations, the largest losses within a month are achieved by the four heavily shorted portfolios – that is, the SIPF 99% (-0.2061), the SIPF 90% (-0.1744), the SIR 90% (-0.1519) and the SIR 99% portfolio (-0.1349). Furthermore, the four heavily shorted portfolios in the 90th and 99th percentiles present a lower mean and a lower median but also a higher maximum loss and a higher maximum gain compared to the market index.

	SIPF 1%	SIPF 10%	SIPF 90%	SIPF 99%	XCMP
Mean	0.0161	0.0157	0.0029	-0.0014	0.0147
Median	0.0086	0.0123	0.0111	0.0002	0.0195
Standard Deviation	0.0448	0.0292	0.0610	0.0765	0.0388
Minimum	-0.0818	-0.0657	-0.1744	-0.2061	-0.0940
Maximum	0.2932	0.1154	0.1719	0.1522	0.0979
Sum	1.5480	1.5036	0.2753	-0.1345	1.4124
Count	96	96	96	96	96

Table 5: Descriptive Statistics of Monthly Returns on SIPF Portfolios

	SIR 1%	SIR 10%	SIR 90%	SIR 99%	XCMP
Mean	0.0191	0.0130	0.0038	-0.0018	0.0147
Median	-0.0057	0.0102	0.0067	0.0008	0.0195
Standard Deviation	0.1101	0.0450	0.0479	0.0509	0.0388
Minimum	-0.1169	-0.0940	-0.1519	-0.1349	-0.0940
Maximum	0.8398	0.2434	0.1243	0.1377	0.0979
Sum	1.8306	1.2485	0.3660	-0.1740	1.4124
Count	96	96	96	96	96

Table 6: Descriptive Statistics of Monthly Returns on SIR Portfolios

5.2 Absolute Performance

The total return of the four SIPF portfolios compared to the market index XCMP for the entire period under examination is shown in figure 2. The two portfolios containing lightly shorted stocks outperform the benchmark, whereas the two formations including heavily shorted stocks experience a much worse development than the XCMP. After eight years, the SIPF 90% portfolio shows an overall performance of only +9.92%, while the SIPF 99% portfolio even has a negative return of -34.32%. Although the SIPF 1% portfolio has the highest total return after eight years (+327.66%), the portfolio did not generate profits between early 2014 and late 2018, and then increased strongly again in 2019. In contrast, the SIPF 10% portfolio has a slightly lower total return (+326.09), but it outperformed the benchmark XCMP (+278.66) consistently and has not seen any major setbacks, with the exception of late 2018.

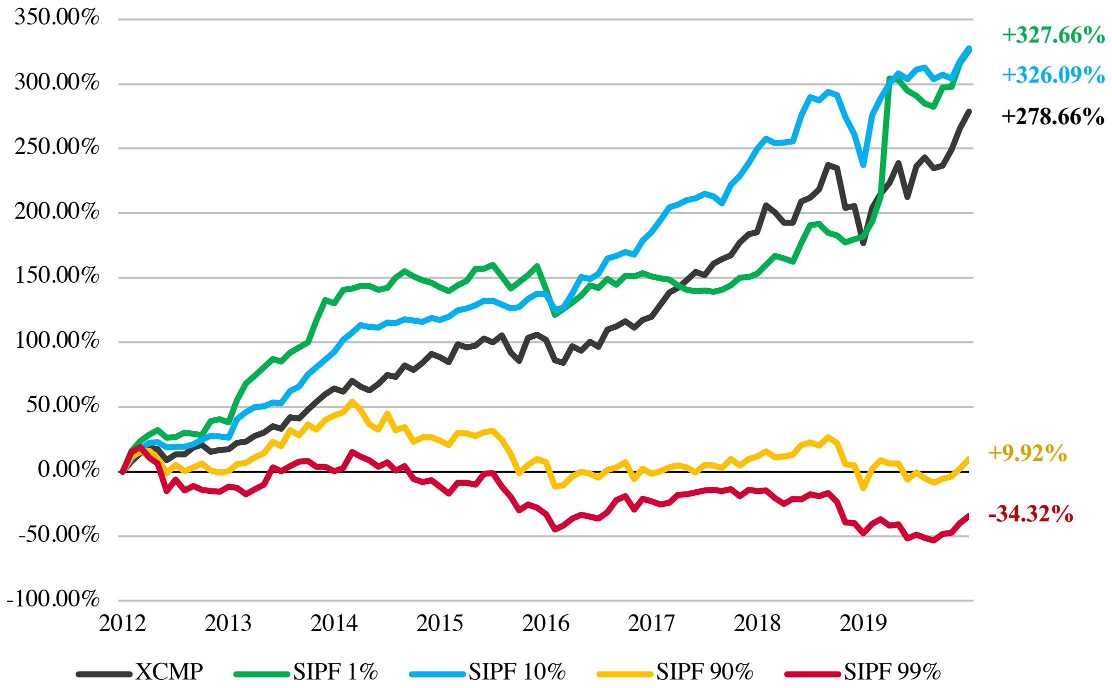

Figure 2: Total Return of SIPF Portfolios 2012–2019

A similar pattern can be observed in the performance comparison of the SIR portfolios, as illustrated in figure 3. The portfolios containing heavily shorted stocks have far poorer returns than their corresponding counterparts. While the SIR 90% portfolio generated a total return of +29.07%, the SIR 99% portfolio lost -25.85% over the whole period. The total return of the benchmark XCMP (+278.66%) was only surpassed by the SIR 1% portfolio (+298.03%). However, the outperformance was not consistent, and the portfolio did not generate a positive return between mid-2015 and early 2019. The total performance of the SIR 1% portfolio is skewed by the one-month return of one included stock undergoing a major corporate action event. More specifically, the shares of the cloud computing company Phunware Inc. rose by more than 2,106% in January 2019 due to a reverse merger (Bylund, 2019). The SIR 10% portfolio had a better return than the XCMP until February 2018, but it underperformed the benchmark over the remaining 23 months, resulting in a lower return (+215.82%).

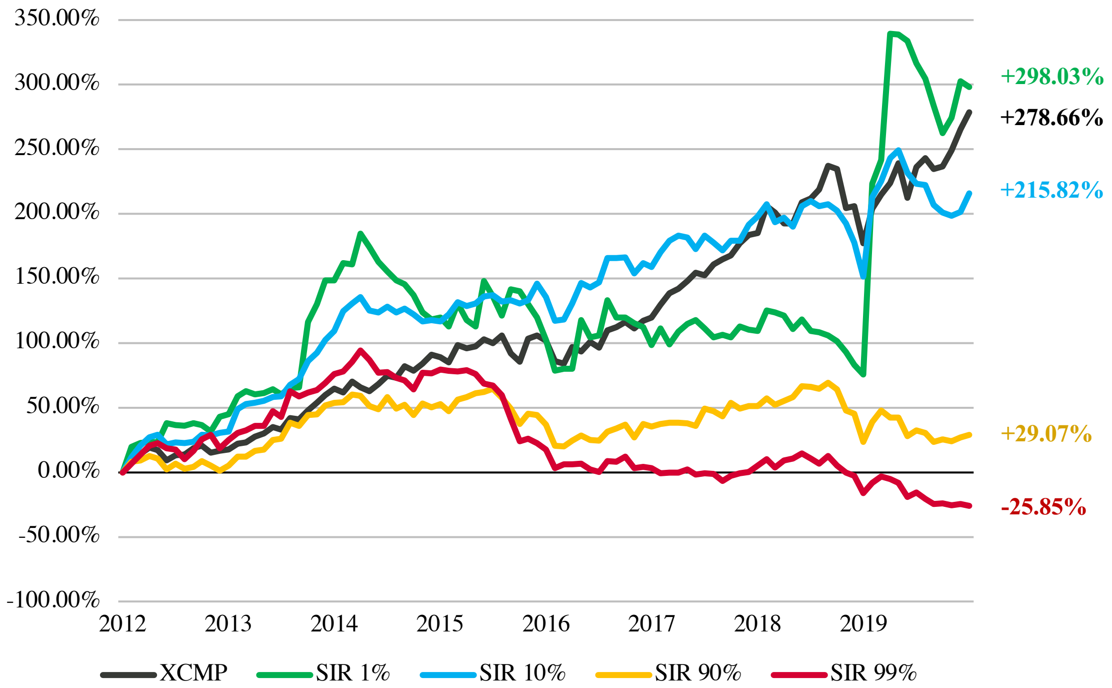

Figure 3: Total Return of SIR Portfolios 2012–2019

As an additional comparison, table 7 displays the GMR and the annual returns of all eight portfolios and the XCMP. The results offer a similar view to the total performance displayed in figures 2 and 3. The highest GMR is attained by the SIPF 10% portfolio (19.92%), followed by the SIPF 1% portfolio (19.86%), both of which experienced only one year with negative returns. A negative GMR is only obtained by the SIPF 99% (-5.12%) and the SIR 99% formation (-3.67%). All of the heavily shorted portfolios have a considerably smaller GMR than the benchmark and report negative annual returns in four out of eight years. However, none of the 90th and 99th percentile portfolios generated a negative return in the years 2013 and 2017. The SIR 1% portfolio has a higher GMR than the XCMP but also yielded a total of four negative annual returns.

	SIPF 1%	SIPF 10%	SIPF 90%	SIPF 99%	SIR 1%	SIR 10%	SIR 90%	SIR 99%	XCMP
GMR	19.86%	19.92%	1.19%	-5.12%	18.85%	15.46%	3.24%	-3.67%	18.11%
2012	38.26%	26.06%	0.53%	-11.65%	44.74%	31.48%	5.15%	24.88%	17.45%
2013	66.37%	52.61%	42.80%	13.76%	71.85%	59.40%	46.38%	41.02%	40.11%
2014	5.56%	12.90%	-13.47%	-11.88%	-11.72%	3.43%	-0.57%	2.11%	14.75%
2015	-0.72%	9.26%	-13.75%	-23.87%	-7.76%	8.75%	-10.47%	-34.55%	6.98%
2016	4.24%	20.14%	-7.96%	14.20%	-1.94%	9.73%	-1.21%	-12.25%	8.87%
2017	0.63%	22.66%	13.45%	10.13%	5.40%	15.26%	11.88%	1.91%	29.64%
2018	11.38%	-3.48%	-21.91%	-38.41%	-16.02%	-15.62%	-18.45%	-20.01%	-2.84%
2019	51.31%	26.69%	25.81%	25.74%	126.43%	25.53%	4.52%	-11.92%	36.68%

Table 7: GMR and Annual Returns of SIPF and SIR Portfolios

5.3 Fama-French Three-Factor Model Regression Analysis

To evaluate the monthly abnormal return or the so-called risk-adjusted return of the composed short interest portfolios, the regression results of the FF3F model were analysed. In theory, abnormal returns can be explained by the application of asset pricing models and will therefore disappear. Thus, if the FF3F regression is conducted using monthly returns of the XCMP minus the monthly risk-free rate as the dependent variable, the intercept will be close to zero.

Table 8 displays the regression results of the FF3F model for each portfolio and includes the calculated *F*-value and the estimated regression coefficients. The corresponding *p*-values at the 0.05 significance level are listed underneath in brackets. Moreover, the second column contains the adjusted R^2, which indicates to what extent the independent variables in the FF3F model are capable of explaining the variance of the dependent variable. The adjusted R^2 value is always between 0 (unusable model) and 1 (perfect model fit). Further details of the regression results are given in Appendix E.

For each regression, the *F*-value is greater than the critical value of the *F*-distribution[9], which results in a *p*-value below 0.05. The null hypothesis can be rejected. Hence, the correlation between at least one beta coefficient and the dependent

[9] $F_{0.05}(3, 92) = 2.704$

variable is statistically significant, although the low adjusted R^2 value in the SIPF 1% portfolio (0.073) and in the SIR 1% portfolio (0.094) indicates that the monthly abnormal returns are not strongly explained by the three factors. The second null hypothesis, stating that the intercept is equal to zero, is rejected for six out of eight portfolios. However, the null hypothesis is not rejected for the SIR 1% and SIR 10% portfolio, as the *p*-value is not statistically significant.

The results for the monthly abnormal returns are consistent with several prior studies (Asquith et al., 2005; Boehmer et al., 2010; Desai et al., 2002; Mohamad, 2017). Regardless of the significance, the intercept for both short interest metrics is highest for the 1% portfolios containing the least shorted stocks. The excess return gradually declines as the short interest threshold of the portfolios increases. The lowest significant monthly abnormal return was attained by the SIPF 99% portfolio (-0.018), while the highest significant alpha was generated by the SIPF 1% portfolio (0.010). With a market risk premium (RM-Rf) above 1.0, the SIPF 90% and SIPF 99% portfolios reacted more strongly to market movements, while the remaining six formations with a beta below 1.0 experienced less sensitivity to the NASDAQ Composite Index. With both metrics, the SMB coefficient is nearly always positive, which is explained by the numerous small-capitalised firms listed at the NASDAQ Stock Market. However, the estimated HML coefficient is predominantly positive and only in three regressions statistically significant, which contradicts the results of previous studies (Asquith et al., 2005; Boehmer et al., 2010; Desai et al., 2002).

Portfolio	Adjusted R^2	*F*-value	Intercept	RM-Rf	SMB	HML
SIPF 1%	0.073	3.497	0.010	0.374	-0.037	-0.005
		(0.019)	*(0.033)*	*(0.003)*	*(0.858)*	*(0.980)*
SIPF 10%	0.460	27.996	0.009	0.448	0.300	0.160
		(<.001)	*(<.001)*	*(<.001)*	*(0.004)*	*(0.102)*
SIPF 90%	0.834	160.437	-0.011	1.077	1.222	0.194
		(<.001)	*(<.001)*	*(<.001)*	*(<.001)*	*(0.086)*
SIPF 99%	0.594	47.250	-0.018	1.248	1.057	0.550
		(<.001)	*(0.001)*	*(<.001)*	*(<.001)*	*(0.014)*
SIR 1%	0.094	4.273	0.008	0.747	0.749	-0.248
		(0.007)	*(0.468)*	*(0.013)*	*(0.139)*	*(0.601)*
SIR 10%	0.409	22.947	0.005	0.609	0.555	0.162
		(<.001)	*(0.221)*	*(<.001)*	*(0.001)*	*(0.301)*
SIR 90%	0.827	152.028	-0.006	0.799	1.026	0.425
		(<.001)	*(0.005)*	*(<.001)*	*(<.001)*	*(<.001)*
SIR 99%	0.495	32.028	-0.011	0.703	0.771	0.377
		(<.001)	*(0.007)*	*(<.001)*	*(<.001)*	*(0.023)*

Table 8: FF3F Regression Analysis Results of SIPF and SIR Portfolios

5.4 Carhart Four-Factor Model Regression Analysis

The regression results of the C4F model are summarised in table 9 (see Appendix F for additional details). As a logical implication, the conducted F-test for each C4F regression also revealed a higher F-value than the critical F-value[10], so that the first null hypothesis can be rejected. By adding the independent variable MOM, the adjusted R^2 marginally increased. Thus, the explanatory power of the regression equation was improved.

The intercepts estimated by the C4F regression differ only moderately from the FF3F regression. With a statistically significant intercept unequal to zero, the null hypothesis can be rejected for the same six portfolio formations as mentioned in section 5.3, while the intercepts of the SIR 1% and SIR 10% portfolio remain insignificant. The momentum factor is negative for each portfolio formation, which is consistent with the findings of Boehmer et al. (2010). With the exception of the SIPF 1% and SIR 99% portfolio, all MOM coefficients are significant. Compared to the FF3F model, the momentum factor has led to less negative abnormal return for the portfolios including highly shorted securities. The largest difference is observed with the SIPF 99% portfolio, where the negative monthly abnormal return was -1.8% under the FF3F model and declined to -1.4% per month under the C4F model. In contrast, the addition of the momentum factor has also resulted in a marginal higher significant alpha for the SIPF 1% (0.011) and SIPF 10% portfolio (0.010), both containing lightly shorted stocks.

Portfolio	Adjusted R^2	F-value	Intercept	RM-Rf	SMB	HML	MOM
SIPF 1%	0.083	3.163	0.011	0.302	-0.050	-0.199	-0.239
		(0.018)	*(0.019)*	*(0.023)*	*(0.809)*	*(0.402)*	*(0.157)*
SIPF 10%	0.479	22.793	0.010	0.397	0.291	0.022	-0.170
		(<.001)	*(<.001)*	*(<.001)*	*(0.005)*	*(0.849)*	*(0.042)*
SIPF 90%	0.859	145.141	-0.009	0.966	1.203	-0.104	-0.366
		(<.001)	*(<.001)*	*(<.001)*	*(<0.001)*	*(0.415)*	*(<.001)*
SIPF 99%	0.668	48.699	-0.014	1.007	1.014	-0.099	-0.797
		(<.001)	*(0.007)*	*(<.001)*	*(<.001)*	*(0.686)*	*(<.001)*
SIR 1%	0.144	4.992	0.014	0.444	0.695	-1.065	-1.004
		(0.001)	*(0.235)*	*(0.156)*	*(0.158)*	*(0.061)*	*(0.013)*
SIR 10%	0.449	20.316	0.007	0.500	0.536	-0.129	-0.358
		(<.001)	*(0.084)*	*(<.001)*	*(0.001)*	*(0.487)*	*(0.007)*
SIR 90%	0.834	119.915	-0.005	0.748	1.017	0.289	-0.167
		(<.001)	*(0.015)*	*(<.001)*	*(<.001)*	*(0.009)*	*(0.031)*
SIR 99%	0.493	24.095	-0.010	0.669	0.765	0.284	-0.115
		(<.001)	*(0.013)*	*(<.001)*	*(<.001)*	*(0.159)*	*(0.420)*

Table 9: C4F Regression Analysis Results of SIPF and SIR Portfolios

[10] $F_{0.05}(4, 91) = 2.472$

5.5 Sector Analysis

In a final step, the sector weightings between the equal-weighted NASDAQ Composite Index (CCMP) and the constructed short interest portfolios were compared. As illustrated in figure 4, the number of health care companies listed on the NASDAQ Stock Market has been steadily increasing since 2012, while the number of firms in the sectors financials, technology, consumer discretionary, communications and energy has been declining. The sector weightings industrials, consumer staples, materials and utilities remained relatively constant between 2012 and 2019.

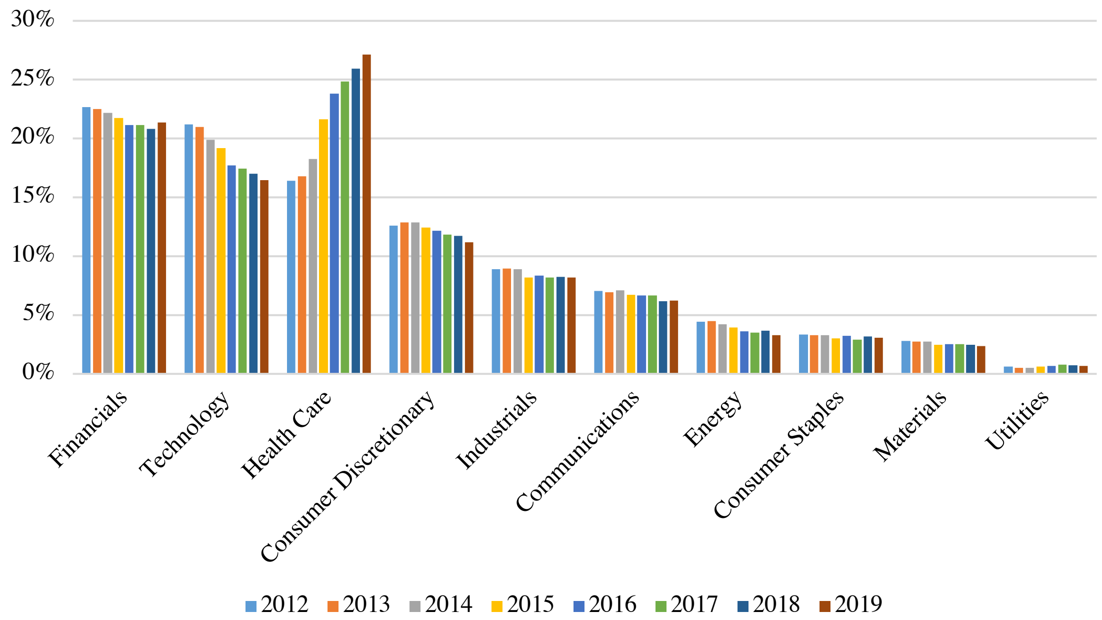

Figure 4: Sector Breakdown Equal-weighted CCMP 2012–2019

Figures 5 and 6 depict the relative difference between the average sector weightings of the constructed portfolios and the market index.[11] As shown in figure 5, the four portfolios containing slightly shorted stocks tend to overweight companies from the financial and industrial sectors, and underweight the sectors technology, health care and consumer discretionary. The exposure of the remaining sectors is broadly the same.

Figure 6 indicates that the stocks above the 90th and 99th percentile have a higher exposure to health care, consumer discretionary and communications than the equal-weighted CCMP. Furthermore, the relative sector weighting in financials, technology and industrials appears to be lower for the portfolios including highly shorted

[11] The annual breakdown for each formation is presented in appendix G. The results are not discussed, because the sector weightings per year have similar characteristics to the average sector weightings.

securities. It is notable that the SIPF and SIR formations in each percentile threshold tend to contain less technology stocks than the market index in relative terms.

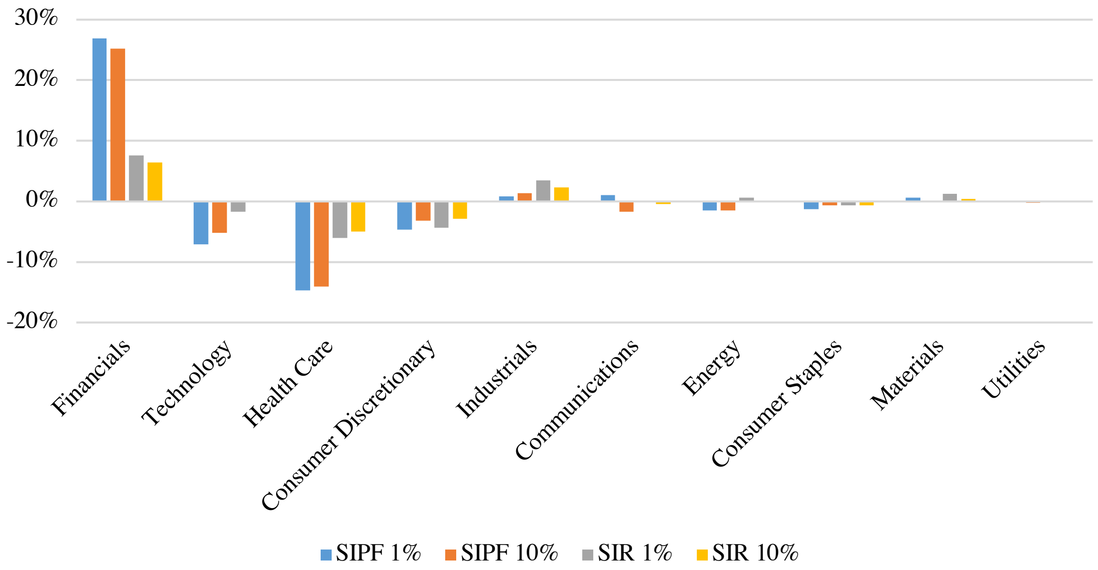

Figure 5: Relative Sector Weightings 1st & 10th Percentile Portfolios vs. Equal-weighted CCMP

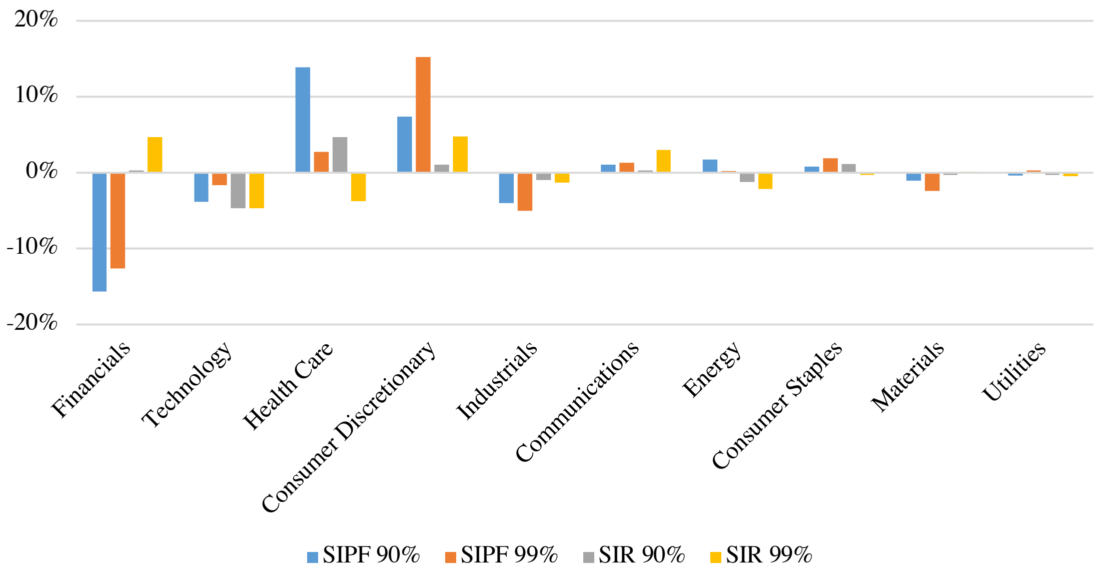

Figure 6: Relative Sector Weightings 90th & 99th Percentile Portfolios vs. Equal-weighted CCMP

6 Conclusion and Outlook

6.1 Conclusion

This paper examines the relation between the monthly published short interest data and subsequent one-month returns of NASDAQ listed stocks from 2012 to 2019. The results suggest that during this period, equal-weighted portfolios containing lightly shorted securities generated a higher absolute and risk-adjusted performance than the market index, whereas equal-weighted portfolios with heavily shorted securities underperformed considerably. These findings are consistent with prior research arguing that a high level of short interest leads to subsequent price declines and lower stock returns, while a low level of short interest leads to future price increases and higher stock returns. The fact that abnormal returns can be generated with short interest data supports the argument that stock markets are inefficient and contradicts the efficient market hypothesis in its weakest form, which states that prices already reflect all historical market trading information.

The regression analysis to measure abnormal returns was conducted on both the Fama-French three-factor model and the Carhart four-factor model. Although the latter included momentum as an additional risk exposure, the explanatory power of abnormal returns only improved marginally. The portfolio formation was performed by considering the two indicators SIPF and SIR. However, the absolute performance over eight years, along with the regression results, revealed that formations considering SIPF produce more significant outcomes and higher abnormal returns than SIR, regardless of the asset pricing model. One plausible explanation could be that the SIR does not provide an adequate indication for the short selling activity of small-capitalised companies with low trading volumes.

Using the superior metric SIPF and applying the Carhart four-factor model, the lightly shorted portfolio generated a significant excess return when containing stocks below the 1^{st} percentile (1.1% per month) and below the 10^{th} percentile (1.0% per month). In contrast, the heavily shorted portfolios generated a significant negative abnormal return if they comprised stocks above the 90^{th} percentile (-0.9% per month) and above the 99^{th} percentile (-1.4% per month).

In conclusion, SIPF can be a valuable sentiment indicator for forecasting future share price development, since short sellers seem capable of identifying overvalued stocks while avoiding undervalued or fairly valued stocks. Although past performance is no guarantee of future results, buying stocks with a low short interest level could potentially lead to higher returns for investors, while stocks with a high short interest level should be avoided or sold.

The relative sector weighting analysis has shown that health care and consumer discretionary stocks may be more exposed to high levels of short interest, while financials and technology stocks tend to be less shorted. However, results of this investigation are not sufficient to draw firm conclusions.

6.2 Limitations of this Thesis

This study has several limitations. First, the dataset may have been biased by removing securities without short interest; by missing data from Bloomberg, as a result of some companies having very low stock liquidity and turnover; or by not detecting and eliminating outliers. Second, the replication of portfolios with such a large number of positions, and rebalancing them on a monthly basis, is associated with substantial transaction costs and is not feasible in practice. Lastly, due to time constraints, the abnormal returns were solely analysed for equal-weighted portfolios, even though prior literature recommends constructing value-weighted portfolios in addition, to avoid conflicting results (Boehmer et al., 2010; Mohamad, 2017).

The findings and interpretation in this paper also require consideration of statistical limitations in the applied research methodology. The sample size of 96 monthly returns for the regression analysis is small, and statistical hypothesis testing generally requires larger number of observations to increase the precision of the estimated coefficients. Furthermore, the applied OLS estimation method for the linear regression equation is based on several assumptions, including the supposition that the residuals are normally distributed and have a constant variance (homoscedasticity). However, insufficient investigation was made into verifying the validity of the OLS assumptions. The *t*-statistics may therefore have led to erroneous outcomes and incorrect alpha coefficients. If the OLS requirements had not been met, a logarithmic transformation of the dependent variable could have been a potential workaround, but this procedure also complicates the interpretation of the regression parameter (i.e., the intercept as the monthly abnormal return).

6.3 Suggestions for Further Research

Future studies could investigate the relationship between short interest and the subsequent stock return for non-U.S. markets. Since only a few stock exchanges publish short interest data by traded volume and position, it would be desirable to implement short interest estimations offered by the financial data providers IHS Markit or S3 Partners. In addition, the short interest level and subsequent price movements could be monitored over shorter time periods, for example on a day-to-day or week-to-week basis. Further studies could also focus entirely on large-capitalised stocks in order to exclude small companies with low market liquidity. Lastly, an empirical study concentrating on the sectoral breakdown of highly shorted stocks over an extended time frame and divided up into sub-periods could give more insight into historical shorting activity in different economic cycles, as little research has been conducted in this context so far.

7 References

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8 Appendix

Appendices A – D

Supplementary Data Files

The separately submitted Microsoft Excel workbooks are divided into four parts:

Appendix A Exported Data from the Bloomberg Terminal and Data Preparation

A1_NASDAQ_Composite_Index_All Members.xlsx

A2_Bloomberg_Export_Values.xlsb

A3_Data_Description.xlsb

Appendix B Stock Ranking and Portfolio Formation

B1_Monthly_Percentile_Ranking_and_Returns.xlsb

B2_Portfolio_Formation_1st_and_10th_Percentile.xlsb

B3_Portfolio_Formation_90th_and_99th_Percentile.xlsb

Appendix C Portfolio Return Analysis and Regression Analysis

C1_Price_History_Nasdaq_Composite_Total_Return_Index.xlsx

C2_F-F_Research_Data_Factors.xlsx

C3_F-F_Momentum_Factor.xlsx

C4_Portfolio_Returns_and_Regression_Analysis.xlsb

C5_Portfolio_Returns_Charts.xlsx

Appendix D Sector Analysis

D1_Relative_Sector_Weightings_and_Number.xlsx

Appendix E

Results of the Fama-French Three-Factor Model Regression Analysis

SIPF 1%	
R-Squared	0.10235726
Adj. R-Squared	0.073086301
Standard Error	0.043138255
Observations	96

	df	*SS*	*MS*	*F*	*p-value*
Regression	3	0.01952217	0.00650739	3.496887834	0.01867089
Residual	92	0.171203629	0.001860909		
Total	95	0.190725799			

	Coefficients	*Standard Error*	*t-Stat*	*p-value*	*[95% Confidence Interval]*	
Intercept	0.010249379	0.004743027	2.160936214	0.033297554	0.000829318	0.019669439
Rm-RF	0.374067022	0.121232837	3.085525611	0.002684016	0.133288144	0.6148459
SMB	-0.037059439	0.206496458	-0.179467676	0.857965172	-0.447179229	0.37306035
HML	-0.004959308	0.194567074	-0.025488936	0.97972018	-0.391386311	0.381467696

Table 10: FF3F Regression Analysis Results of SIPF 1% Portfolio

SIPF 10%	
R Square	0.477234793
Adj. R-Squared	0.460188101
Standard Error	0.021515651
Observations	96

	df	*SS*	*MS*	*F*	*p-value*
Regression	3	0.038879639	0.01295988	27.99574284	5.94016E-13
Residual	92	0.042588937	0.000462923		
Total	95	0.081468577			

	Coefficients	*Standard Error*	*t-Stat*	*p-value*	*[95% Confidence Interval]*	
Intercept	0.009343077	0.002365634	3.949502562	0.00015325	0.004644724	0.014041429
Rm-RF	0.44818025	0.060466132	7.412087345	5.90197E-11	0.328089293	0.568271207
SMB	0.300282713	0.102992245	2.915585656	0.004458868	0.095731224	0.504834201
HML	0.160228583	0.097042342	1.651120331	0.102123685	-0.032505884	0.35296305

Table 11: FF3F Regression Analysis Results of SIPF 10% Portfolio

SIPF 90%	
R Square	0.839528667
Adj. R-Squared	0.834295907
Standard Error	0.024826877
Observations	96

	df	*SS*	*MS*	*F*	*p-value*
Regression	3	0.296667587	0.098889196	160.4370412	1.98852E-36
Residual	92	0.056706394	0.000616374		
Total	95	0.353373981			

	Coefficients	*Standard Error*	*t-Stat*	*p-value*	*[95% Confidence Interval]*	
Intercept	-0.011319363	0.002729701	-4.146740751	7.50106E-05	-0.016740786	-0.005897941
Rm-RF	1.076809619	0.069771779	15.43331174	2.87935E-27	0.938236843	1.215382395
SMB	1.222453203	0.118842598	10.28632177	5.72504E-17	0.986421545	1.458484861
HML	0.194264738	0.111977013	1.73486265	0.086114022	-0.028131276	0.416660752

Table 12: FF3F Regression Analysis Results of SIPF 90% Portfolio

SIPF 99%	
R Square	0.606417789
Adj. R-Squared	0.593583586
Standard Error	0.048779163
Observations	96

	df	*SS*	*MS*	*F*	*p-value*
Regression	3	0.337281866	0.112427289	47.2501339	1.42343E-18
Residual	92	0.218905423	0.002379407		
Total	95	0.55618729			

	Coefficients	*Standard Error*	*t-Stat*	*p-value*	*[95% Confidence Interval]*	
Intercept	-0.017686213	0.005363242	-3.297672233	0.001386782	-0.028338074	-0.007034352
Rm-RF	1.248375923	0.137085665	9.106538736	1.73201E-14	0.976111958	1.520639887
SMB	1.056537496	0.233498655	4.524811905	1.80255E-05	0.592789011	1.52028598
HML	0.549924959	0.220009344	2.499552741	0.014207483	0.112967411	0.986882506

Table 13: FF3F Regression Analysis Results of SIPF 99% Portfolio

SIR 1%	
R-Squared	0.122297503
Adj. R-Squared	0.093676769
Standard Error	0.104754503
Observations	96

	df	*SS*	*MS*	*F*	*p-value*
Regression	3	0.140670646	0.046890215	4.273038712	0.007162456
Residual	92	1.009562542	0.010973506		
Total	95	1.150233188			

	Coefficients	*Standard Error*	*t-Stat*	*p-value*	*[95% Confidence Interval]*	
Intercept	0.008395091	0.011517699	0.728886147	0.467922759	-0.014480053	0.031270235
Rm-RF	0.747449859	0.294394979	2.538935489	0.012798102	0.16275602	1.332143698
SMB	0.748669535	0.501444345	1.493026181	0.13885194	-0.247242217	1.744581286
HML	-0.248166185	0.472475703	-0.52524645	0.600675464	-1.186543713	0.690211343

Table 14: FF3F Regression Analysis Results of SIR 1% Portfolio

SIR 10%	
R Square	0.428008979
Adj. R-Squared	0.409357098
Standard Error	0.034640403
Observations	96

	df	*SS*	*MS*	*F*	*p-value*
Regression	3	0.082607098	0.027535699	22.94722852	3.54021E-11
Residual	92	0.110396091	0.001199958		
Total	95	0.193003189			

	Coefficients	*Standard Error*	*t-Stat*	*p-value*	*[95% Confidence Interval]*	
Intercept	0.004690524	0.003808693	1.231531201	0.221262973	-0.002873869	0.012254917
Rm-RF	0.608525841	0.097351048	6.250840147	1.25902E-08	0.415178256	0.801873426
SMB	0.55489774	0.165818496	3.346416429	0.001186709	0.225567893	0.884227586
HML	0.162469093	0.156239095	1.039874769	0.301123254	-0.147835236	0.472773421

Table 15: FF3F Regression Analysis Results of SIR 10% Portfolio

SIR 90%

R Square	0.832142351
Adj. R-Squared	0.826668732
Standard Error	0.019989423
Observations	96

	df	*SS*	*MS*	*F*	*p-value*
Regression	3	0.182240465	0.060746822	152.0278179	1.56917E-35
Residual	92	0.036761085	0.000399577		
Total	95	0.219001551			

	Coefficients	*Standard Error*	*t-Stat*	*p-value*	*[95% Confidence Interval]*	
Intercept	-0.006309277	0.002197826	-2.870690069	0.005082171	-0.010674348	-0.001944205
Rm-RF	0.798949524	0.056176923	14.22202361	5.89382E-25	0.687377306	0.910521742
SMB	1.025947041	0.095686416	10.7219717	7.01958E-18	0.83590556	1.215988522
HML	0.424505963	0.090158573	4.708437035	8.7958E-06	0.245443255	0.603568671

Table 16: FF3F Regression Analysis Results of SIR 90% Portfolio

SIR 99%

R Square	0.510856423
Adj. R-Squared	0.494906089
Standard Error	0.036218974
Observations	96

	df	*SS*	*MS*	*F*	*p-value*
Regression	3	0.126044129	0.04201471	32.02794513	2.88356E-14
Residual	92	0.120686897	0.001311814		
Total	95	0.246731026			

	Coefficients	*Standard Error*	*t-Stat*	*p-value*	*[95% Confidence Interval]*	
Intercept	-0.010921562	0.003982256	-2.742556557	0.00732697	-0.018830666	-0.003012458
Rm-RF	0.70322628	0.101787358	6.908778171	6.2281E-10	0.5010678	0.90538476
SMB	0.771434173	0.173374884	4.449515155	2.40808E-05	0.427096689	1.115771658
HML	0.377422202	0.163358947	2.310385865	0.02310252	0.052977233	0.701867171

Table 17: FF3F Regression Analysis Results of SIR 99% Portfolio

Appendix F

Results of the Carhart Four-Factor Model Regression Analysis

SIPF 1%	
R-Squared	0.122048357
Adj. R-Squared	0.083457076
Standard Error	0.04289625
Observations	96

	df	*SS*	*MS*	*F*	*p-value*
Regression	4	0.02327777	0.005819443	3.16258889	0.017553574
Residual	91	0.167448029	0.001840088		
Total	95	0.190725799			

	Coefficients	*Standard Error*	*t-Stat*	*p-value*	*[95% Confidence Interval]*	
Intercept	0.01148742	0.004795371	2.395522466	0.018644897	0.001962004	0.021012836
Rm-RF	0.301748111	0.130749585	2.307832259	0.023275497	0.042030122	0.561466099
SMB	-0.04978001	0.205530976	-0.242201984	0.809168667	-0.458042046	0.358482026
HML	-0.199300765	0.236511815	-0.842667268	0.401623923	-0.66910243	0.2705009
MOM	-0.238868345	0.167200762	-1.428631918	0.156533546	-0.570992118	0.093255428

Table 18: C4F Regression Analysis Results of SIPF 1% Portfolio

SIPF 10%	
R-Squared	0.500473691
Adj. R-Squared	0.478516491
Standard Error	0.021147233
Observations	96

	df	*SS*	*MS*	*F*	*p-value*
Regression	4	0.040772879	0.01019322	22.79314679	4.57576E-13
Residual	91	0.040695697	0.000447205		
Total	95	0.081468577			

	Coefficients	*Standard Error*	*t-Stat*	*p-value*	*[95% Confidence Interval]*	
Intercept	0.010222095	0.002364049	4.323977887	3.91411E-05	0.005526203	0.014917988
Rm-RF	0.396833253	0.064457662	6.1564947	1.97673E-08	0.268796027	0.52487048
SMB	0.291251007	0.10132381	2.874457703	0.00503828	0.089983705	0.492518309
HML	0.022244619	0.116596917	0.190782224	0.849121206	-0.209360833	0.253850072
MOM	-0.169598405	0.082427567	-2.057544722	0.042494987	-0.33333064	-0.005866169

Table 19: C4F Regression Analysis Results of SIPF 10% Portfolio

SIPF 90%	
R-Squared	0.86449518
Adj. R-Squared	0.858538924
Standard Error	0.022938972
Observations	96

	df	*SS*	*MS*	*F*	*p-value*
Regression	4	0.305490103	0.076372526	145.1407065	1.28712E-38
Residual	91	0.047883878	0.000526196		
Total	95	0.353373981			

	Coefficients	*Standard Error*	*t-Stat*	*p-value*	*[95% Confidence Interval]*	
Intercept	-0.00942182	0.002564347	-3.67415896	0.000402802	-0.014515582	-0.004328059
Rm-RF	0.965966578	0.069918959	13.81551707	4.60201E-24	0.827081154	1.104852002
SMB	1.202956411	0.109908662	10.94505552	2.76229E-18	0.984636355	1.421276467
HML	-0.103601998	0.126475812	-0.819144757	0.414843964	-0.354830662	0.147626665
MOM	-0.366113002	0.089411399	-4.094701657	9.14398E-05	-0.543717762	-0.188508243

Table 20: C4F Regression Analysis Results of SIPF 90% Portfolio

SIPF 99%

R-Squared	0.681589525
Adj. R-Squared	0.66759346
Standard Error	0.044114718
Observations	96

	df	*SS*	*MS*	*F*	*p-value*
Regression	4	0.379091431	0.094772858	48.69865444	7.78469E-22
Residual	91	0.177095859	0.001946108		
Total	95	0.55618729			

	Coefficients	*Standard Error*	*t-Stat*	*p-value*	*[95% Confidence Interval]*	
Intercept	-0.013555422	0.004931584	-2.748695409	0.007215493	-0.023351407	-0.003759436
Rm-RF	1.007079974	0.134463528	7.489614361	4.30583E-11	0.739984693	1.274175255
SMB	1.014094625	0.211369086	4.797743346	6.2497E-06	0.594235902	1.433953348
HML	-0.098505793	0.243229935	-0.40499042	0.68643502	-0.58165218	0.384640593
MOM	-0.796997115	0.171950101	-4.635048829	1.18734E-05	-1.138554867	-0.455439362

Table 21: C4F Regression Analysis Results of SIPF 99% Portfolio

SIR 1%

R-Squared	0.17994163
Adj. R-Squared	0.143895108
Standard Error	0.101810984
Observations	96

	df	*SS*	*MS*	*F*	*p-value*
Regression	4	0.206974835	0.051743709	4.991927687	0.001104401
Residual	91	0.943258353	0.010365476		
Total	95	1.150233188			

	Coefficients	*Standard Error*	*t-Stat*	*p-value*	*[95% Confidence Interval]*	
Intercept	0.013597038	0.011381449	1.194666678	0.235321775	-0.009010812	0.036204888
Rm-RF	0.443583452	0.31032419	1.429419511	0.156307762	-0.172837429	1.060004332
SMB	0.695220802	0.48781213	1.425181455	0.157525674	-0.27375807	1.664199673
HML	-1.064741532	0.561342792	-1.896775993	0.061029335	-2.17978003	0.050296966
MOM	-1.003666456	0.396838283	-2.529157339	0.01315498	-1.791936956	-0.215395957

Table 22: C4F Regression Analysis Results of SIR 1% Portfolio

SIR 10%

R-Squared	0.471743495
Adj. R-Squared	0.448523429
Standard Error	0.033472178
Observations	96

	df	*SS*	*MS*	*F*	*p-value*
Regression	4	0.091047999	0.022762	20.31619942	5.50724E-12
Residual	91	0.10195519	0.001120387		
Total	95	0.193003189			

	Coefficients	*Standard Error*	*t-Stat*	*p-value*	*[95% Confidence Interval]*	
Intercept	0.006546575	0.003741854	1.749553537	0.083566614	-0.00088616	0.013979309
Rm-RF	0.500106537	0.102024616	4.901822281	4.12018E-06	0.29744717	0.702765904
SMB	0.535827272	0.160376945	3.341049259	0.001211887	0.217258173	0.854396371
HML	-0.128884373	0.184551462	-0.698365492	0.486729496	-0.495473181	0.237704435
MOM	-0.358107432	0.130467669	-2.744798273	0.007294978	-0.617265428	-0.098949435

Table 23: C4F Regression Analysis Results of SIR 10% Portfolio

SIR 90%

R-Squared	0.840535181
Adj. R-Squared	0.833525738
Standard Error	0.019590041
Observations	96

	df	*SS*	*MS*	*F*	*p-value*
Regression	4	0.184078508	0.046019627	119.9146963	2.06552E-35
Residual	91	0.034923043	0.00038377		
Total	95	0.219001551			

	Coefficients	*Standard Error*	*t-Stat*	*p-value*	*[95% Confidence Interval]*	
Intercept	-0.005443166	0.00218997	-2.485497613	0.014763549	-0.009793274	-0.001093059
Rm-RF	0.748356573	0.059711274	12.5329192	1.58756E-21	0.629747462	0.866965683
SMB	1.017047968	0.093862756	10.83547947	4.65695E-18	0.830601134	1.203494803
HML	0.288548333	0.108011217	2.67146637	0.008947413	0.07399732	0.503099346
MOM	-0.167107804	0.076357952	-2.188479404	0.031195101	-0.318783495	-0.015432114

Table 24: C4F Regression Analysis Results of SIR 90% Portfolio

SIR 99%

R-Squared	0.514358915
Adj. R-Squared	0.493012054
Standard Error	0.036286819
Observations	96

	df	*SS*	*MS*	*F*	*p-value*
Regression	4	0.126908303	0.031727076	24.09529518	1.30257E-13
Residual	91	0.119822723	0.001316733		
Total	95	0.246731026			

	Coefficients	*Standard Error*	*t-Stat*	*p-value*	*[95% Confidence Interval]*	
Intercept	-0.010327686	0.004056503	-2.545957844	0.012579211	-0.018385431	-0.002269941
Rm-RF	0.668535615	0.11060376	6.044420296	3.25069E-08	0.448834832	0.888236398
SMB	0.765332241	0.173862876	4.40193019	2.9155E-05	0.419974997	1.110689486
HML	0.284198531	0.200070203	1.420494036	0.158881221	-0.11321635	0.681613412
MOM	-0.114582778	0.14143856	-0.810124046	0.419982355	-0.395533102	0.166367545

Table 25: C4F Regression Analysis Results of SIR 99% Portfolio

Appendix G

Relative Sector Weightings per Year

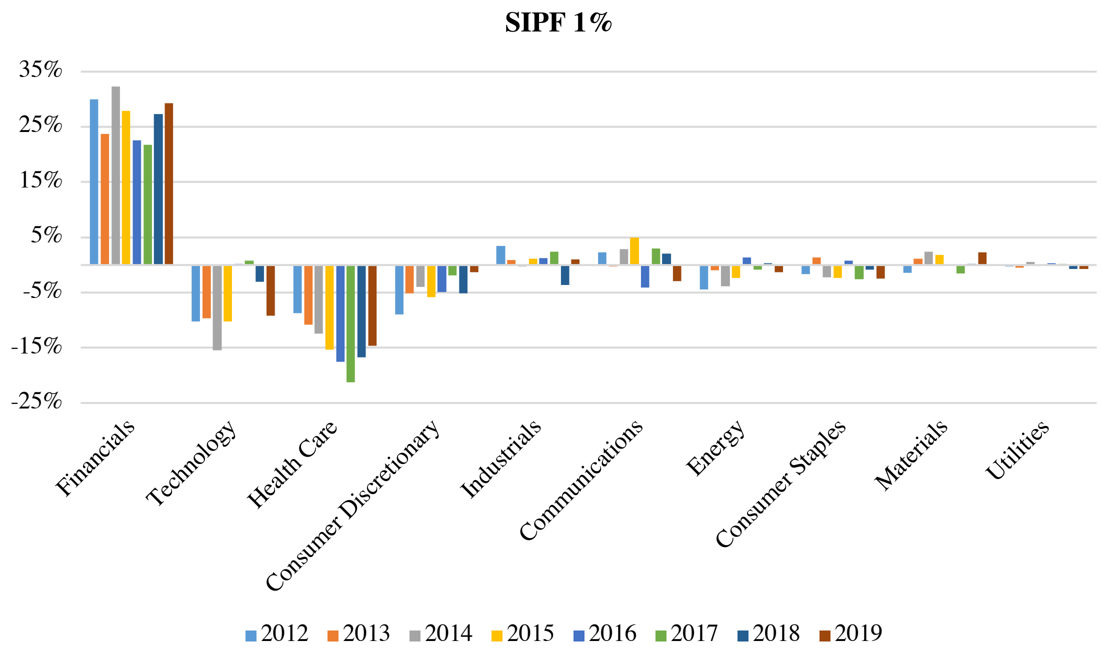

Figure 7: Relative Sector Weightings SIPF 1% Portfolio vs. Equal-weighted CCMP

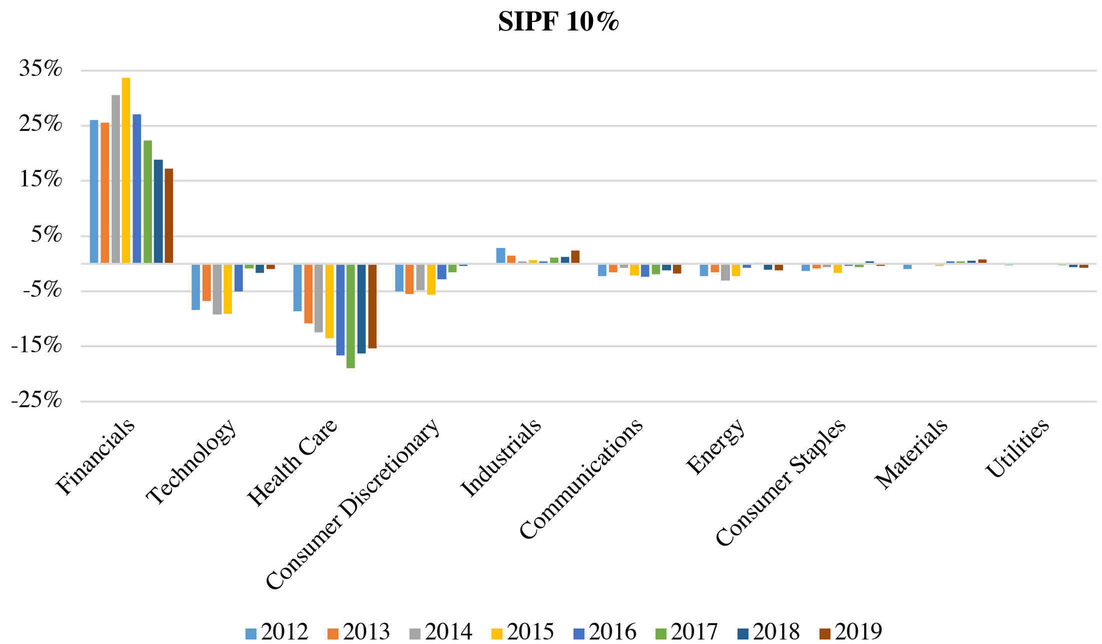

Figure 8: Relative Sector Weightings SIPF 10% Portfolio vs. Equal-weighted CCMP

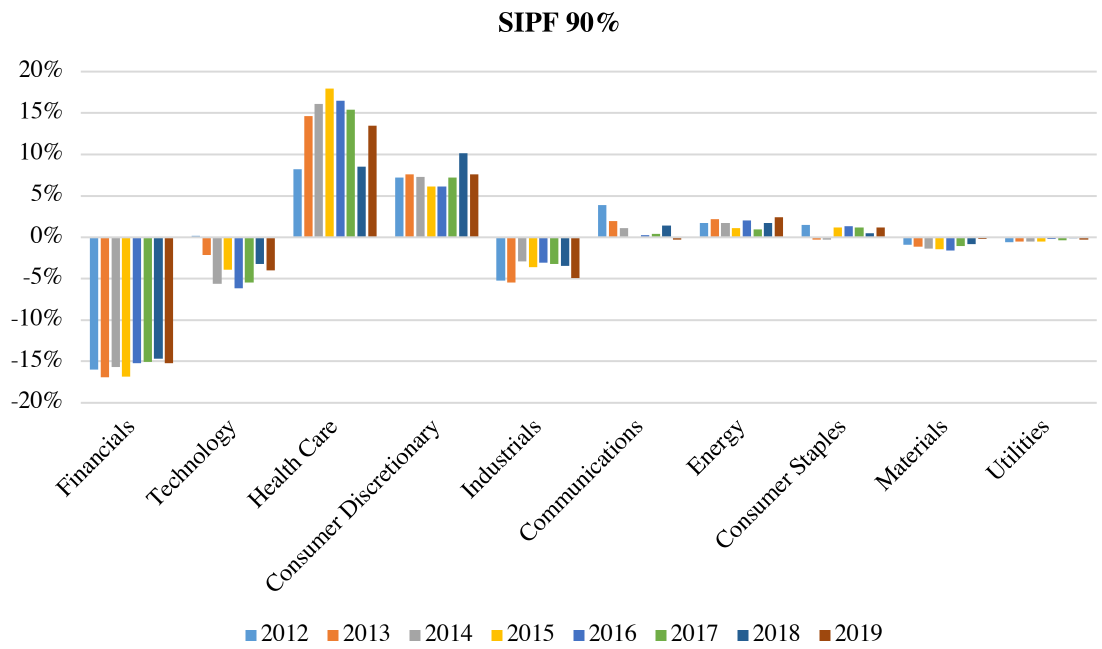

Figure 9: Relative Sector Weightings SIPF 90% Portfolio vs. Equal-weighted CCMP

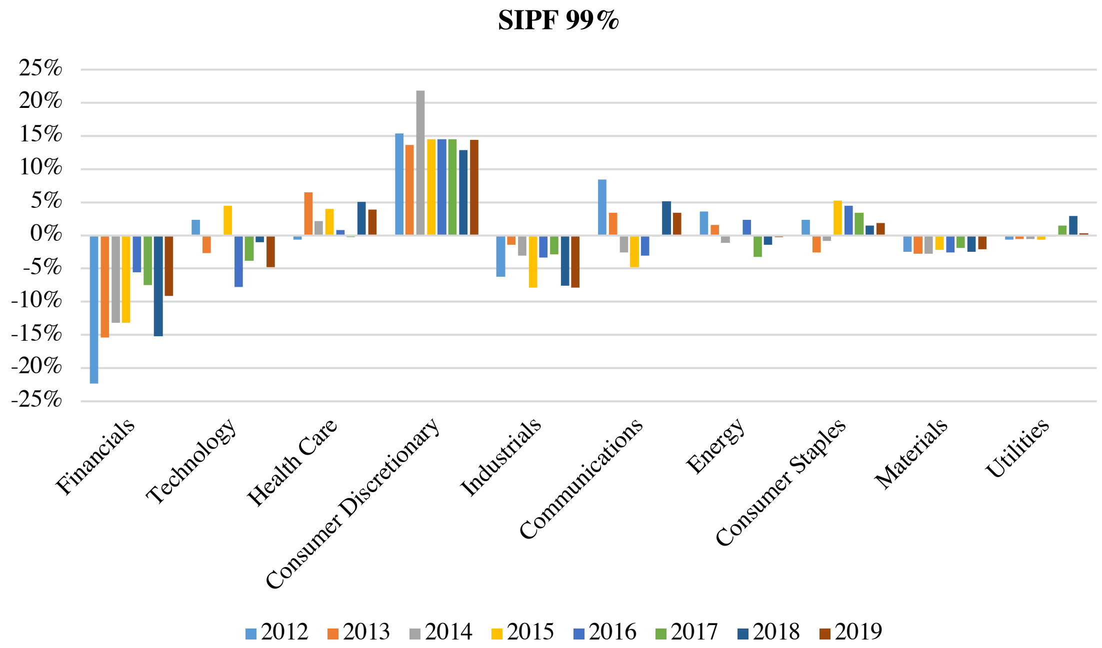

Figure 10: Relative Sector Weightings SIPF 99% Portfolio vs. Equal-weighted CCMP

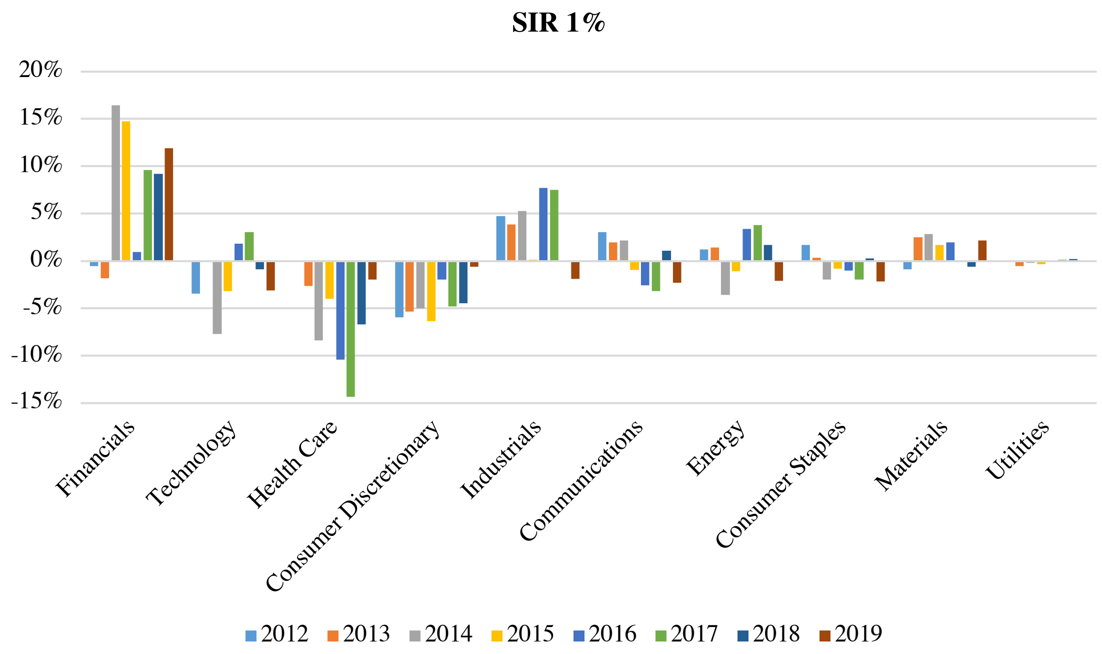

Figure 11: Relative Sector Weightings SIR 1% Portfolio vs. Equal-weighted CCMP

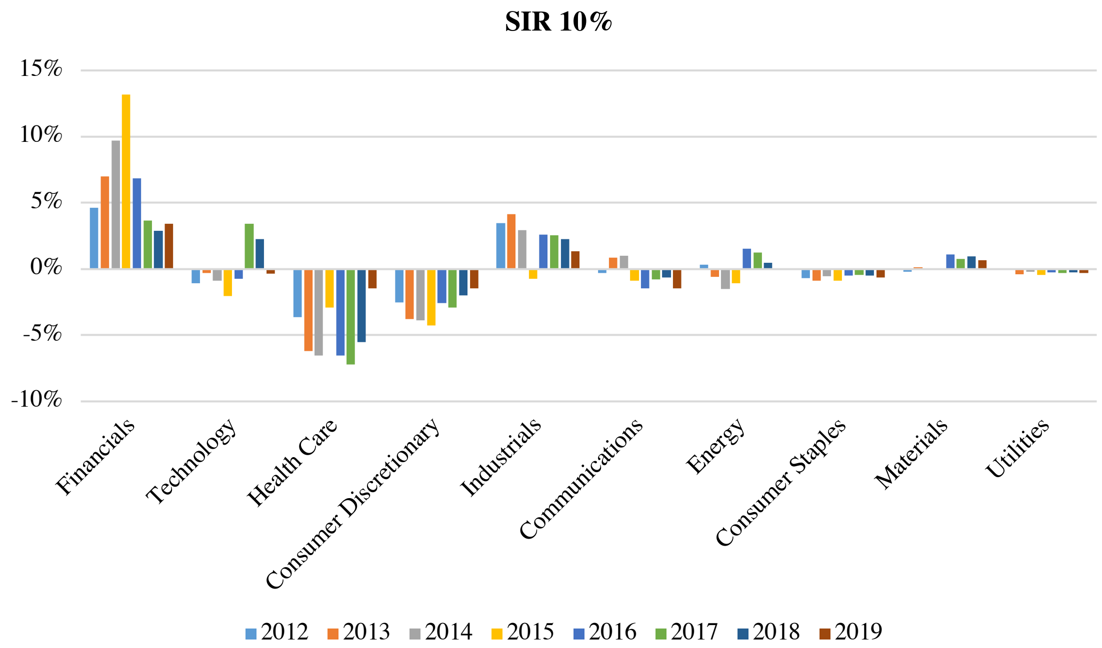

Figure 12: Relative Sector Weightings SIR 10% Portfolio vs. Equal-weighted CCMP

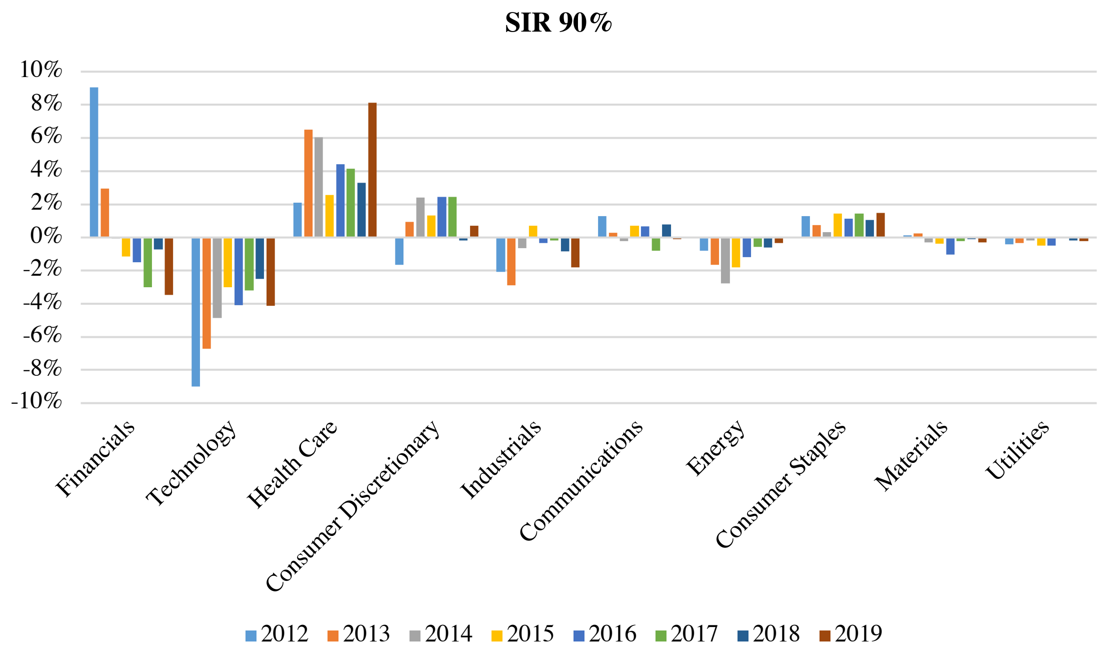

Figure 13: Relative Sector Weightings SIR 90% Portfolio vs. Equal-weighted CCMP

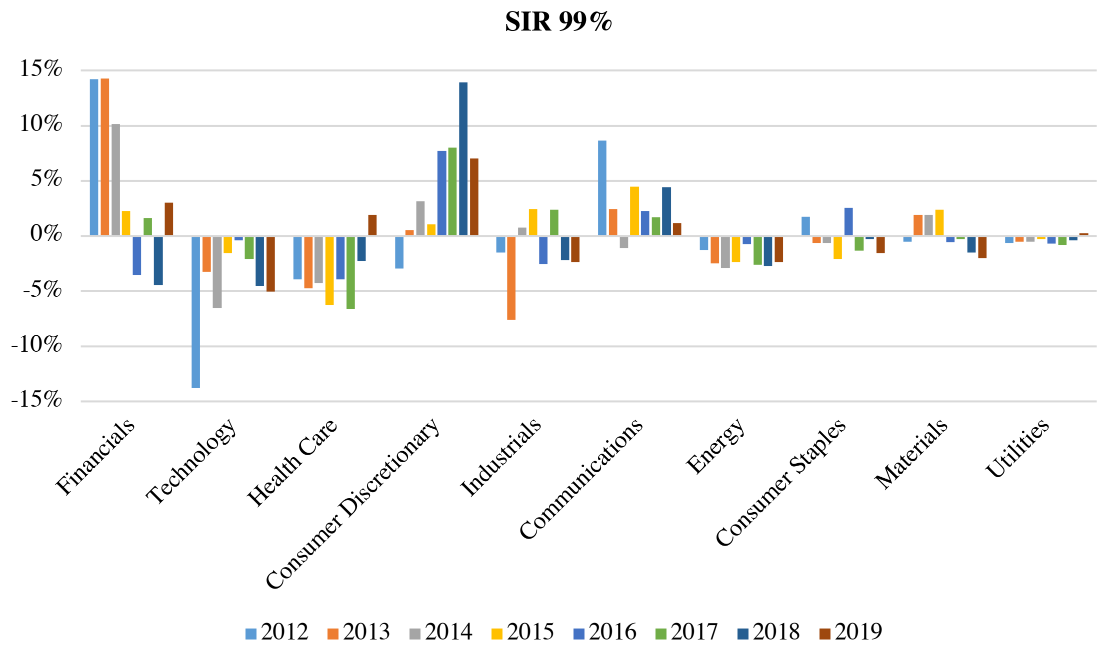

Figure 14: Relative Sector Weightings SIR 99% Portfolio vs. Equal-weighted CCMP