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TREND VS. MOMENTUM IN THE NORDICS IN THE COVID-19 ERA

Master Thesis

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MSc in Business with Major in Finance

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ABSTRACT

In this thesis, we test the Quantitative Momentum Strategy (QMS) and Trend-Following Simple Moving Average (SMA) Strategy in five different Nordic markets during the COVID-19 era. Four markets consist of the 100 largest stocks in terms of market capitalization in Denmark, Finland, Norway and Sweden. The fifth market is a combined market containing the top 100 stocks in terms of market capitalization from each country.

We test various QMS and SMA strategies in the Nordic combined market against the Nordic MSCI Nordic index. The QMS(H6F36) and SMA(5) exhibit the greatest performance among the strategies in the combined market. The best performing QMS and SMA strategies are then applied to each Nordic country specific market and tested against their respective indices.

Our research show that the SMA(5) strategy outperforms the market in all countries except the for the combined Nordic Market. In the combined portfolio, the MSCI index beats the SMA(5) strategy. The QMS (H6F36) does not outperform the market in any countries, nor in the Nordics.

1.0 INTRODUCTION

Throughout history, investors have primarily aimed to outperform the market through predicting its direction. During the COVID-19 pandemic, this would be no easy task. The majority of investment strategies can be categorized as either fundamental or technical analysis. Fundamentalists, also known as value investors, focus on buying stocks that are trading at a low price relative to various fundamentals. The value investors believe that the fundamentals of the companies take precedence, and stock prices eventually reflect this. In other words - buy low, sell high.

On the other hand, we have technical analysts, often referred to as speculators. These have a short-term perspective and make buying decisions based on the performance of securities. If the security performs badly, they sell. This strategy comes in many forms, but is commonly known as "momentum" or "trend-following". It's simple enough for anyone to grasp, your grandmother could probably do it - just buy the winners. And during the recent COVID-19 pandemic, she probably did.

Could a strategy that simple really work? Many have criticized these strategies. Value investor Benjamin Graham calls it “the exact opposite of sound business sense” (Graham & Zweig, 2006, p. 2-3). Others say the momentum strategies can exploit market anomalies, but do not yield profitability after accounting for transaction costs (Lesmond et al., 2004, Carhart, 1997, Novy-Marx & Velikov, 2015). Ross et al. (2017) say otherwise, providing evidence of a momentum premium from a long-only strategy after accounting for transaction costs, frictions and taxes. Some critics of momentum strategies point to its occasional tendency to crash. According to Daniel and Moskowitz (2016), momentum crashes predominantly occur due to shorting, while the long position in winners does well.

In the early months of 2020, governments worldwide implemented severe measures in response to the global COVID-19 pandemic. The restrictions had far-reaching consequences, leading to economic downturns and heightened levels of volatility, akin to previous instances of financial crises (Sharif et al., 2020). According to Shanaev et al. (2020), the prevailing viewpoint suggests that government interventions have emerged as the primary catalyst for adverse shocks in the global market. The pandemic presented policymakers with challenging choices as they had to balance between preserving human life and maintaining economic stability (Coibion et al., 2020). These governmental interventions entail mandatory closures of businesses and stringent limitations on customer mobility, resulting in significant negative repercussions and markets plummeting all over the world. Baker et al. (2020) contend that the impact of COVID-19 on the stock market surpasses that of any previous disease outbreak.

The COVID-19 pandemic provided a significant level of uncertainty in stock markets, triggering an unprecedented and notable market reaction. The presence of asymmetric information and confusion was notably manifested in several ways (Glaeser et al., 2020). Investors and market participants faced challenges in accurately assessing the impact of the virus in various industries, companies, and economies. The lack of transparency and clarity regarding the severity and duration of the pandemic led to increased market volatility, as investors grappled with uncertain future prospects. Moreover, misinformation and disinformation proliferated during the pandemic, leading to confusion and mistrust. Rumors, false claims, and conspiracy theories circulated, making it difficult for individuals to distinguish accurate information from misleading or inaccurate sources (Islam et. al. 2020). This not only affected public health measures but also impacted economic activities and market behaviors.

The subject of investment strategies during the pandemic emerged as a captivating topic, capturing the attention of not just institutional and professional investors but also retail investors (this is where all the grandmothers comes in), as a global pandemic at this scale has not presented itself in newer times (Pagano, 2021). The progression of the pandemic witnessed various phases in the markets. The markets crashed, but quickly recovered, and not only that, but hitting all-time highs while the pandemic was still on-going. Looking back, this market development sounds illogical, but so does betting on past winning stocks (to some at least).

The objective of this research paper is to test the return of the Quantitative Momentum Strategy (QMS) and a Simple Moving Average (SMA) Trend-Following Strategy under the challenging market conditions of the COVID-19 pandemic, and to discern which, if any, are most likely to yield the highest returns, and beat the market in future pandemics or global crises. QMS and SMA strategies has historically performed well under market conditions containing clear market trends (Cooper, 2005, Rey, 2022).

Our understanding is that there is a notable lack of research on momentum and trend-following strategies within the Nordic region in the official COVID-19 time period. This is evidenced by the limited academic literature on the topic in the Nordics and our selected investment strategies during the COVID-19 pandemic. This is probably due to the COVID-19 pandemic officially ended on the 5th of May 2023 (WHO, 2023).

This thesis strives to answer the following research question:

Which of the selected investment strategies (Quantitative Momentum Strategy and Simple Moving Average Strategy) can outperform the Nordic market indices during the COVID-19 pandemic?

We answer the question by creating an investable universe of 100 stocks from each of our selected Nordic Markets (Denmark, Finland, Norway and Sweden), and implementing a Quantitative Momentum Strategy (QMS) serving as our momentum strategy inspired by Gray and Vogel's (2016). The creators of this model claim that the QMS outperforms the U.S. stock market in risk-adjusted and absolute returns, building on the Generic Momentum Strategy (GMS) of Jegadeesh & Titman (1993) (Gray & Vogel, 2016).

Secondly, we implement a trend-following strategy, using different Simple Moving Average (SMA) Strategy. Moving Averages has been used for decades by the trading industry and fund managers, but has often been looked down upon by academics (Malkiel, 1981).

Lastly, in our analysis we present the results from our regression analysis using the Capital Asset Pricing Model (CAPM), Fama & French Three-Factor model (FF3), Fama & French Five-Factor model (FF5) and the Fama & French Six-Factor model (FF6) to assess the alphas of the chosen investment strategies.

The thesis is organized as follows. In Section 2, we provide background for the COVID-19 era. In Section 3, a review of the relevant literature is presented. Section 4 provides an overview of the data used in the study. The methods employed are detailed in Section 5. The analysis outcomes and robustness tests are reported in Section 6. Section 7 presents the concluding remarks of the research. Lastly, Section 8 provides limitations and recommendation for future research on the topic.

2.0 BACKGROUND

In this section, we will provide a concise overview of the impact of the COVID-19 crisis on the Nordic markets.

2.1 COVID-19 OUTBREAK

The detection of the first case of COVID-19 in Wuhan, China, in late December 2019 marked the onset of a global crisis. In the following months, the virus swiftly spread to all continents, resulting in a surge of positive cases across numerous countries by March 2020. On March 11th, 2020, the World Health Organization officially declared COVID-19 as a global pandemic (WHO, 2020a).

To contain the virus, governments worldwide implemented various restrictions on the population (WHO, 2020b). These measures encompassed the closure of workplaces and schools, travel bans, and limitations on public and private gatherings. Additionally, several countries offered income support to individuals who experienced partial or complete loss of income due to these restrictions. As countries implemented shutdowns, uncertainty within the markets escalated, leading to significant declines in many stock markets (Ashraf, 2020).

In March 2020, the Nordic markets dropped significantly. This is illustrated in Figure 1, by the 26.53% drop in the MSCI Nordic Index during Q1 of 2020 (Investing.com, 2023).

Figure 1. MSCI Nordic Countries Index. Data collected from Investing.com (2023).

In the months to follow, the Nordic stock markets recovered. On the 5th of October 2020, the MSCI Nordic Countries Index hit a new all-time high of 278.9 Euro. The MSCI Nordic Countries Index yielded 26.8% in 2020. This development continued, and in 2021 the index returned 19.1%. In 2022, the markets turned and delivered returns of -17.62% (MSCI, 2023a).

Research into volatility patterns during past crises offers valuable insights into the COVID-19 crisis. Goswami et al. (2020) examined the effect of both local and global crises on volatility within advanced equity markets and discovered a significant increase in market volatility during global crises. A similar trend was observed by Antonakakis & Scharler (2009) in their study of the S&P 500 spanning from 1928 to 2009, where they noted not only an increase in volatility preceding and following a market crash, but also a sustained period of high volatility post-crash. Several studies have also focused specifically on volatility during the COVID-19 crisis. For instance, Chaudhary et al. (2020) analyzed how COVID-19 influenced volatility in the top 10 countries by GDP, and their results clearly indicate a rise in volatility during the COVID-19 crash (January 2019 to June 2020). According to the research of Baker et al. (2020), the volatility in the equity markets influenced by the COVID-19 pandemic surpasses that of any previous disease outbreak, including the Spanish flu, swine flu, SARS, Ebola, and MERS.

In Figure 2, we have calculated the realized volatility as the sum of squared weekly returns of the MSCI Nordic Countries Index in an effort to see how Nordic markets were affected. The sample period is from the January 7th 2017 to the 5th of March 2023. The data is collected from investing.com (2023). The COVID-19 period is highlighted in yellow. In Figure 3, the COVID-19 period is extracted, running from January 5th 2020 to May 5th 2023.

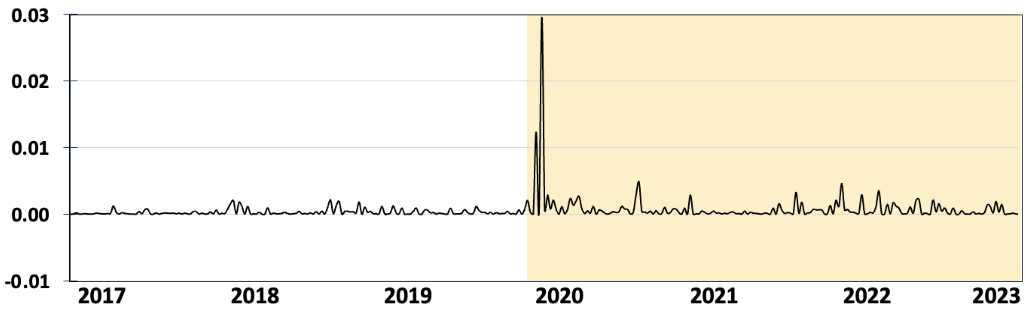


Figure 2. Volatility of the MSCI Nordic Countries Index

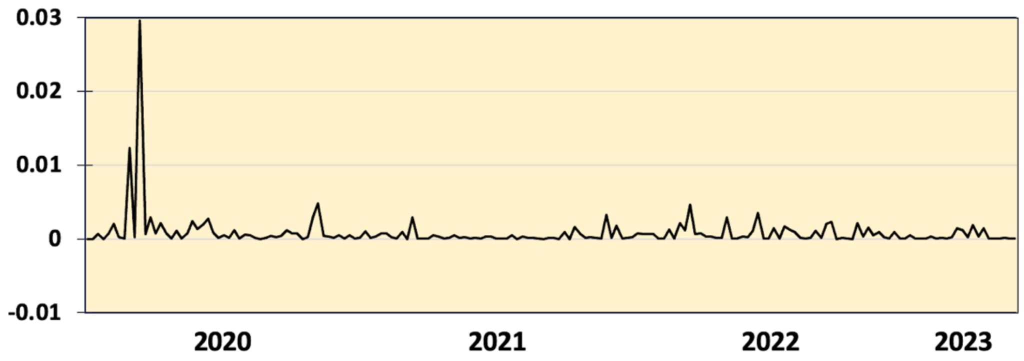


Figure 3. Volatility of the MSCI Nordic Countries Index (COVID-19 Period)

According to Coibion et al. (2020) and Fernandes (2020), the economic repercussions caused by the COVID-19 crisis were on par with the losses experienced during the Global Financial Crisis of 2008. In Figure 4, we can observe the significant drop in Gross Domestic Product (GDP) growth in the four Nordic countries. We also observe an ever bigger decline in GDP growth during the Global Financial Crisis from mid 2007 to early 2009 indicating a more efficient response by governments during the COVID-19 Pandemic.

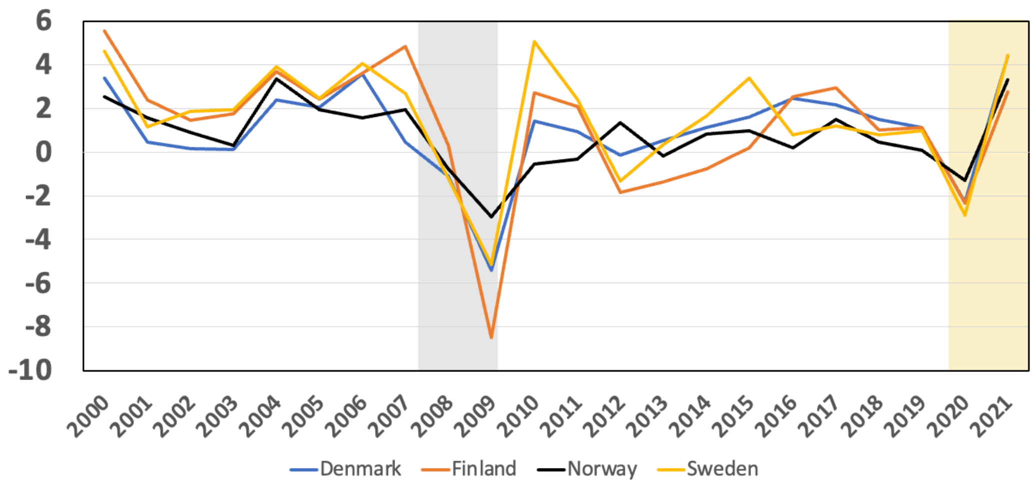


Figure 4. Gross Domestic Product in the four Nordic countries. Data collected from The World Bank (2023).

COVID-19 could take place in the next decade as viruses are expected to emerge more frequently (Bloomberg, 2023). Baker et al. (2022) argues that recent global changes have increased the risk of infectious disease outbreaks, even if sanitation and health care have had considerable progress worldwide. Marani et al. (2021)

suggests that there is a 38% probability of observing a pandemic similar to COVID-19 in one's lifetime. Their research argues that the probability is expected to rise, and might double due to rapid global changes.

3.0 LITERATURE REVIEW

Momentum investing and trend-following has been a topic of interest for many years, and several influential research papers have made substantial contributions to the understanding of the strategy and its implementation.

Jegadeesh & Titman (1993) present empirical evidence that a strategy of buying past winners (stocks that have performed well) and selling past losers (stocks that have performed poorly) yields significant abnormal returns. They discover that the return patterns persist for 3 to 12 months, contradicting the efficient market hypothesis (EMH) which suggests that past information should not predict future returns (Fama & French, 1970).

The EMH remains a debatable subject within financial theory. The theory introduced by Fama (1970) posits that financial markets efficiently reflect all relevant information in asset prices, making it effectively impossible to consistently achieve abnormal returns through active trading or investment strategies. The EMH has since been challenged by many researchers providing empirical evidence of abnormal returns and market inefficiency. Jensen (1978) provides evidence contradicting the EMH and highlights instances where abnormal returns can be achieved by exploiting market behaviors. Jensen (1978) suggests that stocks with low price-to-book ratios generate higher returns than stocks with high price-to-book ratios and that small-cap stocks outperform large-cap stocks, contradicting the EMH.

Jensen's paper from 1978 sparked considerable debate and research on market anomalies. With technological advances, researchers intensified their work, and more evidence of abnormal returns became evident, once again challenging the EMH. In a search for an explanation to the anomalies, the theory of behavior finance arose as a popular theory. Behavioral finance combines principles from psychology and finance to understand how cognitive and emotional factors influence financial decisions and market outcomes. It examines the psychological biases, cognitive limitations and irrational behavior that individuals and groups exhibit when making financial choices, serving as an explanation for why the markets are not always efficient.

Many researchers explain the momentum-effect by either overreaction or an underreaction to information by investors (Hong et al, 2000, Jegadeesh & Titman, 1990). Da et al. (2014) explored how investors' limited attention affects the gradual diffusion of information and referred to this phenomenon as the "Frog-in-the-Pan". The analogy is used to describe how investors react differently to the rate of which a stock price increases. A quick 100% increase would attract massive attention, but a slow 100% increase would not. The researchers argue that a slow increase in stock price would be more likely to be underpriced. Cooper et al., (2005) found that momentum portfolios tend to outperform the market during times with a clear market trend in a bullish/bearish direction. Da et al. (2014) found that momentum strategies that consider the path dependency of momentum exhibit a significantly stronger momentum effect. The discovery is consistent with the study conducted by Barberis et al. (1998), which argues that the momentum anomaly is a product of the market's tendency to underreact to positive news. In the Jegadeesh & Titman (1993) paper, the authors attributed the abnormal returns to underreaction to company-specific information by investors. Ever since, researchers have explored if momentum implies market inefficiency or reasonable risk compensation.

Jegadeesh & Titman (2001) revisits the paper from 1993 providing alternative explanations and aims to identify the main drivers of momentum profitability and to verify their own strategy. The authors argue against the risk-based explanation, where higher returns are compensation for higher risk. Instead, they find that momentum profits result primarily from the cross-sectional dispersion in stock returns, not from time-series predictability. Rouwenhorst (1998) has similar findings from 1980 to 1995 in 12 European Countries providing compelling evidence of profitability in all 12 countries, all using Jegadeesh & Titman 1993 method. Fuertes et al. (2009) showed that the strategy of Jagadeesh and Titman (1993) was profitable, but prone to irregularly crashing due to a negatively skewed leptokurtic yield distribution. Daniel and Moskowitz (2016) find that momentum crashes are primarily driven by shorting, while the long position in winners remains favorable. Their research revealed that the issue lay in market exposure. By adopting a strategy that buys winners and sells losers, a momentum approach following a bear market would involve being short high-beta stocks and long low-beta stocks. Consequently, when the bear market ends and the market experiences a sudden upswing, the short positions on high-beta stocks incur substantial losses.

In summary, Daniel and Moskowitz (2016) demonstrated that all momentum crashes resulted from being short on the losers rather than being long on the winners, proving that a long-only momentum strategy can still perform well even during these "momentum crashes". This is confirmed by Ross et al. (2017) who present findings of a momentum premium in a long-only strategy even when accounting for transaction costs, frictions, and taxes. Assogbavi and Leonard (2008) also builds their research upon a modern variation of the approach of Jegadeesh & Titman (1993) in pursuit of finding the optimal variation of holding and formation periods. Their findings show that a 9-month formation and holding period is optimal. Nevertheless, they argue that momentum stem from a rising number of market participants. Thus, Assogbavi and Leonard (2008) recommend shorter holding and formation periods.

Gray and Vogel (2016) developed a Quantitative Momentum Strategy (QMS). This strategy is based on several empirical proofs from the academic literature on momentum investing, with roots in behavioral finance. Gray and Vogel (2016) put forward a strategy that aims to purchase stocks exhibiting the highest quality of momentum. This is achieved through the algorithm developed by Da et al. (2014) which aims to consider the path dependency for maximum momentum effect, which is much based on Jagadeesh & Titman's paper from 1993. The approach capitalizes on the empirical evidence regarding two aspects of investor behavior. The first is a tendency to prefer gambling-like assets, the second is the limited attention of the investor.

Trend-following strategies are a distant relative of momentum strategies. The difference lies in the approach and is often associated with day traders and technical analysis. Even 200 years ago, renowned classical economist David Ricardo advised to "cut your losses and allow your profits to run", hinting at an early focus on trend monitoring (Grant, 1838). Traders may use different indicators, such as moving averages (MA) or trendlines, to determine the presence and direction of trends (Hurst et al., 2012). The general idea of MA's is to "smoothen" the data and remove the short term volatility. The MA is constantly "moving" since it is constantly fed with new data. In a SMA, each data point is given the same weight. A greater n will give a slower moving trend-line and vice versa. The SMA is the simplest way of discovering trend-lines. The moving average strategies are often looked down upon in the academic literature. Malkiel (1981) described the academic bullying tactics on Moving Average methods as rooted in two considerations: “ (1) The method is patently false; and (2) it's easy to pick on”. Nevertheless, technical analysis is still widely used, and has been for some time. Every financial information provider lets you add different measures of trend and trendline. The same goes for every Bloomberg terminal, and newsletters or publications from brokerage firms all contain technical commentary. Menkhoff (2010) collected answers from 692 fund managers in the US, Germany, Switzerland, Italy and Thailand. Menkhoff (2010) presented evidence that 87% of fund managers find technical analysis somewhat important, but that it does not drive decision making. Rey (2022) found evidence that a SMA-strategy performed better in a market with containing clear directional bullish or bearish trends. Even with contradicting results, they argue that prior research from da Costa et al., (2015) showed that short-term moving averages investments were more profitable in the Brazilian market. Papailias & Thomakos (2015) also presented results that showed short-term moving average investments performed better in the S&P500 than a buy-and-hold strategy.

Technical analysis was heavily questioned after the EMH was presented in the Fama and French (1970) paper. Fama & French (1992, 1993, 2006, 2015) has later followed up their research with presenting different factor models proving great explanatory powers of factors. Factor investing is a strategy that selects securities on attributes that are associated with higher returns. The CAPM is the financial model known for establishing a linear relationship between the required return on an investment and its risk. The model was introduced by Treynor (1961), Sharpe (1964), Mossin (1966) and Lintner (1965a, 1965b) independently building on the earlier work of Markowitz (1952, 1959). The model incorporates the Beta, risk-free rate and equity risk premium (Berk & DeMarzo, 2011, p. 379-383). Factor investing really came to prominence with the FF3 model, which expanded on the CAPM by adding size and value factors, marking the origin of factor investing as we know it (Fama & French, 1992). In 2015, Fama and French introduced profitability and investment patterns in average stock returns as factors, introducing the FF5 model, building on their previously renowned FF3 model (Fama & French, 2015) and their 2006 paper. Fama & French (2015) argue that the FF5 model performs better than the FF3 model due to enhanced explanatory power presenting empirical support, nevertheless this is a subject of debate as the models vary across different time periods and asset classes. The FF5 model demonstrated superior performance compared to both the CAPM and the FF3 model. It exhibited the ability to explain 70% to 94% of the variation in average stock returns over the period spanning from July 1963 to December 2013. Fama and French (2015, 2016, 2020) argue that the model's biggest flaw is its failure to capture the low average returns on small stocks, due to their returns behaving like those of firms that invest a lot despite low profitability. In 2018, Fama & French continued to build on their factor-model and introduced a Six-factor model (FF6), introducing momentum as the sixth factor (Fama & French, 2018).

4.0 DATA

4.1 DATA COLLECTION

This thesis utilizes data from Refinitiv Eikon, Investing.com, and Global Financial Data spanning from January 10th 2020, to May 5th 2023. The chosen timeframe aligns with the official COVID-19 period (WHO, 2023). While we have confidence in the reliability of these three sources, it is important to acknowledge the possibility of factual errors given the substantial volume of data collected. Therefore, for the purposes of this study, the data entries collected from the respective sources are assumed to be correct.

The dataset contains the 400 largest companies based on market capitalisation in the four selected Nordic markets. These are the largest public traded companies on the Nasdaq Copenhagen in Denmark, Nasdaq Helsinki in Finland, Oslo Stock Exchange in Norway and Nasdaq Stockholm in Sweden. The empirical data consists of historical stock prices, market capitalization, book values, total assets and operating incomes.

The data for the Morgan Stanley International Capital Indices (MSCI) for the Nordic and respective countries has been obtained from Investing.com. The three-month Euro Interbank Offered Rate (EURIBOR) has been collected from Global Financial Data. The calculations of the EURIBOR are carried out by the Global Rate Set Systems (GRSS) (Global Rate Systems, 2023).

All the data points are plotted on a weekly basis (n=174) during the time period. Companies delisted during the period due to bankruptcy or any other reason are included to avoid survivorship bias in our data.

4.2 INVESTABLE UNIVERSE

When performing the selected trading strategies, the investable universe is selected to consist of the 100 largest companies from the Norwegian, Swedish, Danish, and Finnish markets. The sector variations within each country and in the Nordic in whole can be observed in appendix 1-0.

Figure 5. The Investable Universe

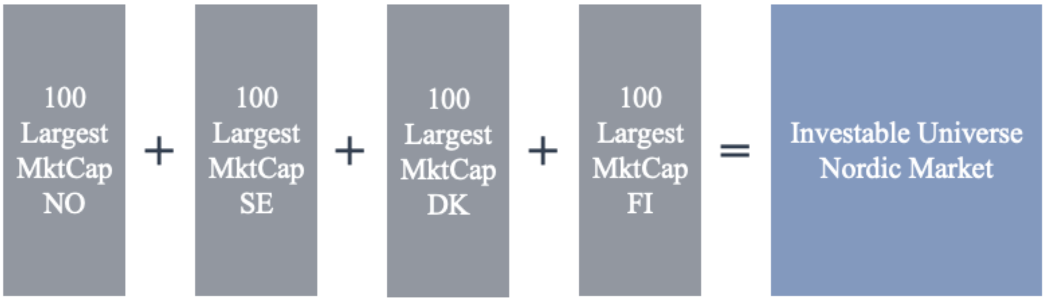


Figure 5 illustrates our investable universe in the Nordics

In addition, the EURIBOR serves as the risk-free rate and the MSCI indices as the market benchmark. The excess market return is defined as the difference between the country specific MSCI indices (rm) and the EURIBOR (rf) across all markets.

Table 1. Benchmark description

Benchmark	**Description**
MSCI NORDIC COUNTRIES INDEX	The MSCI Nordic Countries Index captures large and mid. cap representation from Norway, Denmark, Finland and Sweden. The Index covers approx. 85% of the float-adjusted market capitalization in each of the four markets (MSCI, 2023a).
MSCI DENMARK INDEX	The MSCI Denmark Index aims to gauge the performance of the major and medium-sized companies in the Danish market. Comprised of 16 constituents, this index represents about 85% of Denmark's market capitalization after adjusting for free float (MSCI, 2023b).
MSCI NORWAY INDEX	The MSCI Norway Index aims to gauge the performance of the major and medium-sized companies in the Norwegian market. Comprised of 12 constituents, this index represents about 85% of Norway's market capitalization after adjusting for free float (MSCI, 2023c).
MSCI FINLAND INDEX	The MSCI Finland Index aims to gauge the performance of the major and medium-sized companies in the Finish market. Comprised of 12 constituents, this index represents about 85% of Finland's market capitalization after adjusting for free float (MSCI, 2023d).
MSCI SWEDEN INDEX	The MSCI Sweden Index aims to gauge the performance of the major and medium-sized companies in the Norwegian market. Comprised of 45 constituents, this index represents

	about 85% of Sweden's market capitalization after adjusting for free float (MSCI, 2023e).

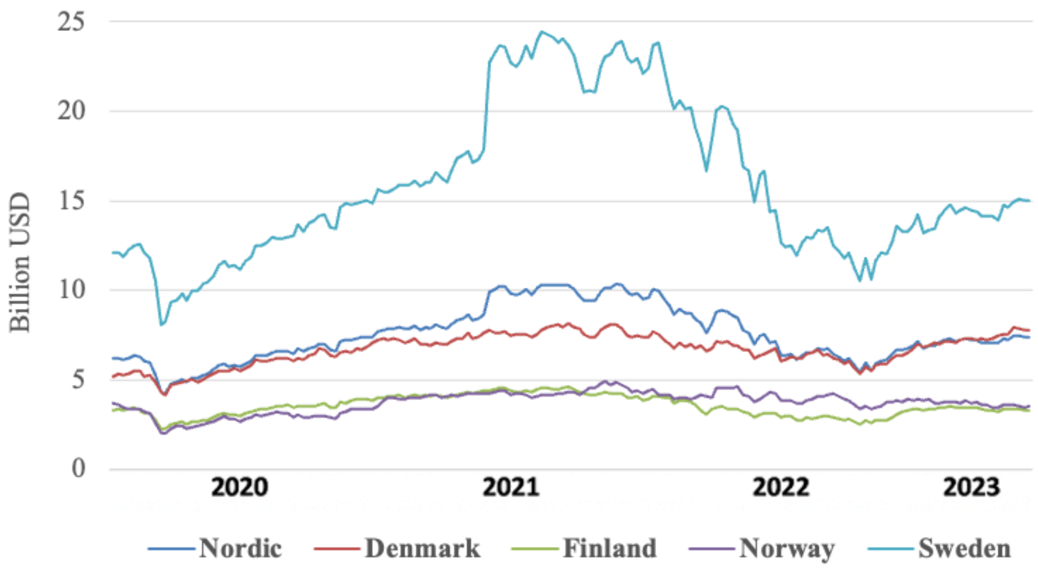
In reviewing previous research articles and evaluating various approaches to construct the investable universe, we discovered that the creation of samples for data analysis is often subjective, and there are often no rules nor methods for inferring the sample results of a population (Henry, 1990). Nevertheless, we have identified four important factors in our straightforward method for data collecting:

Table 2. Factors considered when creating the investable universe

Factor	Description
Diversification	By including the exact same number of stocks from each exchange we enhance diversification and reduce the exposure to specific market risks associated with a single sector and industry. We assume this will allow for a more dynamic market environment and would serve to reduce the impact of any single stock event overall in the portfolio(s).
Market Coverage	Incorporating an equal number of companies from the four exchanges enables our portfolios to gain exposure to a broader spectrum of companies, sectors, and market conditions. We believe that this approach enhances the portfolios' ability to capture stocks with the highest momentum, and trend shifts.
Market Liquidity	In selecting the largest companies on each exchange, we assume that the investor will not face liquidity challenges and can benefit from low transaction costs. This approach is expected to minimize the impact of share purchases on stock prices (Asness et al., 2013). Moreover, we expect the approach to minimize the presence of substantial bid/ask spread in each market.
Investment Strategy	Our objectives is to investigate strategies that are driven by momentum and trend shifts. Therefore, it is important to exclude stocks that have lower trading volumes and therefore also less shifts in direction (up/down).

The 100 companies selected have different characteristics and touch upon multiple industries. The total market cap of each country specific market differs. Figue 6. illustrates the development of the market capitalization during the period for the 100 selected stocks of each respective country included in the investable universe.

Figure 6. Market capitalization development by country



5.0 METHODOLOGY

The variables are in logarithmic form to address potential issues related to stationarity. Taking the logarithm of variables will help stabilize their variance over time, making them more suitable for statistical analysis, particularly when dealing with financial data (Succarat, 2019, p. 155). In addition, by utilizing logarithmic returns for modelling and statistical purposes, we take advantage of the linear property inherent in multiperiod continuously compounded returns. This enhances convenience in statistical analysis (Campbell et al., 1997).

5.1 RETURN DEFINITIONS

The weekly log return of every stock i at the end of week t ($r_{i,t}$) is calculated as follows:

$$r_{i,t} = \ln\left(\frac{r_{i,t}}{r_{i,t-1}}\right)$$

$r_{i,t}$ represents the value of the return of stock *i* at the end of week *t*, while $r_{i,t-1}$ represents the value of the return of the stocks at the end of previous week *t-1*.

For the Quantitative Momentum Portfolios, we utilize equal-weighted portfolios. The weekly logarithmic returns of portfolio p at the end of each week t ($r_{p,t}$) is calculated as:

$$r_{p,t} = \Sigma\left(w_{i,t} \cdot r_{i,t}\right)$$

$r_{p,t}$ represents the portfolio returns at observation *t.*

$w_{i,t}$ represents the weight of stock *i* in the portfolio.

$r_{i,t}$ represents the return of stock *i.*

The weight of the stocks in each portfolio p is determined by dividing the USD value of stock *i* by the total USD value of the total portfolio p. We opt for an equal-weighted portfolio for all p, due to the simplicity in implementation.

The weight w_i of stock i is therefore defined as:

$$w_i = \frac{1}{n}$$

Where n is the number for stocks in each portfolio p.

For the Trend-Following Portfolios, we implement value-weighted portfolios. The weighting methodology assigns portfolio allocation based on the market value of the underlying stocks. Within this approach, the stocks with larger market capitalizations receive higher allocations in the portfolio. The purpose is for the portfolio to reflect the market's evaluation of their importance or impact. This weighting methodology acknowledges the role of market capitalization in determining the portfolio composition in trend-following strategies. Hence, the weight w_i of stock i is defined as:

$$w_i = \frac{MV_i}{TMV}$$

MV_i represents the market value of stock i.

TMV represents is the total market value of all assets in the portfolio,

The portfolios p are then summed to equal 1, independent of the number of stocks in the portfolios p.

The one-week simple net return of stock i at the end of each week t, $R_{i,t}$ is:

$$R_{i,t} = \frac{r_{i,t} - r_{i,t-1}}{r_{i,t-1}}$$

5.2 CONSTRUCTION OF QMS PORTFOLIOS

Assogbavi & Leonard (2008) based their portfolios on the same principles as Jegadeesh & Titman (1993), they both suggest that the best performers in the past 3-month to 12-month period are more likely to be future winners. The dataset used in this thesis is more limited and contain more volatile observations during the COVID-19 period, with weekly observations. Hence, we adjust the holding and formations periods to 6, 12, 24 and 36 in order to utilize the periods to be as close as possible to replicate the prior research conducted with the COVID-19 dataset.

We sort the stocks based on performance in the formation period (logarithmic returns). When the stocks are sorted, we select the top decile with the best past performance. After they are ranked, and the top 10% is selected, we rank them again to identify the "momentum quality". There are several techniques that can be used to identify the momentum quality. The chosen technique is by comparing the cumulative returns in the selected top 10% stocks, and then split them into two groups: "High Quality" and "Low Quality" momentum quality. The cumulative return for each stock is computed as follows:

$$cr_t = (1 + return_{t-1}) \cdot (1 + return_{t-2}) \cdot \ldots \cdot (1 + return_{t-n}) - 1$$

cr_t represents the cumulative return of stock *i* over the formation period at time *t*.

$(1 + return_{t-n})$ represents the individual returns of stock *i* over the respective period.

By utilizing the cumulative returns technique, we capture the compounded effect of the individual stock's return over the specified formation period, allowing us to identify stocks with strong past performance for inclusion in the portfolio.

After screening stocks in the top 10% decile by the quality of their momentum, we select the ones with high-quality momentum and construct an equal-weighted portfolio. Finally, we hold the portfolio over *t* weeks (holding period). This can be seen in Figure 7.

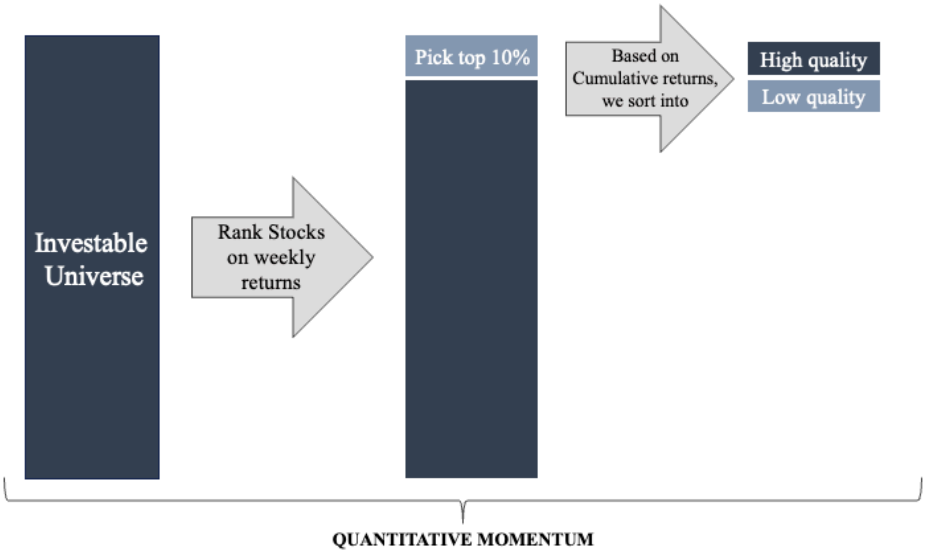


Figure 7. Illustrates the screening process for constructing the QMS portfolios. We screen the stocks based on their past weekly returns (depending on formation period) into the top 10% decile. The stocks are then divided into "high quality" and "Low quality" based on their cumulative returns.

5.3 CONSTRUCTION OF SMA PORTFOLIOS

Rey (2022) found evidence that the SMA strategy performed better in a market containing clear directional bullish or bearish trends. We argue that the COVID-19 period is indeed a market with clear trends. We analyse the Trend-Following Strategy by utilizing SMA´s to determine the trend in each of the stocks at the end of each period *t*, before holding the portfolios throughout the period. We construct portfolios with the different moving averages: t = 5, 10, 15 and 20. The Simple Moving Average is computed as follows (West, 2023):

$$SMA_k = \frac{1}{k} \Sigma_{i=n-k+1}^{n} p_i$$

k: window size

n: total of observed values

$i = n - k + 1$: total values minus window size plus one

p_i: represents single observed value

When calculated for each stock in the SMA period, we compare the current price of the stock to the moving SMA to determine the trend direction. If the price is above the moving average, it indicates an uptrend. If the price is below the SMA, it indicates a downtrend.

Figure inspired by illustration in Rey (2022, p. 5):

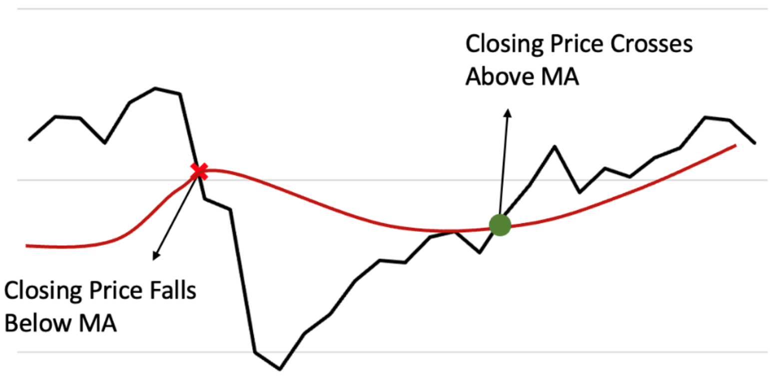


Figure 8. Simple Moving Average buy/sell signals illustration as published in Rey (2022, p. 5)

Based on the trend direction and the previous trend, there are being generated three signals: buy, sell or hold. If the current price is above the moving average and the previous trend was a downward trend, it generates a buy signal indicating a potential entry point for a long position. If the current price is below the moving and the previous trend was an upward trend, it generates a sell signal indication a potential exit opportunity. If the current price is in the same direction as the previous trend (above the SMA in an upward trend or below the SMA in a downward trend), generates a hold signal indicating that no action should be taken.

Based on these signals created during the SMA period, the portfolios are created. The signals are created for each of the stocks, and the top-trending stocks are included in the portfolio *p*.

5.4 ANALYSIS OF THE RETURN OF THE PORTFOLIOS

We create 16 QMS strategies in total with different holding and formation periods, and 4 SMA strategies with different moving averages. In total these portfolios will be implemented in the investable universe (Nordic) and regressed on the market using CAPM, FF3, FF5 and FF6. The QMS and SMA portfolios that generates the greatest alphas will be transferred to each country and tested against each other and against the market excess return. To compute the p-values and the t-statistics for the average weekly returns, we employ the cumulative distribution (LaMar,2017)

In order to evaluate the effectiveness of the momentum and trend strategies, we analyse the weekly returns of all portfolios during the official COVID-19 period. The hypothesis tests, aim to compare the net returns of the selected investment strategies to their corresponding MSCI Indices. First, we test if the Quantitative Momentum Portfolios yield better net returns than the broad market on average. Second, we test if the SMA portfolios yield better net returns than the market on average. The hypothesis is expressed as follows:

Null hypothesis (H0): The alpha (α) of the regression model (CAPM, FF3, FF5 or FF6) is equal to zero, indicating no outperformance compared to the comparative market.

Alternative hypothesis (Ha): The alpha (α) of the regression model (CAPM, FF3, FF5 or FF6) is equal to zero, indicating statistically significant outperformance compared to the comparative market.

5.5 TRANSACTION COSTS

In order to consider the impact of transaction costs on the performance of our strategies, we implement transaction costs into the strategies. To simplify the calculation, we include a transaction cost of 1 basis point per transaction. It is important to note that the thesis does not consider the costs of holding the stocks or MSCI Indices. Taxes are not considered.

5.6 ANALYSIS OF THE PORTFOLIOS ALPHAS

To evaluate the momentum strategies on a risk-adjusted basis, we estimate the alphas produced by them using (1) CAPM, (2) FF3, (3) FF5 and (4) FF6. We run weekly regressions of the strategies on the risk-factors return. The models are as follows:

$$(1) \qquad r_{pt} = \alpha_{pT} + \beta_{pT} \cdot MKTRF_t + e_{pt}$$

$$(2) \qquad r_{pt} = \alpha_{pT} + \beta_{pT} \cdot MKTRF_t + \beta_{pT} \cdot HML_t + \beta_{pT} \cdot SMB_t + \varepsilon_{pt}$$

$$(3) \qquad r_{pt} = \alpha_{pT} + \beta_{pT} \cdot MKTRF_t + \beta_{pT} \cdot HML_t + \beta_{pT} \cdot SMB_t + \beta_{pT} \cdot RMW_t + \beta_{pT} \cdot CMA_t + \varepsilon_{pt}$$

$$(4) \qquad r_{pt} = \alpha_{pT} + \beta_{pT} \cdot MKTRF_t + \beta_{pT} \cdot HML_t + \beta_{pT} \cdot SMB_t + \beta_{pT} \cdot RMW_t + \beta_{pT} \cdot CMA_t + \beta_{pT} \cdot MOM_t + \varepsilon_{pt}$$

r_{pt} represents the return on the portfolios p in excess of the EURIBOR 3-month return.

$MKTRF_t$ represents the return on the MSCI indices of the corresponding country in excess of the EURIBOR 3-month return.

To calculate the rest of the risk factors, we have followed the method by Fama & French (1993, 2015, 2018). All the relevant data are retrieved from Refinitiv Eikon.

The value factor (HML) is measured based on book value (BV) of equity and market close price of stock which is assumed as book-to-market (B/M) ratio. All the firm are sorted on the B/M ratio. We assume high B/M ratio firm's portfolios minus low B/M ratio firm's portfolios.

The size factor (SMB) is measured based on market capitalization. The firms are sorted on market-cap, and then split into two portfolios: small-cap and big-cap. Size factor is measured as small market-cap minus big market-cap portfolio.

The profitability factor (RMW) is calculated by sorting the stocks by their operating profitability. They are split into low-operating-profitability and high-operating-profitability.

The investment factor (CMA) is calculated by sorting the stocks on their total assets' valuation. Stocks with lower asset valuation are classified as high investment stocks, while those with higher asset valuation are classified as low investment stocks.

The momentum factor (MOM) is calculated as in the QMS portfolios and split into two portfolios based on their momentum. Each stock is ranked based on previous returns of the formation period and top ranked stocks are taken into consideration to construct the winner's portfolio.

In addition, there has been calculated risk factor exposures by estimating the factor exposure of each portfolio by regressing their excess returns against the factor returns of MKTRF, SMB, HML, RMW and CMA. This step helps determine the sensitivity of the portfolio to each of the factors. See appendix 5-0 and 5-1 for sensitivity charts.

6.0 RESULTS

The results obtained in this research paper are extensive with results from 16 QMS strategies and 4 SMA strategies. The QMS portfolios are created by combining four formation periods (6, 12, 24, and 36 weeks) with four holding periods (6, 12, 24 and 36 weeks) and applied to the Nordic market. The SMA portfolios are created by utilizing different Simple Moving Averages (5, 10, 15 and 20 weeks) and applied to the Nordic market. Presenting all our findings for all the portfolios for all the markets (Denmark, Finland, Norway, Sweden and Nordic) would make the thesis crowded and difficult to follow. Hence, portfolios for QMS and SMA are first applied to the Nordic market, then the best performing strategies in the Nordic market (one QMS and one SMA strategy) is then adapted to the country specific markets. This yields a simpler basis for comparison of the markets. When presenting our findings, we will first focus on the Nordic market, and then provide more detailed results for Denmark, Finland, Norway and Sweden.

The Results section presents findings from CAPM, FF3, FF5 and FF6 to attempt to explain the variations in the strategies. Even though we appreciate unique findings regarding them all, the FF5 operates as the main model in the thesis. This is based on prior research by Fama & French (2015) and the idea that FF6 could potentially deliver problematic results due to correlation between the QMS and the factor MOM.

This section starts by presenting summary statistics of the weekly returns of the QMS and SMA strategies for the combined Nordic portfolio. Then, we present the performance analysis for the combined Nordic portfolios. From this analysis we pursue to answer our main research question and find the best performing QMS and SMA strategy in the Nordic portfolio. From there we select one QMS and one SMA that is identified as adaptable for the markets for each country's portfolio. More details about their performance and regressions within each country can be found in Appendix 2-1 to 2-4 and Appendix 3-1 and 3-2. The robustness tests entails evaluation of the strategies on a risk-adjusted basis with the estimation of alpha using the four models of performance measurement: CAPM, FF3, FF5 factor and FF6 models.

6.1 SUMMARY OF STATISTICS (NORDIC)

Table 6-1 and 6-2 presents the summary statistics of the weekly log-return distributions used as the basis for further performance analysis of the strategies we cover in this thesis.

Table 6-1: Summary of Weekly Log Return Distributions for Portfolios with distinct Weekly Holding- and Formation periods, Nordic

Holding Period Formation Period	6 6	12 6	24 6	36 6	6 12	12 12	24 12	36 12	6 24	12 24	24 24	36 24	6 36	12 36	24 36	36 36	MSCI Nordic	EURIBOR 3-Month
Mean	0.001	0.001	0.006	0.004	0.004	0.004	0.011	0.008	0.009	0.009	0.008	0.010	0.010	0.012	0.012	0.012	0.002	0.001
Standard Deviation	0.038	0.067	0.102	0.127	0.140	0.161	0.181	0.179	0.185	0.188	0.198	0.204	0.208	0.207	0.215	0.218	0.029	0.011
Min	-0.206	-0.322	-0.504	-0.634	-0.634	-0.634	-0.634	-0.634	-0.634	-0.634	-0.642	-0.698	-0.719	-0.703	-0.734	-0.706	-0.172	-0.006
Max	0.116	0.210	0.356	0.358	0.358	0.388	0.521	0.449	0.482	0.482	0.554	0.531	0.574	0.590	0.588	0.596	0.070	0.033
Median	0.005	0.008	0.014	0.016	0.012	0.011	0.025	0.022	0.020	0.023	0.024	0.025	0.025	0.023	0.021	0.024	0.005	-0.005

This table shows the summary statistics for the weekly log-returns of the QMS applied to the Nordic market. The number of observations is 174 in each strategy, covering the weekly returns observed between January 2020 and the beginning of March 2023. The sample includes the stocks in the Nordic investable universe as defined in Figure 5.

Table 6-2: Summary of Weekly Log Return Distributions for Portfolios with distinct Simple Moving Averages, Nordic

SMA	5	10	15	20	MSCI Nordic	EURIBOR 3-Month
Mean	0.003	0.005	0.004	0.004	0.002	0.001
Std Dev	0.038	0.034	0.032	0.032	0.029	0.011
Min	-0.195	-0.099	-0.099	-0.099	-0.172	-0.006
Max	0.140	0.141	0.098	0.114	0.070	0.033
Median	0.006	0.005	0.005	0.003	0.005	-0.005

This table shows the summary statistics for the weekly log-returns of the TFS applied to the Nordic market. The number of observations is 174 in each strategy, covering the weekly returns observed between January 2020 and the beginning of March 2023. The sample includes the stocks in the Nordic investable universe as defined in Figure 5.

The research of Jegadeesh & Titman (1993) presented results stating that monthly returns tend to be lower on average the longer the holding period is. Our results for the QMS portfolios, which can be seen in Table 6-1, demonstrate a more random pattern regarding average returns, regardless of the length of holding periods. Thus, we cannot observe a clear pattern in the data. Regardless of holding periods, there seems to be a more consistent pattern when we observe the returns in light of the formation period. The four portfolios with the longest formation periods (36 weeks) all yield more than 1% average weekly returns. When seen in relation to the standard deviation, the same four portfolios generate the highest standard deviation with all four portfolios having standard deviations over 20%. This finding contradicts the findings of Jegadeesh & Titman (1993), which presented almost identical standard deviations across holding and formation periods. Our findings rather show a clear pattern of rising standard deviations when the formation period is increased.

Table 6-2 presents the summary statistics for the SMA strategies. When compared to the findings by Rey (2022), we find similar, but some contradicting patterns. When Rey (2022) compared SMA strategies of 10, 25, 50 and 100 daily observations he found that the SMA length based on a moving average of 10 observations (daily) produced the highest return on average of strategies based on less than SMA(200). In our analysis, we found that the strategy with the highest returns on average was the SMA strategy based on a moving average of 10 observations (weekly). The optimal SMA strategy according to Rey (2022), in terms of average returns, was the SMA(450). Our dataset contains 174 weekly observations during the COVID-19 pandemic, which does not align with testing a SMA(450) strategy. Our findings show that the SMA strategies based on shorter moving averages yield a higher standard deviation without rising returns. When comparing the SMA portfolios to the QMS portfolios, we observe that the majority of the QMS portfolios tend to yield higher returns than most of the SMA portfolios at the cost of an unproportional level of higher risk.

6.2 PERFORMANCE ANALYSIS (NORDIC)

Table 6-3 and 6-4 displays and compares the statistical analysis of the performance and risk profile of the QMS Nordic, TFS Nordic and MSCI Nordic.

Table 6-3: Performance Analysis of QMS, Nordic

Holding Period Formation Period	6 6	12 6	24 6	36 6	6 12	12 12	24 12	36 12	6 24	12 24	24 24	36 24	6 36	12 36	24 36	36 36	MSCI Nordic	EURIBOR 3-Month
Annualized Net Return (%)	2.76	5.05	28.68	18.30	22.62	19.37	56.09	43.44	45.77	44.94	39.16	51.10	53.68	60.19	64.75	60.19	10.53	5.74
Annualized Volatility (%)	27.43	48.56	73.59	91.89	100.68	116.26	130.34	128.93	133.63	135.47	142.59	147.44	150.18	149.11	154.72	156.86	21.05	8.16
Annualized Sharpe Ratio	0.10	0.10	0.39	0.20	0.22	0.17	0.43	0.34	0.34	0.33	0.27	0.35	0.36	0.40	0.42	0.38	0.5000	
Min Net weekly Return (%)	-20.56	-32.16	-50.43	-63.39	-63.39	-63.39	-63.39	-63.39	-63.39	-63.39	-64.16	-69.76	-71.93	-70.32	-73.39	-70.64	-17.19	-0.59
Max Net Weekly Return (%)	11.65	21.03	35.56	35.79	35.79	38.85	52.11	44.85	48.24	48.24	55.39	53.05	57.40	58.96	58.77	59.64	6.95	3.28
CAPM Alpha	-0.05%	0.00%	0.44%	0.24%	0.33%	0.26%	0.97%	0.73%	0.78%	0.76%	0.64%	0.89%	0.93%	1.06%	1.14%	1.06%		
FF3 Alpha	-0.17%	-0.19%	0.10%	-0.12%	-0.06%	-0.17%	0.44%	0.23%	0.29%	0.24%	0.11%	0.33%	0.36%	0.50%	0.57%	0.50%		
FF5 Alpha	-0.07%	-0.02%	0.42%	0.19%	0.28%	0.22%	0.93%	0.68%	0.72%	0.70%	0.59%	0.84%	0.89%	1.01%	1.09%	1.01%		
FF6 Alpha	-0.08%	-0.04%	0.38%	0.15%	0.24%	0.19%	0.89%	0.64%	0.67%	0.66%	0.55%	0.81%	0.85%	0.98%	1.05%	0.97%		
CAPM P-Value	26.83%	67.00%	52.97%	61.39%	70.87%	67.32%	71.27%	74.26%	78.34%	74.66%	76.17%	86.35%	83.72%	82.77%	81.25%	83.95%		
FF3 P-Value	24.07%	63.69%	49.29%	57.31%	65.79%	62.50%	65.09%	67.58%	71.96%	68.33%	70.94%	80.74%	78.28%	77.62%	76.26%	78.37%		
FF5 P-Value	21.08%	57.39%	44.38%	54.21%	63.18%	62.29%	67.54%	69.38%	73.08%	69.79%	71.46%	81.75%	78.89%	77.78%	76.30%	78.90%		
FF6 P-Value	38.83%	76.29%	65.38%	73.37%	83.86%	78.11%	83.85%	87.09%	91.40%	86.00%	85.64%	94.48%	91.06%	90.62%	89.41%	92.32%		

Annualized net return is calculated by multiplying weekly returns by 52 (weeks) and subtracting the transaction costs over the period. For both strategies, the transaction costs are equal to 1 basis point per transaction made in the portfolios. There is no cost for holding a position in the MSCI Nordic. Annualized volatility is calculated by multiplying weekly standard deviation by the square root of 52. Annualized Sharpe ratio equals annualized net returns in excess of the EURIBOR 3-month rate divided by the annualized volatility. We report Min and Max weekly net returns. Portfolio alphas and p-values are given for CAPM, FF3, FF5 and FF6 for hypothesis tests where we test whether weekly returns for QMS and TFS are greater than weekly returns on market index. P-values are computed using cumulative distribution functions (LaMar, 2017).

As discussed in section [6.1] and observed again in Table 6-3, the highest returns are obtained from the portfolios with the longest formation periods. The QMS(H24F12) portfolio is an exception from this pattern, which yields relative high returns with a shorter formation period. The Annualized Volatility shows a pattern where the portfolio is more volatile as the length of the formation period increases. The Sharpe ratio is a measure of risk-adjusted return which assesses how well an investment or portfolio compensates for the level of risk taken. A higher Sharpe ratio indicates better risk-adjusted performance, conversely a lower ratio suggests poorer risk-adjusted performance (Sharpe, 1994). Christie (2005, p. 4) refers to the sharpe ratio as "ubiquitous in the finance industry… arguably the most widely used general measure of fund manager performance". As presented in Table 6-3, the Sharpe ratios increase on average as the length of formation periods increases. Even in the outliers, the QMS(H24F6) and QMS(H24F12), we can see the tendency of the patterns of a higher sharpe ratio as the formation period increases. Even though we see the difference in risk-adjusted return for the QMS portfolios, they all fail to beat the MSCI Nordic Countries Index which yields a Sharpe Ratio of 0.5. The majority of the QMS portfolios manages to produce positive alphas, but as we can see from the presented p-values, no QMS portfolio is able to statistically significantly yield returns greater than the market.

Assogbavi & Leonard (2008) concludes that their results are also inconsistent with no clear patterns, but rather tendencies. Assogbavi & Leonard (2008) argues that their results indicate that the highest returns can be achieved through a 9 month formation period and a 9 month holding period. Due to our difference in the size of the dataset we are not able to identify the same tendencies. Even though they still discuss the possibility that seasonality effects are more important than length of any formation periods, which brings in the importance of EMH. In our dataset we do identify tendencies that the longer the formation- and holding periods tend to generate the highest returns.

Table 6-4: Performance Analysis of SMA, Nordic

SMA	5	10	15	20	MSCI Nordic	EURIBOR 3-Month
Annualized Net Return (%)	16.226	26.532	22.230	18.445	10.526	5.737
Annualized Volatility (%)	27.658	24.782	22.776	23.123	21.051	8.157
Annualized Sharpe Ratio	0.587	1.071	0.976	0.798	0.500	
Min Net Weekly Return (%)	-19.467	-9.861	-9.879	-9.913	-17.190	-0.588
Max Net Weekly Return (%)	14.044	14.115	9.785	11.449	6.950	3.280
CAPM Alpha	0.505%	0.498%	0.439%	0.472%		
FF3 Alpha	0.504%	0.496%	0.440%	0.474%		
FF5 Alpha	0.504%	0.497%	0.437%	0.470%		
FF6 Alpha	0.504%	0.496%	0.437%	0.470%		
CAPM P-Value	75.382%	48.516%	88.041%	84.893%		
FF3 P-Value	73.390%	51.172%	95.367%	78.540%		
FF5 P-Value	87.951%	27.622%	92.695%	81.317%		
FF6 P-Value	91.103%	54.375%	97.291%	74.333%		

Annualized net return is calculated by multiplying weekly returns by 52 (weeks) and subtracting the transaction costs over the period. For both strategies, the transaction costs are equal to 1 basis point per transaction made in the portfolios. There is no cost for holding a position in the MSCI Nordic. Annualized volatility is calculated by multiplying weekly standard deviation by the square root of 52. Annualized Sharpe ratio equals annualized net returns in excess of the EURIBOR 3-month rate divided by the annualized volatility. We report Min and Max weekly net returns. Portfolio alphas and p-values are given for CAPM, FF3, FF5 and FF6 for hypothesis tests where we test whether weekly returns for QMS and TFS are greater than weekly returns on market index.P-values are computed using cumulative distribution functions (LaMar, 2017)

From Table 6-4 we observed positive returns for all the SMA portfolios. All the SMA portfolios generate risk-adjusted returns that are greater than the MSCI Nordic Index Sharpe ratio of 0.5. We observed that the SMA(10) generated the highest risk-adjusted return with a Sharpe ratio of 1.07. All the portfolios generate positive alphas across CAPM and the Fama-French models. Most importantly, we observe that they all still fail to statistically significantly fail to beat the MSCI Nordic Countries Index with all p-values greater than our significance level of 5%.

To summarize the Tables 6-3 and 6-4, the majority of Nordic QMS and SMA portfolios manage to produce positive alphas in the Nordic market, but fail to statistically significantly outperform the market with p-values higher than our significance level of 5%. We can therefore conclude that for the Nordic Market, we cannot discard our null hypothesis for any of the strategies in the Nordics.

6.3 QMS(H6F36) vs. SMA(5) PERFORMANCE ANALYSIS (COUNTRIES)

Although neither the QMS nor the SMA portfolios exhibit statistically significant results to outperform the MSCI Nordic Countries Index, the situation differs when considering the country-specific portfolios. Therefore, we showcase results for the portfolios of each country to provide a basis for a stronger and more engaging discussion. We provide results for the QMS(H6F36) and SMA(5) strategies. This is justified by the fact that SMA(5) is the only SMA strategy that generates a valid statistically significant p-value for the FF5 regression across all countries. The QMS portfolios on the other hand, do not yield such valid results. Therefore, we select the QMS(H6F36) as it provides the most suitable basis for a comparison to showcase the results, given that the periods have an identical match. Each country's portfolio competes against its corresponding MSCI Country specific index.

Table 6-5: Performance Analysis of the TFS SMA(5)

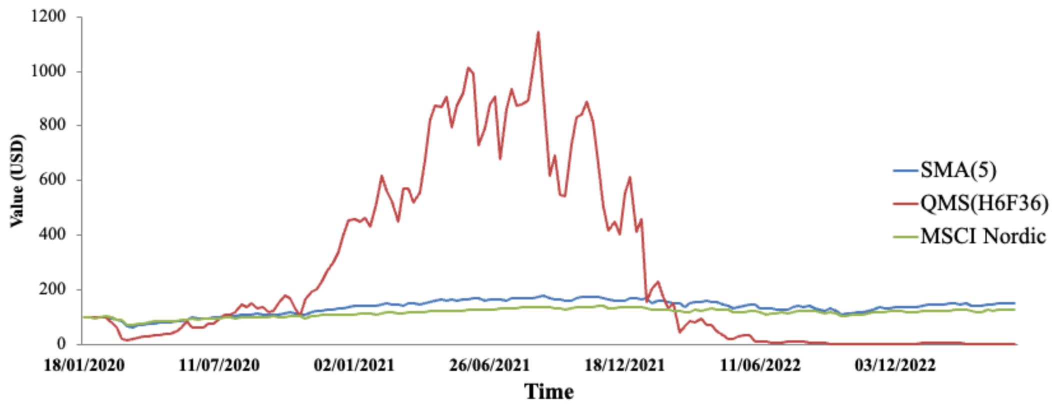
SMA(5)	Denmark	Finland	Norway	Sweden	MSCI Nordic	EURIBOR 3-Month
Annualized Net Return (%)	13.745	12.611	19.053	19.221	10.526	5.737
Annualized Volatility (%)	22.158	26.255	34.045	34.532	21.051	8.157
Annualized Sharpe Ratio	0.620	0.480	0.560	0.557	0.500	
Min Net Weekly Return (%)	-15.539	-19.247	-22.075	-21.418	-17.190	-0.588
Max Net Weekly Return (%)	10.951	12.669	17.689	17.950	6.950	3.280
Median Net Weekly Return (%)	0.629	0.494	0.492	0.905		
CAPM Alpha	0.155%	0.120%	0.255%	0.243%		
FF3 Alpha	0.075%	0.009%	0.178%	0.094%		
FF5 Alpha	0.142%	0.163%	0.180%	0.282%		
FF6 Alpha	0.070%	0.083%	0.084%	0.166%		
CAPM P-Value	4.716%	3.583%	11.174%	3.297%		
FF3 P-Value	4.174%	3.549%	13.401%	2.209%		
FF5 P-Value	1.870%	0.840%	1.074%	1.119%		
FF6 P-Value	68.892%	38.845%	51.303%	65.655%		

Table 6-6: Performance Analysis of the QMS(H6F36)

QMS(H6F36)	Denmark	Finland	Norway	Sweden	MSCI Nordic	EURIBOR 3-Month
Annualized Net Return (%)	74.981	26.432	56.071	19.032	10.526	5.737
Annualized Volatility (%)	130.436	138.778	114.421	158.927	21.051	8.157
Annualized Sharpe Ratio	0.575	0.190	0.490	0.120	0.500	
Min Net weekly Return (%)	-52.163	-79.939	-68.950	-72.410	-17.190	-0.588
Max Net Weekly Return (%)	53.876	64.718	67.110	62.336	6.950	3.280
Median Net Weekly Return (%)	1.772	0.947	0.961	2.490		
CAPM Alpha	1.331%	0.441%	0.908%	0.257%		
FF3 Alpha	0.822%	0.040%	0.195%	-0.212%		
FF5 Alpha	1.339%	0.357%	0.814%	0.193%		
FF6 Alpha	1.295%	0.338%	0.745%	0.187%		
CAPM P-Value	72.183%	90.581%	25.187%	78.375%		
FF3 P-Value	71.572%	97.074%	18.913%	78.559%		
FF5 P-Value	60.849%	95.439%	20.646%	71.808%		
FF6 P-Value	78.160%	88.327%	39.731%	74.328%		

As presented in Table 6-5 and table 6-6, the SMA(5) delivers positive alphas with statistically significant returns with p-values below the significance level 5% for the Fama French 5 Factor model. All SMA(5) country specific portfolios deliver a higher risk-adjusted return than the corresponding MSCI country specific index. As mentioned, the case is worse for the QMS(H6F36) and the rest of the QMS strategies, which despite delivering positive alphas, does not deliver statistically significant returns from any of the regression analysis'. In short, the results regarding QMS portfolios, we cannot conclude with anything else than that the test results are inconclusive. But, from the results we have so far, the SMA(5) results can be trusted on a 5% significance level, which beats the market indices in all countries, except for the Nordic market portfolio.

Figure 9. Value of 100USD Invested in the Nordic Market



This figure presents the cumulative value for the QMS(H6F36), SMA(5) and the MSCI Nordic Index (Jan 2020-May 2023). The other charts for all markets are in appendices 2-1 to 2-4.

Figure 9 illustrates the effect of compounding 100 USD invested over the COVID-19 period. The advantages of QMS(H6F36) lead to an impressive spread when compared to the passive benchmark, making the profits of the strategy in excess of four times the MSCI Nordic Countries Index. An interesting point to make about the extreme return of the QMS(H6F36) in the year 2021 is in line with findings from Cooper et al., (2005), which states that "... the profits to momentum strategies depend critically on the state of the market". They also find that a momentum portfolio with a 6-month holding period is only profitable following periods of market gains. In our data, 2021 was a good year for the Nordic markets, indicating a clear bullish trend in the market, before it declined in 2022. When the market trend changed at the start of 2022, the QMS portfolios dropped at a significant rate, which can argue to be in line with prior research on the field.

7.0 CONCLUSION

The main goal of this thesis is to investigate if any of the selected strategies would outperform the market during the COVID-19 pandemic with clear market trends. We applied the long-only Quantitative Momentum Strategy inspired by Jegadeesh & Titman (1993) and Gray & Vogel (2016) to the combined Nordic market and compared its performance with the MSCI Nordic Index during the period from January 10th 2020 to May 5th 2023. We did the same comparison for the much criticized Simple Moving Average Trend-following strategy inspired by Rey (2022) across four nordic markets and one combined Nordic market. To conclude whether the various portfolios outperform the market, we needed the strategies to generate a positive alpha and to establish a p-value less than the significance level at 5%.

For the QMS portfolios, our results did yield positive returns for any of the markets regardless of the formation and holding periods investigated. The estimated alphas are in the majority positive for the QMS portfolios, yet the returns are not statistically significant. Thus, we cannot conclude that the QMS portfolios beat the country specific markets or the combined Nordic portfolio. Therefore, the findings for the QMS in this paper do not allow us to distinguish conclusions the one or the other way. Yet, we observe similar tendencies as Cooper et al., (2005) regarding momentum portfolios' tendency to outperform the market during times with a clear market trend in a bullish/bearish direction. In addition, there are probably other explanations for these results than what is captured by the models utilized in this paper. The authors of this paper request further research on the topic to establish more robust results on the subject in the Nordic markets.

The Trend-Following Strategies with SMA strategy tells a more appealing story. The SMA(5) generated positive alphas across all markets (except the Nordic) with statistically significant p-values below 5% for the Fama-French Five factor model. We based the SMA portfolios at Rey’s (2022) Single Moving Average portfolios using different sizes in the MA length due to restrictions regarding our dataset and number of observations. Even though Rey (2022) goes further in the research regarding different MA techniques, we argue that we observe similar results based on our analysis’. Rey (2022) discovers that the SMA(10) beats the SMA(25, 50, 100 and 150). Our results also showcase the highest average returns for the SMA with 10 observations. We end up analyzing the SMA(5) further in the country portfolios due to statistical significance across markets. We therefore conclude that with our results and prior research, the SMA(5) beats the market in all countries, and can therefore discard the null hypothesis.

The thesis started by discussing Jegadeesh & Titman (1993) which presented empirical evidence that a strategy of buying past winners and selling past losers would in fact yield significant abnormal returns. The empirical results disproves the EMH that was first introduced by Fama & French (1970). Since then, the EMH has been challenged throughout history as in Jensen (1978), Fuertes et al., (2009), Da et al., (2014) and Gray & Vogel (2016) for various momentum strategies, and Costa el al., (2015), Papailias & Thomakos (2015) and Rey (2022) using various moving averages strategies.

In closing, the only conclusion we really can draw is that the SMA(5) was profitable during the sample period we tested. However, based on the analysis, we claim that the strategy yields consistent results which suggests that it may be a profitable strategy for the future as well. We believe that in periods with similarities as the COVID-19 period, investors will suffer from irrationality leading to under-overreaction to news, which is consistent with the findings of Barberis et al., (1998). Even though there is reason to believe that automatized strategies will continue to grow, we believe that it is likely that the "career risk" premium will persist. On the other hand, if an investor seeks return with low/no exposure towards the market, the SMA(5) is not likely to be a top selection. With risk exposure towards the market in mind, investors will enjoy the profitability and significant outperformance of the Nordic countries with a SMA(5) strategy during similar market conditions as the COVID-19 pandemic.

8.0 LIMITATIONS & FURTHER RESEARCH

Every research thesis in the field of finance demonstrates the ability to engage in constructive and critical analysis of its own findings while acknowledging inherent limitations and seeking possibilities for improvement. With this objective in mind, we shall now proceed to provide a concise overview of the potential limitations within this thesis and explore alternative methodologies that could have yielded more robust results. Furthermore, we will leverage our experience to present recommendations for future research that have the potential to support or undermine the robustness of our conclusions.

In order to obtain robust results for the QMS portfolios we encourage future research on the topic to obtain a dataset with a greater number of observations (daily). The number of observations was the biggest difference in this thesis' analysis' and prior research on the topic. We believe this would secure robust results in the future. For the SMA, it would be interesting to compare various MA strategies in the Nordic markets. With inspiration from Rey (2022), it would be possible to create various strategies with different approaches, for instance by comparing SMA, EMA and MA crossover strategies to each other, and the market. We would also encourage incorporating a more detailed transaction cost and a cost of holding the MSCI indices in order make the results more applicable to real world scenarios. We would also encourage to include a classic buy-and-hold strategy for comparison. This thesis contains only two types of strategies that can be categorized to be in the same trading strategy group. We would encourage future research to include more strategies, for instance, breakout strategies, swing trading strategies and seasonal trading strategies.

With these self-critical observations above, we urge our descendants to discover their own opinion on the research thesis, since there are many aspects within the topic that are still to be explored in the future research literature.

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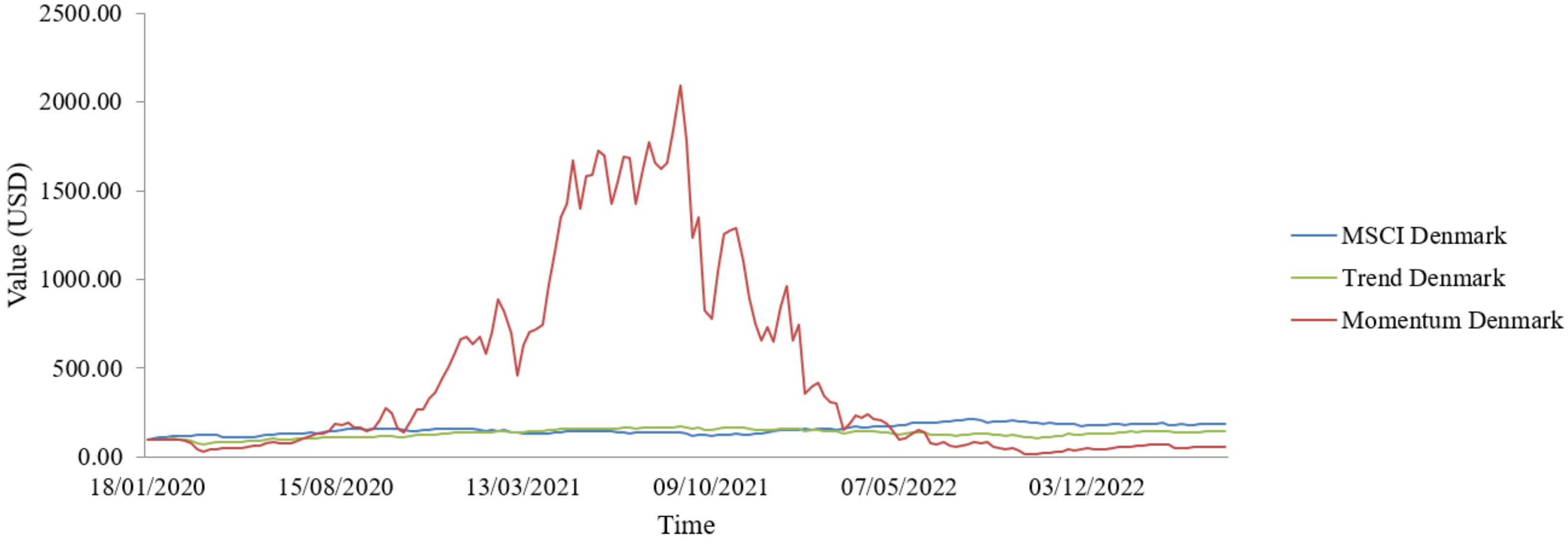
Appendix 1-0: **Sector variations in the Investable Universe**

Sector	Denmark	Finland	Norway	Sweden	Nordic
Aerospace & Defense			1	1	2
Air Freight & Logistics	1		1		2
Automobile Components		1		1	2
Automobiles				1	1
Banks	19	4	11	3	37
Beverages	3	2			5
Biotechnology	4		2	3	9
Broadline Retail		4	1		5
Building Products	1	1		5	7
Capital Markets	1	6	1	4	12
Chemicals	4	1	4	1	10
Commercial Services & Supplies	1	4	1	3	9
Communications Equipment	1	1		2	4
Construction & Engineering	2	2	3	5	12
Construction Materials	1				1
Consumer Staples Distribution & Retail		1		1	2
Containers & Packaging	1	1	1	1	4
Diversified Telecommunication Services		1	1	1	3
Electric Utilities	1	1			2
Electrical Equipment	3	2	1	1	7
Electronic Equipment, Instruments & Components		5	1	4	10
Energy Equipment & Services			9		9
Entertainment		2	1	2	5
Financial Services	2			4	6
Food Products	3	2	9	1	15
Ground Transportation	1				1
Health Care Equipment & Supplies	4	2	1	4	11
Health Care Providers & Services		3			3
Health Care Technology	1	1		1	3
Hotels, Restaurants & Leisure	3	2		3	8
Household Durables	4	4		1	9
Household Products		1		1	2
Independent Power and Renewable Electricity Producers			1		1
Industrial Conglomerates		1	3	3	7
Insurance	3	1	3		7
Interactive Media & Services	1		1	1	3
IT Services	3	5	2	1	11
Leisure Products		2		2	4
Life Sciences Tools & Services	2	1		1	4
Machinery	3	7	4	12	26
Marine Transportation	3		10		13
Media	2	3	1	1	7
Metals & Mining		2	1	2	5
Oil, Gas & Consumable Fuels	1	1	13		15
Paper & Forest Products	1	3	1	2	7
Passenger Airlines		1	1		2
Pharmaceuticals	3	1		1	5
Professional Services		4	2	1	7
Real Estate Management & Development	6	2	4	11	23
Semiconductors & Semiconductor Equipment			2		2
Software	3	7	2	3	15
Specialty Retail	1	2		1	4
Technology Hardware, Storage & Peripherals	1				1
Textiles, Apparel & Luxury Goods	2	2			4
Tobacco	1				1
Trading Companies & Distributors	2	1		3	6
Transportation Infrastructure	1				1
Wireless Telecommunication Services				1	1
Nordic	**100**	**100**	**100**	**100**	**400**

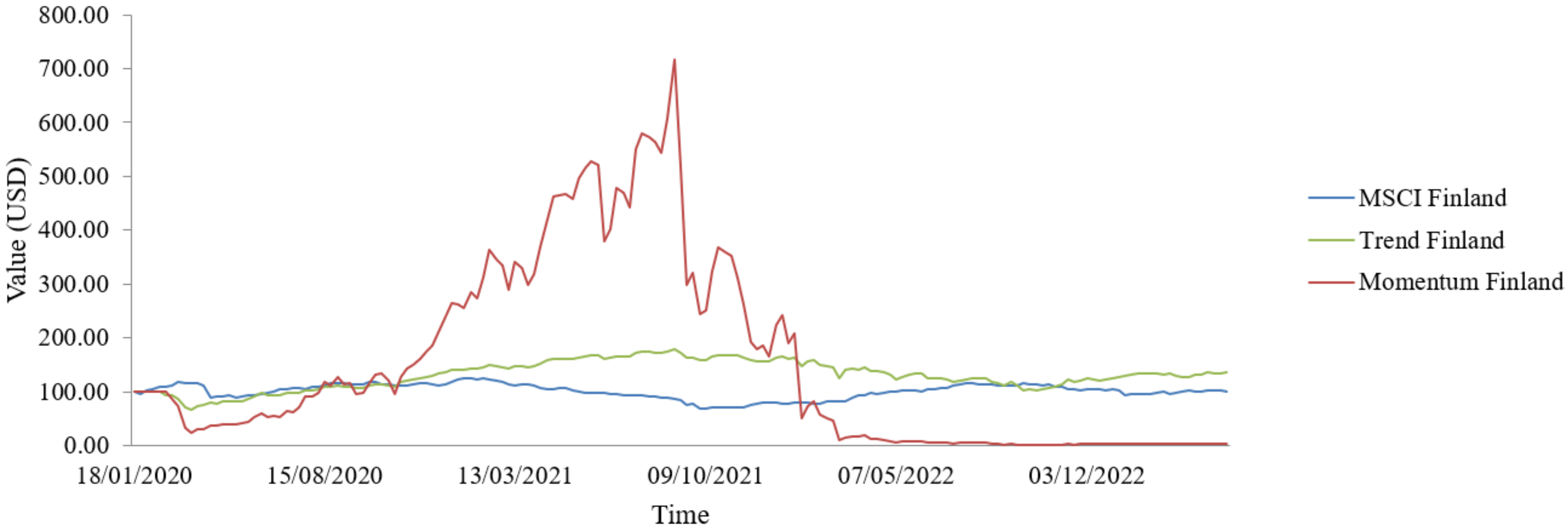
This table shows the variations of sectors within each country of the investable universe.

Appendix 2-1: **Value of 100 USD Invested in the Danish Market**



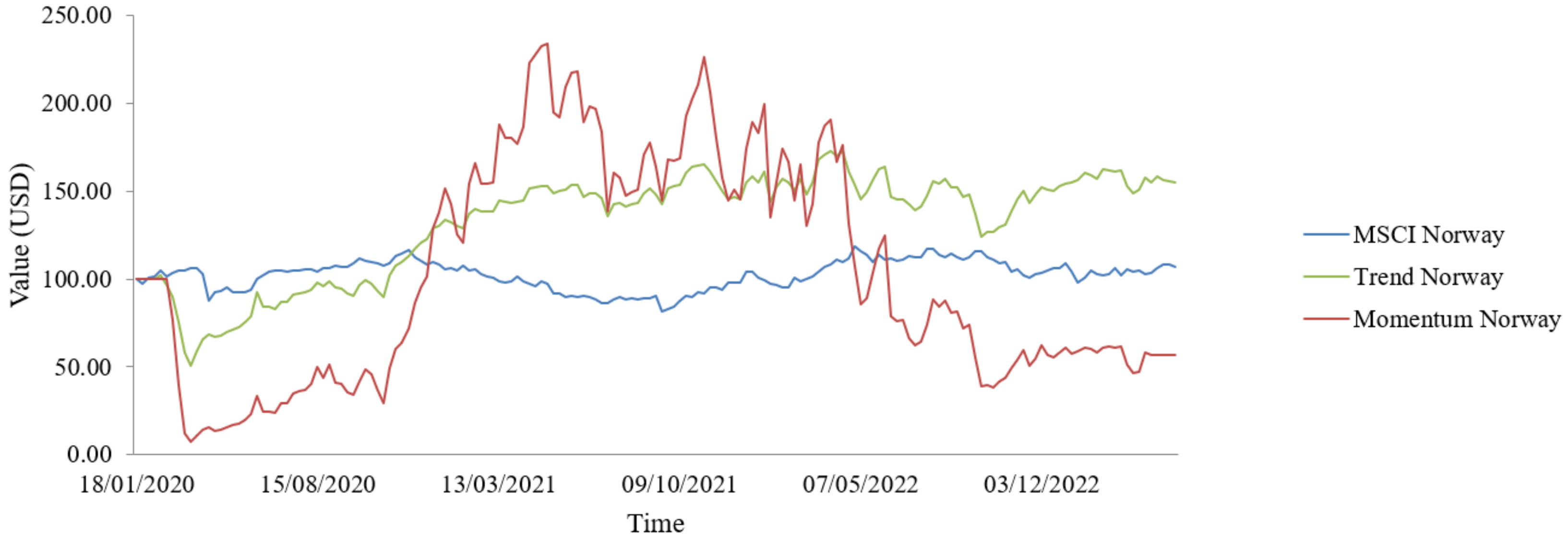
This figure presents the cumulative value for the QMS(H6F36), SMA(5) and the MSCI Denmark Index (Jan 2020-May 2023).

Appendix 2-2: **Value of 100 USD Invested in the Finnish Market**



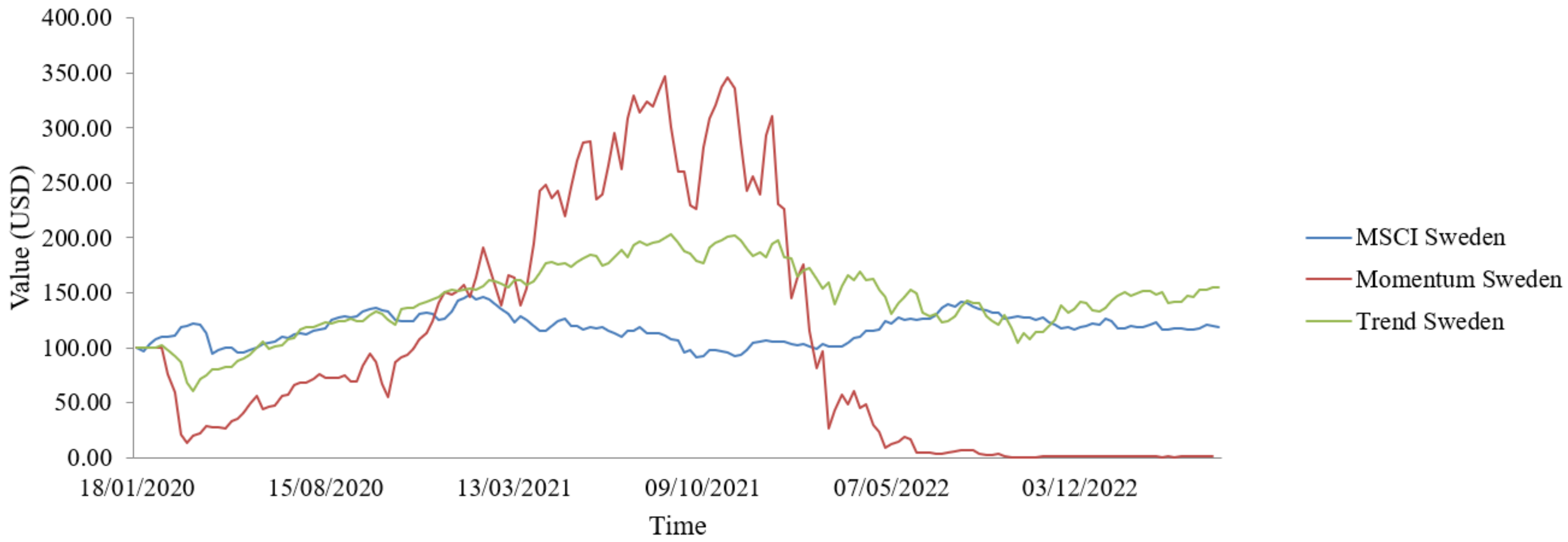
This figure presents the cumulative value for the QMS(H6F36), SMA(5) and the MSCI Finland Index (Jan 2020-May 2023).

Appendix 2-3: **Value of 100 USD Invested in the Norwegian Market**



This figure presents the cumulative value for the QMS(H6F36), SMA(5) and the MSCI Norway Index (Jan 2020-May 2023).

Appendix 2-4: **Value of 100 USD Invested in the Swedish Market**



This figure presents the cumulative value for the QMS(H6F36), SMA(5) and the MSCI Sweden Index (Jan 2020-May 2023).

Appendix 3-1: **Asset Pricing Coefficient Estimates for the QMS(H6F36)**

Nordic, QMS(H6F36), Weekly

	Alpha	MKTRF	HML	SMB	RMW	CMA	MOM	N	R-squared	P-value
CAPM	1.06%	0.001						174	0.02%	83.95%
T-statistic	0.634	0.203								
FF3	0.50%	0.002	-0.008	0.068				174	2.14%	78.37%
T-statistic	0.292	0.275	-0.316	1.765						
FF5	1.01%	0.002	-0.331	-3.454	0.900	0.456		174	1.74%	78.90%
T-statistic	0.601	0.268	-0.107	-1.305	0.572	0.161				
FF6	0.97%	0.001	0.092	-3.372	1.066	0.949	0.227	174	2.14%	92.32%
T-statistic	0.576	0.097	0.029	-1.272	0.672	0.329	0.818			

Denmark, QMS(H6F36), Weekly

	Alpha	MKTRF	HML	SMB	RMW	CMA	MOM	N	R-squared	P-value
CAPM	1.33%	0.002						174	0.07%	72.18%
T-statistic	0.960	0.357								
FF3	0.82%	0.002	0.008	0.067				174	2.63%	71.57%
T-statistic	0.574	0.365	0.359	2.074						
FF5	1.34%	0.003	-2.173	-3.111	-0.089	-0.844		174	3.47%	60.85%
T-statistic	0.969	0.513	-0.851	-1.425	-0.068	-0.363				
FF6	1.30%	0.001	-1.700	-3.019	0.097	-0.291	0.254	174	4.19%	78.16%
T-statistic	0.938	0.278	-0.657	-1.383	0.074	-0.123	1.113			

Finland, QMS(H6F36), Weekly

	Alpha	MKTRF	HML	SMB	RMW	CMA	MOM	N	R-squared	P-value
CAPM	0.44%	-0.001						174	0.01%	90.58%
T-statistic	0.299	-0.119								
FF3	0.04%	0.000	-0.013	0.047				174	1.50%	97.07%
T-statistic	0.026	-0.037	-0.525	1.359						
FF5	0.36%	0.000	0.174	-2.625	1.350	0.480		174	1.58%	95.44%
T-statistic	0.240	-0.057	0.063	-1.119	0.968	0.192				
FF6	0.34%	-0.001	0.380	-2.585	1.431	0.721	0.111	174	1.70%	88.33%
T-statistic	0.227	-0.147	0.136	-1.098	1.016	0.281	0.450			

Norway, QMS(H6F36), Weekly

	Alpha	MKTRF	HML	SMB	RMW	CMA	MOM	N	R-squared	P-value
CAPM	0.91%	0.005						174	0.77%	25.19%
T-statistic	0.746	1.150								
FF3	0.19%	0.006	-0.012	0.088				174	7.47%	18.91%
T-statistic	0.158	1.319	-0.637	3.195						
FF5	0.81%	0.006	-0.254	-2.342	1.361	-0.311		174	3.52%	20.65%
T-statistic	0.668	1.268	-0.113	-1.218	1.191	-0.152				
FF6	0.74%	0.004	0.488	-2.198	1.652	0.556	0.398	174	5.80%	39.73%
T-statistic	0.617	0.849	0.216	-1.153	1.447	1.447	1.999			

Sweden, QMS(H6F36), Weekly										
	Alpha	MKTRF	HML	SMB	RMW	CMA	MOM	N	R-squared	P-value
CAPM	0.26%	0.002						174	0.04%	78.37%
T-statistic	0.152	0.275								
FF3	-0.21%	0.002	0.007	0.059				174	1.38%	78.56%
T-statistic	-0.121	0.273	0.263	1.487						
FF5	0.19%	0.002	-1.403	-3.800	1.393	1.051		174	2.14%	71.81%
T-statistic	0.114	0.362	-0.448	-1.419	0.875	0.368				
FF6	0.19%	0.002	-1.338	-3.787	1.418	112.700	0.035	174	2.15%	74.33%
T-statistic	0.110	0.328	-0.420	-1.409	0.881	0.385	0.124			

Appendix 3-2: **Asset Pricing Coefficient Estimates for the SMA(5)**

Nordic, SMA(5), Weekly	Alpha	MKTRF	HML	SMB	RMW	CMA	MOM	N	R-squared	P-value
CAPM	5.05%	-0.001						174	0.06%	75.38%
T-statistic	63.321	-0.314								
FF3	5.04%	-0.001	0.005	0.006				174	0.18%	73.39%
T-statistic	60.480	-0.341	0.355	0.342						
FF5	5.04%	0.000	0.318	-0.452	0.283	-1.894		174	3.24%	87.95%
T-statistic	63.379	-0.152	0.216	-0.360	0.379	-1.414				
FF6	5.04%	0.000	0.273	-0.461	0.266	-1.946	-0.024	174	3.26%	91.10%
T-statistic	63.173	-0.112	0.183	-0.365	0.352	-1.416	-0.179			

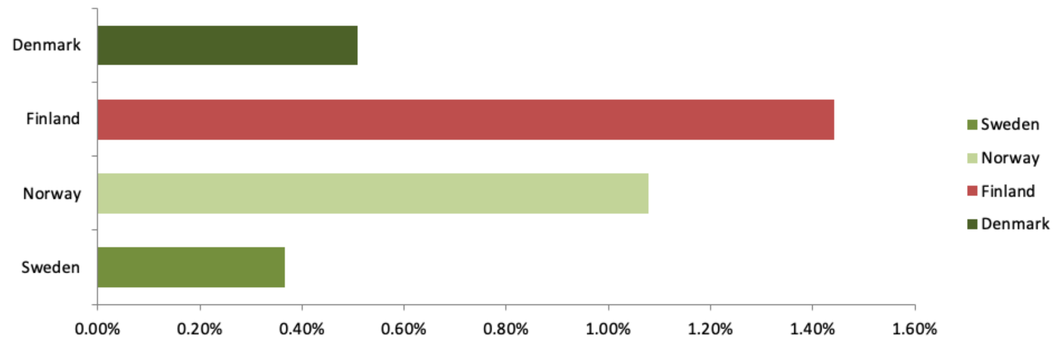
Denmark, SMA(5), Weekly	Alpha	MKTRF	HML	SMB	RMW	CMA	MOM	N	R-squared	P-value
CAPM	0.16%	0.282						174	6.74%	0.06%
T-statistic	0.654	3.504								
FF3	0.08%	0.304	-0.005	0.007				174	9.05%	0.03%
T-statistic	0.314	3.663	-1.378	1.330						
FF5	0.15%	0.311	-1.044	0.047	0.118	-0.660		174	13.20%	0.01%
T-statistic	0.637	3.917	-2.372	0.125	0.532	-1.658				
FF6	0.06%	0.151	-0.240	0.161	0.423	0.192	0.402	174	68.61%	0.24%
T-statistic	0.441	3.084	-0.889	0.711	3.131	0.783	17.068			

Finland, SMA(5), Weekly	Alpha	MKTRF	HML	SMB	RMW	CMA	MOM	N	R-squared	P-value
CAPM	0.13%	0.322						174	6.44%	0.08%
T-statistic	0.448	3.422								
FF3	0.01%	0.345	-0.005	0.013				174	9.44%	0.05%
T-statistic	0.047	3.561	-1.136	1.923						
FF5	0.18%	0.349	-1.468	-0.375	-0.808	-1.183		174	22.82%	0.01%
T-statistic	0.678	3.986	-3.024	-0.909	-3.297	-2.696				
FF6	0.08%	0.171	-0.574	-0.249	-0.469	-0.237	0.446	174	72.84%	0.16%
T-statistic	0.512	3.215	-1.958	-1.012	-3.187	-0.888	17.435			

Norway, SMA(5), Weekly	Alpha	MKTRF	HML	SMB	RMW	CMA	MOM	N	R-squared	P-value
CAPM	0.25%	0.002						174	1.48%	11.17%
T-statistic	0.682	1.599								
FF3	0.18%	0.002	0.002	0.011				174	2.34%	13.40%
T-statistic	0.457	1.506	0.334	1.259						
FF5	0.18%	0.003	-1.303	-1.782	0.973	-1.201		174	32.07%	1.07%
T-statistic	0.572	2.580	-2.238	-3.582	3.290	-2.263				
FF6	0.08%	0.000	-0.270	-1.581	1.379	0.006	0.554	174	78.55%	51.30%
T-statistic	0.474	0.656	-0.812	-5.635	8.203	0.020	18.909			

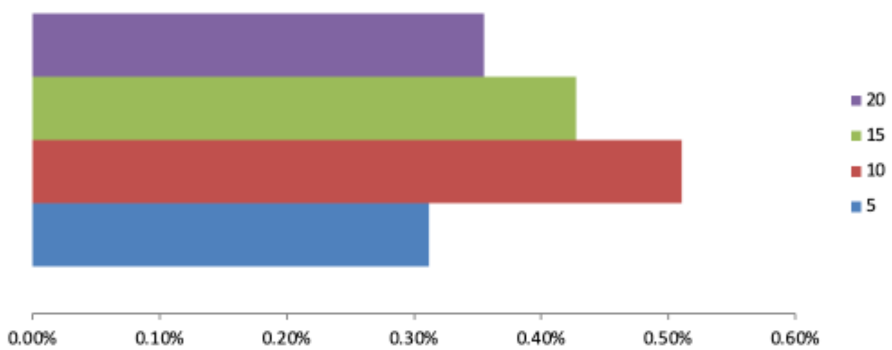
				Sweden, SMA(5), Weekly						
	Alpha	MKTRF	HML	SMB	RMW	CMA	MOM	N	R-squared	P-value
CAPM	0.24%	0.003						174	2.65%	3.30%
T-statistic	0.656	2.150								
FF3	0.09%	0.003	-0.013	0.013				174	7.18%	2.21%
T-statistic	0.250	2.311	-2.138	1.531						
FF5	0.28%	0.003	-1.620	-0.301	-0.709	-1.241		174	12.53%	1.12%
T-statistic	0.792	2.566	-2.461	-0.535	-2.120	-2.068				
FF6	0.17%	0.000	-0.374	-0.059	-0.219	0.216	0.669	174	80.71%	65.65%
T-statistic	0.991	0.445	-1.188	-0.221	-1.381	0.749	24.148			

Appendix 4-1: **Net Return by Country, QMS(H6F36)**



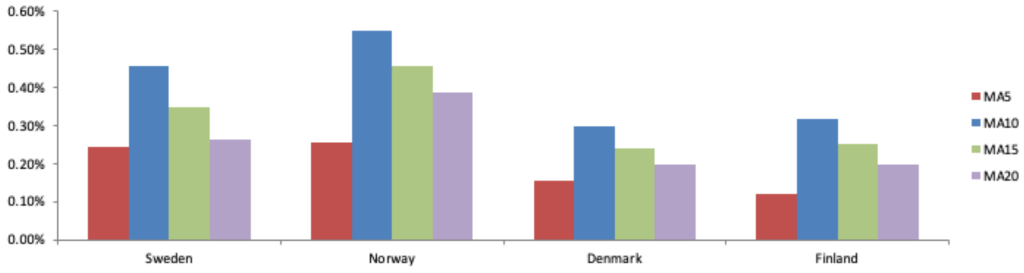
This table shows the net return by country of the QMS (H6F36)

Appendix 4-2: **Net Return by SMA(20, 15, 10, 5)**



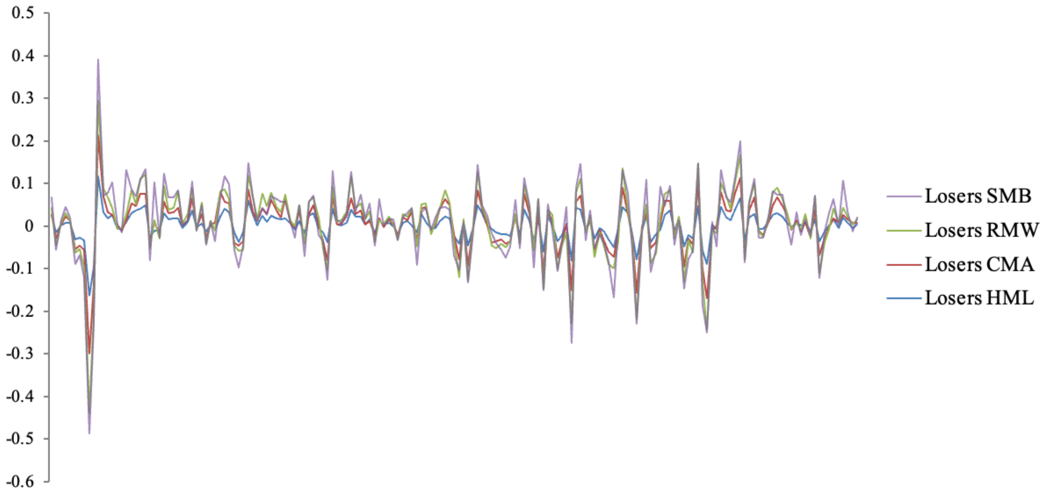
This table shows the net return by country of the SMA(20, 15, 10, 5)

Appendix 4-3: **Alpha by Country, SMA strategies, all countries**



This figure shows the alpha of the SMA(20, 15, 10, 5) in each country

Appendix 5-0: **Sensitivity of FF5 loser portfolio**



Appendix 5-1: **Sensitivity of FF5 winner portfolio**