TIME-VARYING FACTOR PREMIA IN NORDIC EQUITIES MARKET

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ABSTRACT

<table>
<tr><td colspan="2">Author
Juho Laine</td></tr>
<tr><td colspan="2">Title
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Factor premia is a reward for taking on all of the risk in Nordic capital markets. Many important characteristics of factor investing have already been established, such as the significance of factor timing and existence of global factor premia in multiple asset classes. However, the reasons for time variation of factor excess returns, are poorly understood. Therefore, the aim of this thesis is to determine whether the performance of the selected factors is consistent across Nordic stock markets and time, as well as which variables may be explaining the time-varying performance differences in factor performance.

In this thesis it is explored whether factor diversification is more beneficial than country diversification. In addition, one of this thesis’ research sections examines the commonalities between factors and uses the return dispersion to assess potential correlations between them. This way it is possible to see, how market integration has developed through time and which factors show more similarities in performance between Nordic countries. The study uses factor excess returns as a metric to calculate whether the factors have been significant in the Nordic stock market. The findings of this study are useful for investors who want to gain a better understanding of the Nordic stock market’s dynamics and variables that explain higher returns on specific investing strategies.

During the study period, the results show that betting against beta, momentum, and quality factor strategies produced excess returns in the Nordics. All factor premia are cyclical, but momentum is the most stable over time producing consistent positive returns. The cross-section of factor excess returns does not appear to be explained by macroeconomic variables. The only variables that can be generalized to have an impact in the Nordics are real exchange rates, interest rate environment, and VIX. Market integration between Nordic countries is found to increase during good times, while market integration decreases during bad times. Factor diversification also outperforms country diversification by a significant margin.</td></tr>
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Tiivistelmä

Faktoripreemio on palkkio riskin ottamisesta pohjoismaisilla osakemarkkinoilla. Monia tärkeitä faktorisijoittamisen osa-alueita on jo tutkittu, kuten faktoriajoituksen merkityksellisyyttä ja globaalin faktoripreemion olemassaoloa monissa omaisuusluokissa. Kuitenkin faktoriylituottojen ajallisen vaihtelun syistä tiedetään vain vähän. Siksi tämän tutkimuksen tarkoituksena on selvittää, onko valittujen faktoreiden suorituskyky yhdenmukaista pohjoismaisilla osakemarkkinoilla ja ajan kuluessa, sekä mitkä muuttujat voivat selittää ajallisia vaihteluita faktorien suorituskyvyssä.

Tässä työssä tutkitaan myös, onko faktorihajauttaminen hyödyllisempää kuin maiden välinen hajauttaminen. Lisäksi yksi tämän työn tutkimusosioista tutkii faktoreiden yhtenäisyyttä. Sillä pyritään selvittämään, kuinka markkinaintegraatio on kehittynyt ajan kuluessa ja mitkä faktorit osoittavat enemmän samanlaisuuksia omassa suorituskyvyssään. Tutkimus käyttää faktoriylituottoja mittaamaan sitä, onko faktorien suorituskyky ollut merkitsevää. Tämän tutkimuksen tulokset ovat hyödyllisiä sijoittajille, jotka haluavat saada paremman käsityksen pohjoismaisten osakemarkkinoiden dynamiikasta ja muuttujista, jotka selittävät tiettyjen sijoittamisstrategioiden korkeampia tuottoja.

Tulokset osoittavat, että tutkimusperiodin aikana, betting against beta-, momentum-, ja laatufaktoristrategiat tuottavat ylituottoja pohjoismaissa. Kaikkien faktoreiden preemio on ajallisesti vaihtelevaa, mutta momentumin preemio on ollut kaikista vakainta ajan kuluessa tuottaen jatkuvia positiivisia tuottoja. Faktoriylituottojen poikkileikkausta ei pystytä selittämään makroekonomisten muuttujien avulla. Ainoat muuttujat, joilla voidaan yleistää olevan vaikutusta pohjoismaissa ovat reaaliset vaihtokurssit, korkotaso, ja volatiliteetti-indeksi. Markkinaintegraatio pohjoismaiden välillä todetaan lisääntyvän hyvinä aikoina, kun taas integraatio vähenee vaikeina aikoina. Faktorihajauttaminen myös tuottaa merkittävästi enemmän hajauttamisetuja kuin maiden välinen hajauttaminen.

Asiasanat
Ajallisesti muuttuja faktoripreemio, faktorihajauttaminen, Pohjoismaiset osakemarkkinat,

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CONTENTS

LIST OF TABLES AND FIGURES

1 INTRODUCTION

Investors always try to achieve a balance between good profitability and risk level that feels comfortable for them. The idea behind factor theory is that equities earn risk premiums because they face factor risks at the same time. Risk premium is simply a compensation for accepting a certain amount of risk. Academics have been extensively researching these factor premiums for about 30 years and during the past three decades hundreds of factors have been proposed yielding returns that exceed the market. The object of this study is to investigate the reasons for factor excess returns and how the factor performance varies over time.

The first risk factor proposed was the market risk factor of the capital asset pricing model (CAPM) (Treynor 1961, Sharpe 1964, Lintner 1965, and Mossin 1966). According to the CAPM, the return on investment is a function of its exposure to the market factor beta. The CAPM is applied in an efficient market because, according to the CAPM, information is costless and accessible to all investors. Thus, the theory of efficient market hypothesis states that active management is a loser's game and investors cannot beat the market. For example, Jensen (1978) has confirmed this theory of efficient market hypothesis and thus the absence of abnormal returns. However, in certain situations some arising evidence of inconsistencies were found (Jensen 1978).

After the development of the CAPM, there was not much development in factor investment research for the next 30 years until more advanced technology finally made it possible to conduct more rigorous tests, find inconsistencies in prevailing theories, and develop a functional factor model that could capture its effects. One of the most fundamental discoveries in the field of factor investing is the famous three-factor model of Fama and French (1993). These Fama and French stock market factors include the overall market factor as well as factors related to the size and book-to-market share of the company. This three-factor model is based on anomalies which fight against the efficient market hypothesis. It was found that additional risk premiums can be collected in more inefficient markets where information is costly and not available to many investors like in small market capitalizations.

Fama and French (1993) three-factor model is a perfect example of a multi-factor model, as opposed to single-factor model it considers multiple factors influencing asset prices at the same time. Multifactor models are found to perform better than single factor models. For example, Asness, Ilmanen, Israel, and Moskowitz (2015) have found that significant diversification benefits exist when investing in multiple factors simultaneously.

When applying the three-factor model Fama and French (1993) found a negative correlation between firm size and expected return, and a positive correlation between book-to-market ratio and expected return. Still, most importantly these three factors seem to explain the average returns on stocks. Over time the three-factor model is extended to include other factors such as momentum (Carhart 1997) and profitability and investment (Fama and French 2016). Fama and French (2016) argue that the five-factor model typically performs better than the three-factor model. Other well-functioning risk factors that have been found to explain returns include volatility (Ang, Hodrick, Xing, and Zhang 2006) and liquidity (Pástor and Stambaugh 2003). For example, Pástor and Stambaugh (2003) conclude that market-wide liquidity appears to be a state variable that is important for pricing common stocks. This practically means that stocks that are more sensitive to aggregate liquidity have substantially higher expected returns (Pástor and Stambaugh 2003).

Some of the factors have been raised to a higher value by researchers and professionals, as there is robust academic research and a clear economic rationale for them (Asness et al. 2015). These factors include value, momentum, and low volatility. In addition, Asness et al. (2015) state that an effective factor investment strategy uses leverage, shorting and derivatives to provide large and necessary diversification benefits to investors.

The purpose of this thesis is to review the literature on various risk factors and to conduct a complete study of the significance of the chosen factors in the Nordic stock market. The following are my research questions. The first question is how factor performance in Nordic stock markets varies over time. The hypothesis is that factor premia should change over time and behave differently at various points in the macro cycle. For example, a counter-cyclical trend is expected to be seen in the risk premia for market, size, and value factors and pro-cyclical trend for momentum. The second question is how rational explanations explain the variation in factor performance in different Nordic stock markets? The hypothesis based on previous literature is that rational reasons should only play small or no role at all in time-variation of factor performance. The final question is about market integration, and it asks how commonality in factor performance varies over the sample period. The hypothesis is that return dispersion should follow a business-cycle trend, with lower levels of return dispersion during expansions and higher levels during recession.

This master’s thesis is structured as follows. Chapter two deals with theoretical background on factor theory, various risk factors and time variation of factor performance. Chapter three presents data, portfolio construction and research methods. The data used includes all the stocks in the Nordic stock markets excluding Icelandic companies and the methodology will use for example return dispersion and OLS regression. Chapter four discusses the empirical findings of different tests. It will provide an answer to the question which factors have historically provided significant excess returns in the Nordic stock market. In addition, empirical findings will exhibit how the factor performance has evolved during the last 30 years in the Nordic stock market and which variables could explain this development. Also, chapter four will examine how similarly the factors have performed in the Nordic countries and what could explain these differences in performance. Part five discusses the final conclusions.

2 THEORETICAL FRAMEWORK

2.1 Development of factor investing

The first capital asset pricing model, developed by Jack Treynor (1961), began the advancement of factor theory in the 1960s. The capital asset pricing model is the most well-known and oldest stock return model, and it has served as the foundation for modern financial theory. Sharpe (1966) has created portfolio valuation models based on or closely related to this asset pricing model. According to CAPM, assets are risky because they are more volatile than the market so they must offer higher risk premiums to their investors. CAPM is a one-factor model that only considers market returns, while multifactor models take into account a variety of variables that affect asset prices. Expected returns seem to be best explained by multifactor models (Chan and Chen 1991). Sharpe (1966) demonstrated that mutual fund performance can be measured using a simple yet theoretically acceptable measure that takes into account both average return and risk. The concept of factor theory is similar to that of Sharpe, in which assets receive risk premiums while simultaneously facing factor risks.

Factor investing is one of the most fashionable concepts in the investment and asset management world today. Asness, Moskowitz, and Pedersen (2013) are among the most influential factor investing researchers of the last decade, finding a consistent value as well as a momentum return premium across eight different market areas and asset classes, as well as a clear common factor structure among their returns. The financial crisis of 2008–2009 marked a watershed moment in the field of factor investing research. Due to the crisis, it got a lot of attention. Taking a closer look at what happened during the crisis can explain why there has been an increase in interest. Many volatile assets saw their prices fall, and most asset groups saw their prices plummet all at once. Cash and long-term US treasuries were the only assets in the US that increased in value during the crisis. As a result of the crisis, it became clear that the majority of assets are made up of factor exposures, which, as in the case of financial crisis, become a reality during volatile times. Overall, factor theory notes that assets bear several risks, which are referred to as factors, and that investors must be compensated for bearing all the risk, which is referred to as factor risk premium. Essentially, risk premiums are generated by the risk exposure of assets, rather than by the assets themselves.

The aim of all investors is to create indexes or funds outside of conventional market capitalization, so systematic investment strategies are proposed. Investors that invest in the index purchase a large number of large company stocks. However, it may not be the most sensible course of action. Bootstrap simulations, on the other hand, indicate that only a few funds achieve benchmark-adjusted expected returns adequate to cover active management costs (Fama and French 2010). Investment through factors is a strategy or model for investing that aims to isolate, as far as possible, the investment in specific factors or sources of profitability that different asset classes have. A quality of an asset, such as a stock, that can lead to a higher risk-adjusted return than the market or an index is known as an investment factor. The various factors are the characteristics or collection of characteristics that drive the profitability and risk of an investment portfolio with demonstrated positive outcomes in terms of higher risk-adjusted returns than conventional approaches. Investing based on investment factors is a more scientific and systematic method of doing so. It necessitates that the investor selects the stocks carefully and understands which characteristics distinguish winners.

2.2 CAPM

The underlying factor risks determine the risk premiums of assets. There have been hundreds of different factor risks discovered, but even more will be discovered in the future. CAPM is the most well-known, oldest, and most important. The CAPM states that the market return is the return exceeding the return of T-bills and it is the only factor driving all asset returns. The CAPM, on the other hand, is a very simplified form, but it is a crucial starting point for factor investing theory. Furthermore, in the factor theory, this market excess return is usually considered the first factor.

Jack Treynor (1961), William Sharpe (1964), John Lintner (1965) and Jan Mossin (1966) designed the CAPM. It is based on Harry Markowitz's (1952) diversification and mean-variance utility principles. When CAPM was first implemented in the 1960s, it completely changed the way people thought about asset risk. Prior to CAPM, an asset's risk behavior was only perceived in isolation. For the first time, CAPM acknowledged that asset risk is more dependent on how an asset moves in relation to the market as a whole and to other assets.

Despite the fact that CAPM was a ground-breaking idea that is still commonly used by finance practitioners today, it has been shown in many empirical studies that it does not hold. A static CAPM, it is widely agreed, cannot adequately explain the cross-section of average stock returns (Jagannathan and Wang 1996). Despite this failure, CAPM has given asset owners a greater understanding of risk premiums and risk management. Furthermore, the CAPM's basic rule remains true. This rule states that risk premiums are determined by the underlying factors of assets, and risk premiums are compensation for losses during difficult times.

According to the theory, there is only one factor, and that factor is the market portfolio, which holds each stock in proportion to its market capitalization. To put it another way, the investors do not own an individual asset but rather the factor. The factor can be optimally created by diversifying all idiosyncratic risk by keeping a large number of assets. Idiosyncratic risk is not compensated with a risk premium so investors should always diversify it away.

Diversification is the most important principle in CAPM theory, and it is still valid today. Diversification means that as certain assets fall in value, other assets rise in value, mitigating potential losses. As a result, every investor has the most diversified portfolio, which is the market portfolio, which is the best one. The mean-variance efficient portfolio becomes a market factor in equilibrium since all will have the same mean-variance efficient portfolio, which is the best investment portfolio that all investors could have.

In CAPM, the equilibrium principle is also crucial. The term equilibrium refers to when investor demand and supply for assets are equal. Because of this equilibrium, the market portfolio has a risk premium, and this equilibrium also prevents the risk premium from disappearing. As a result, the market factor is referred to as a systematic risk factor since it cannot be diversified away and affects all assets.

Despite the fact that all investors own the same market portfolio, they will keep it in different proportions based on their capital allocation line position. As a result, each investor has their own optimal factor risk exposure. Nonetheless, the average investor would hold 100% of his or her money in the market portfolio which is the point where the capital allocation line intersects the mean-variance frontier. As a result, depending on their risk tolerance, investors are exposed to less or more market factor.

Capital allocation line for individual investor is called capital market line in equilibrium. The market risk premium is included in the calculation for the capital market line:

$$E(r_m) - r_f = \bar{\gamma}\sigma_m^2$$

The market risk premium, or the expected return on the market above the risk-free rate, is $E(r_m) - r_f$. $\bar{\gamma}$ is the average investor's risk aversion, and σ_m^2 is the market portfolio's volatility. According to the CAPM, as the market becomes more volatile, the market's expected return rises as stock prices decline. During the financial crisis, when stock prices plummeted and volatility increased, this phenomenon occurred. Variances irritate investors, but expected returns entice them. Therefore, they have mean-variance preferences according to the CAPM. This also makes the market risk premium proportional to market variance. Furthermore, the market risk premium rises as the average investor becomes more risk averse to variance.

The factor exposure of an individual asset is used to calculate the risk of that asset. A high exposure to a factor with a positive risk premium results in a high expected return on an asset. To put it another way, risk is the same as factor exposure. The standard beta pricing relationship, formally known as the security market line, is another pricing relationship in the CAPM. The risk-free return is r_f, and the return of stock i is r_i, according to the security market line. The risk premium of any stock is proportional to the market risk premium, according to the security market line:

$$E(r_i) - r_f = \beta_i(E(r_m) - r_f)$$

The risk premium for a single stock is determined by the stock's beta value. The beta of an asset is high when the co-movement of the stock with the market portfolio is high, and the beta of the asset is low when the co-movement is low. The advantages of diversification are the focus of mean-variance investing, and high betas imply low diversification benefits. If an investor has a well-diversified portfolio, assets with high betas or assets that grow in tandem with the market and vice versa, would be unappealing.

The CAPM's risk premium is a reward for how an asset pays off in tough times, according to another way of thinking about the security market line relationship. High beta assets are risky, and investors will only hold them if the anticipated return on investment is high. Low beta assets, on the other hand, pay off in difficult times, resulting in a low risk premium. Poor returns are classified as low market portfolio returns in the CAPM.

The CAPM is calculated based on a set of very strong assumptions. The first assumption is that investors only have financial wealth. Another assumption is that investors have a mean-variance utility. The next assumption is that investors have a single investment horizon of one year. The next assumption is that investors' preferences are all the same. The following premise is that no taxation or transaction costs exist. Related to this assumption is also the next assumption, because when people move prices, the market is likely to be illiquid and there is a lot of trading frictions. So, the next assumption is that individual investors are price takers.

The final assumption is that all investors have free access to the information. However, data processing and collection are not free, and not all investors have access to all information. Several deviations from the CAPM, for example, are highest in equities with small market capitalization and equities trading in illiquid markets where information is not effectively disclosed. In conclusion, it is reasonable to expect that when the CAPM's assumptions are violated, additional risk premiums will arise. One explanation why modern economists no longer believe markets are efficient in the original form given by the CAPM is the expectation of perfect information.

2.3 Factor theory fundamentals

In the CAPM, bad times mean poor returns in a market portfolio. Instead, bad times are characterized more broadly in multifactor models. The first multifactor model, known as Arbitrage Pricing Theory (APT), was developed by Stephen Ross in 1976. The name of the theory comes from the word arbitrage, since factors, including the single market component in the CAPM, cannot be arbitraged or diversified away. Despite the fact that the CAPM associates bad times exclusively with low market portfolio returns, each element in the multifactor model has its own definition of bad times. Typically, bad times are characterized as periods of low economic growth, but there are also other indicators that investors are experiencing difficulties. Volatility is one of them, and it is an important factor because many assets perform poorly when volatility is large.

The idea of a pricing kernel is used in the multiple factor asset pricing approach to capture the dynamic meaning of poor times when many variables are taken into account. The stochastic discount factor is another name for the pricing kernel (Rosenberg and Engle 2002). The stochastic discount factor is a predictor of difficult times, and difficult times are determined by a variety of variables and states of nature. When a single stochastic discount factor encompasses all difficult times, different meanings of difficult times with multiple variables can be caught very effectively. Another benefit of using the pricing kernel is that the world is nonlinear, while the CAPM limits the stochastic discount factor to be linear.

However, the idea behind using pricing kernels is the same as in the CAPM, since assets that pay off in hard times are valuable to hold in the multifactor model. As a result, these assets' prices are high, and the expected return is low. Multiple factors in the stochastic discount factor give rise to a multi-beta relation for an asset's risk premium, just as the CAPM gives rise to assets having betas with respect to the market, where $\beta_{i,K}$ is the beta of asset i relative to factor k and $E(f_K)$ is the risk premium of factor k:

$$E(r_i) = r_f + \beta_{i,1}E(f_1) + \beta_{i,2}E(f_2) + \cdots + \beta_{i,K}E(f_K)$$

The fundamental concepts of multifactor models are very similar to those of the CAPM. Diversification works, according to the first premise. A factor's tradeable version diversifies away idiosyncratic risk. The second principle is that for each factor risk, each investor has their own optimum exposure. The market is held by the average investor, according to the third principle. The fourth principle is that, assuming no arbitrage or equilibrium, risk premiums exist for each factor. The fifth principle notes that an asset's risk is determined by the asset's factor exposures. The final idea is that assets that pay off in difficult times are appealing and have a low risk premium.

Economists today do not believe in a fully efficient market. Grossman and Stiglitz (1980) created a model that makes the market nearly efficient. Prices, according to their model, serve as a means of communicating knowledge from the informed to the uninformed. Grossman and Stiglitz's near-efficient markets are a good match for Ross' (1976) APT multifactor risk framework. Active managers and arbitrageurs according to Ross' multifactor model, push the expected return on assets to a value that is compatible with the risk-reward trade-off. Factors, in their purest form, pose a risk that cannot be removed, and investors must be compensated for taking on that risk. The efficient market hypothesis is still widely tested in the literature, despite the modern notion that the market is not completely efficient. Talented investors may identify areas of inefficiency where active management is most effective in the Grossman-Stiglitz sense.

In recent decades, the efficient market theory has been refined to fix many of the CAPM's original flaws, such as incomplete information and transaction costs, financing, and agency costs. What is important to remember is that inefficiency can take two forms: rational and behavioral. In the rational form, high returns compensate for losses in tough times. This is the pricing kernel approach to asset pricing. In behavioral form, high expected returns are caused by agents' under- or overreaction to news or events. DeBondt and Thaler (1985), for example, looked at how overreaction of agents influences stock prices. Furthermore, Daniel, Hirshleifer, and Subrahmanyam (1998) investigated the hypothesis of under- and overreactions in the stock market based on two well-known psychological biases. Investors' overconfidence in the accuracy of private information and skewed self-attribution, which results in asymmetric shifts in investor confidence as a function of investment success, are examples of these biases. The persistence of a behavioral bias, when there are obstacles to capital entry, is a stronger foundation for investment, at least for slow-moving asset owners. The behavioral bias can be exploited for a long time if there is a systemic barrier to entry. Some risk premiums have rational explanations such as volatility, while others have behavioral explanations, such as momentum, while some have a mix of rational and behavioral explanations, such as value/growth investing. In general, the investor does not care if the rationale for risk premiums is rational or behavioral, the more critical question is whether the investor varies from the typical investor facing rational or behavioral constraints and if the source of return is expected to persist in the future at least in the short term.

During the financial crisis, many volatile investments experienced similar disastrous outcome. This is consistent with the multifactor model, which states that multiple asset groups are affected by the same factors. In contrast to the rejection of financial risk theory, which has been claimed by some opponents, the prevalence of returns in the face of these factor risks is clear evidence in favor of multi-factor risk models. Risk premiums are paid on assets to compensate for their vulnerability to the underlying risk factors. Long-term asset risk premiums are high to compensate for poor returns in tough times. Some critics contend that the events of 2008 show a failure of diversification. The value of diversification, on the other hand, has not gone anywhere, and it is also important to remember the built-in factor risks, or the fact that assets are made up of factor risks. In the world of investing, diversification is known as the only "free lunch". Stocks with low factor exposure perform similarly to stocks with high factor exposure, so the long-short portfolio hedges the risk associated with the factors while just marginally lowering the expected return (Herskovic, Moreira, and Muir 2019). To put it another way, Herskovic et al. (2019) demonstrate that risk factors can be hedged for little to no cost. Factor exposure can and does change over time, resulting in time-varying correlations and highlighting the importance of understanding the true factor drivers of risk premiums.

Risk premiums are influenced by a variety of factors. Several studies have stressed the advantages of allocating to alternative factor premiums, such as equities' value and momentum premiums or fixed income's term spread (Ilmanen and Kizer 2012). Ilmanen (2011), discovered empirical evidence that highlights the advantages of factor diversification over asset class diversification. The economic theory behind the factors can be either rational, with high long-term returns compensating for low short-term returns, or behavioral, with factor risk premiums resulting from agent actions that arbitrage cannot remove. Risk factors, according to factor theory, have an effect on assets. Risk factors offer extra premiums to investors to reimburse them for losses during bad times.

Factors can be divided into two categories. The first category contains macro-factors, also known as fundamental factors. Macro-factors include economic growth, inflation, volatility, productivity, and demographic risks. The market factor of the capital asset pricing model and the value strategy factor are examples of investment style or dynamic factors. The CAPM factor is a market portfolio, and it can be exchanged such as low-cost index funds, exchange-traded funds, and equity futures. However, macro-factors such as inflation and economic growth are seldom tradeable, with the exception of volatility, and therefore dynamic factors have the distinct advantage of being simple to incorporate into an investor's portfolio. The Fama and French (1993) tradeable multifactor model is the most well-known example of dynamic factors. Dynamic factors are also known as style and investment factors and they are often referred to as smart beta or alternative beta, but only by practitioners. The investment world's lingo is complicated, and it is made even more so by the need to advertise attractively. Remember that beta refers to a stock, portfolio or fund's volatility or systematic risk in comparison to the entire market. The sum of market beta and alternative risk premiums or investment factors would be the smart beta. Factor investing is frequently mistaken for smart beta. The main distinction between factor investing and smart beta is that smart beta is usually used to describe long-only factor investing. While some research advocate for a long-short approach to factor investing (Ilmanen and Kizer 2012), others advocate for a long-only approach. Long positions account for nearly all of the size, 60% of the value, and half of the momentum returns (Israel and Moskowitz 2013). Israel and Moskowitz (2013) also show that the long and short sides of the portfolio return contributions of both value and momentum strategies are roughly equal, and that long-only value and momentum portfolios continue to generate abnormal returns.

Three factors explain asset returns according to the Fama-French (1993) model. In the 1970s, Robert Merton (1973), Stephen Ross (1976), and others developed a theoretical multifactor model framework, but it took another two decades for research to show that factors other than the market are empirically significant. So Fama and French did not discover these effects; instead, they presented a model to capture them. When two new factors, SMB and HML, emerge alongside the conventional CAPM market factor, two additional factors provide a size and a value/growth effect:

$$E(r_i) = r_f + \beta_{i,MKT}E(r_m - r_f) + \beta_{i,SMB}E(SMB) + \beta_{i,HML}E(HML)$$

Stocks with a high exposure to the market factor, i.e., stocks with a high beta $\beta_{i,MKT}$, appear to perform poorly when the market is performing poorly. The CAPM predicts that stocks with a high beta would have a higher average return than a market portfolio in the long run, allowing investors to cover losses during bad times, which the CAPM describes as times of low market returns. SMB, which represents the differential returns of small stocks minus big stocks, is one of the factors in the Fama-French model, in addition to the market factor. The terms small and big refer to the market capitalization of the shares. SMB is intended to demonstrate that small enterprises perform better than large corporations. The HML factor, which equals the returns on high book-to-market value shares minus the returns on low book-to-market value shares, is the second factor in the Fama-French model. Prices can, however, be normalized using methods other than book value. Fama and French's SMB and HML factors are built into factor-mimicking portfolios. These factors are long-short portfolios and take positions away from the market portfolio. A security led by a manager who wants to buy companies that trade below their fundamental value, such as book value, has a positive HML beta $\beta_{i,HML}$ in the Fama-French model. The Fama-French model increases the risk premium of the security to account for its value because HML is designed to earn a positive risk premium because it buys high book-to-market shares that are high return value stocks and sells low book-to-market shares that are low return growth shares. The expected return of a growth firm is lower relative to the CAPM since the HML beta is now negative, indicating that the growth firm is no longer a value stock but rather a growth stock with a lower return. This occurs for example in the case of a growing business that has expanded rapidly through acquisitions. The Fama-French model prices growth and value stocks in relation to the market. The SMB and HML betas in the Fama-French model are centered around zero. Both the CAPM and Fama-French models presume constant betas. Empirical evidence, on the other hand, shows that the exposure of certain assets to systematic factors varies over time and increases, especially during hard times. As a result, factor risks indicate a period of difficulty for the investor. The three-factor model failed to explain the cross-sectional variation in the returns of portfolios sorted by momentum, prompting the development of the four-factor model (Fama and French 1996). Carhart (1997) added momentum to the three-factor model, making it a four-factor model, and Fama and French (2017) added profitability and investment factors, making it a five-factor model. Three-, four- and five-factor regressions are widely used in a variety of applications, including portfolio performance evaluation (Fama and French 2010). The five-factor model's greatest flaw is that it cannot account for the low average return on small stocks, which behave like returns of businesses that invest heavily despite low profitability (Fama and French 2015).

Low consumption growth, catastrophes, or long-term risks define an equity risk premium, which is a reward for bearing losses in bad times. Theoretically, equity risk premiums are predictable, but statistically, predictability is difficult to identify, while equity volatility is far more predictable. In terms of stock returns, the decade of the 2000s was a disaster. By the end of the decade, the $ 1 invested in equities at the start of the decade will have only risen to $ 1.05. Over the long term, equities have had a high risk premium compared to bonds and cash, despite their poor performance during the lost decade. Over time, there has been a large equity premium over bonds, but stocks have also been much more volatile. Will there be a high equity premium in the future? To find an answer to this issue, it must first be determined what factors account for equity return performance and volatility, as well as whether these risk factors will continue to have an impact in the future. These risk factors are mostly related to market anomalies and trading frictions.

Value, momentum, size, low volatility, and quality are the most important investment factors. The term value factor refers to an investor's attempt to make a fundamental investment in a low-cost business. Consistent with rational pricing, a high BE/ME indicates persistently low earnings, whereas a low BE/ME indicates good earnings (Fama and French 1995). The momentum factor looks for companies that have better short-term relative behavior than others. Value premium, or the higher average return on value stocks compared to growth stocks, as well as momentum, have been observed in international returns by Asness, Moskowitz, and Pedersen (2013), for example. Eun, Lai, de Roon, and Zhang (2010) also estimated the monthly size, value, and momentum factors for the period July 1993 to December 2010. Size factor means that investor invests in companies with small market capitalizations. While Israel and Moskowitz (2013) point out that this relationship is not robust for momentum in other sample periods, they show that value and momentum returns are inversely related to the size of securities over the period studied. Israel and Moskowitz (2013) also looked at the relationship between size, value, and momentum profitability, as well as aggregate trading costs and institutional investment over time, but found little evidence that these strategies' returns differ with either variable. Low volatility factor means that investor invests in low volatility companies. When investing in businesses that have a strong competitive position in the industry they operate in, as well as a strong financial position, the quality aspect comes into play. In other words, investors look for businesses with strong financials.

Stambaugh and Yuan (2017) use a factor pricing approach to anomalies and find that a four-factor model that involves two mispricing factors in addition to market and size accommodates several anomalies for the years 1967 to 2013. The q-factor model captures the Fama-French (2015-2018) 5- and 6-factor models in spanning tests, while the q^5 model captures the Stambaugh-Yuan (2017) model (Hou, Mo, Xue, and Zhang 2019). When new factors are created, the current literature has systematically attempted to assess their contribution to a benchmark model, usually by estimating and evaluating the alpha of new factor regression onto existing factors (Fama and French 2018). Other factors worth mentioning include Fama and French's (2006) profitability and investment factors, growth factor, dividend factor, liquidity factor, carry factor and the downside risk factor of Ang, Chen, and Xing (2006). Average stock returns in North America, Europe, Asia-Pacific are increasing in lockstep with the book-to-market ratio (B/M) and profitability and are negatively correlated with investment, with Japan's average return to B/M ratio being particularly high, but average returns have little to do with profitability or investment (Fama and French 2017).

The term growth factor refers to when investors invest in businesses that have a high potential for business expansion, resulting in the company's size growing. Dividend factor means that investors invest in high dividend yield companies. Acharya and Pedersen (2005) have looked into the importance of liquidity in asset pricing. Liquidity variation is a risk priced in the stock market, according to Acharya and Pedersen (2005). Koch, Ruenzi, and Starks (2016) investigated the demand side sources of significant liquidity commonality among stocks driven by institutional ownership level. Koch et al. (2016) discovered that equities with a high mutual fund ownership have about twice as big co-movements in liquidity as equities with a low mutual fund ownership by concentrating on the correlated trading of mutual funds. Global carry returns have been documented by Koijen, Moskowitz, Pedersen, and Vrugt (2018).

One of the most recent factor investing studies is by Hou, Xue, and Zhang (2020), who attempted to reproduce all of the anomalies and measure how well they performed. According to Hou et al. (2020), 65 percent of the 452 anomalies, including 96 percent of the trading frictions group, was unable to pass the single test hurdle with an absolute t-value of 1.96. When using a critical value of three, Hou et al. (2020) discovered that 85 percent of anomalies are insignificant. In order to prevent data mining, Harvey, Liu, and Zhu (2016) recommend that the statistical significance value should be increased. When the backtest excludes illiquid microcaps, which are described as the lowest 2% of the market in terms of market cap, Hou et al. (2019) found that 64% of the factors are unable to produce statistically significant alpha. Feng, Giglio, and Xiu (2020) provide a framework for systematically evaluating the contribution of individual factors to existing factors and conducting appropriate statistical conclusions in this high-dimensional environment. The literature has recently begun to make progress in integrating machine learning with equilibrium asset pricing (Feng et al. 2020), and this remains a promising area for future study.

2.4 Size factor

The first factor, in the Fama-French model, in addition to the market factor, is SMB, which refers to the differential returns of small stocks minus big stocks, with small and big simply referring to the market capitalization of stocks. For example, based on the median size, Eun et al. (2010), divided their size-ranked portfolios into small and big categories. The market capitalization of the stock is commonly used to calculate the size effect. The SMB factor was created to capture small businesses' outperformance as opposed to larger businesses. The size effect, according to Chan and Chen (1991), is due to the distressed-firm factor in returns and expected returns.

The size effect was discovered by Banz (1981), and Reinganum (1981) with similar findings, and the size effect indicated that when stocks' betas are adjusted, small stocks outperform larger stocks. Smaller companies, on average, had higher risk adjusted returns than larger firms, according to Banz (1981). There was also evidence that the mean of daily abnormal return distributions in January was higher than in the other eleven months, and that the relationship between abnormal returns and size was always negative and more pronounced in January than in any other month, even in years when large firms received higher risk-adjusted returns than small firms on average (Keim 1983). In other words, the size effect was higher in January, according to Keim (1983). Since no substantial size effect has been identified since the mid-1980s, the past tense is appropriate. In addition, Fama and French (2012) found no evidence of a size premium in recent international results. During their study period, Fama and French (2012) found no size premium in any area. When controlling for quality, Asness, Frazzini, Israel, Moskowitz, and Pedersen (2018) looked at the size effect. In comparison to Fama and French (2012), Asness et al. (2018) discovered that managing a firm's quality or its opposite, junk, eliminates the size premium challenge. Interestingly, larger companies are more costly and control for quality, which is a required prerequisite for returns of the size effect (Asness et al. 2018). Furthermore, Stambaugh and Yuan's (2017) size factor shows a small-firm premium that is nearly double the normal estimates.

There are two answers to the absence of the size effect, in addition to the results of Asness et al. (2018). The first thought is that Banz's (1981) size effect could not have occurred at all, and that Banz (1981) and Reinganum's (1981) discovery was pure chance. This point is backed by a study by Harvey, Liu, and Zhu (2016), who found that using normal statistical significance cut-offs in asset pricing tests was a major mistake in the past because it allowed for eventual data mining. As a result, previously discovered factors may have been misrepresented as statistically significant.

Another possibility is that the size effect occurred, but that cautious, committed investors, acting in reaction to press reports of the discovery, drove up the price of small business stock until the effect vanished. Schwert (2003), for example, argued that after the papers highlighting the size effect were written, the effect would seem to have diminished or vanished. McLean and Pontiff (2016) have used an out-of-sample approach in their analysis of anomalies, and the findings indicate a drop in the performance of the found anomalies after publication, which is consistent with statistical bias. Portfolio returns are 26 percent lower out-of-sample and 58 percent lower after publication, according to McLean and Pontiff (2016). In other words, McLean and Pontiff (2016) claim that after a stock market anomaly is published, it becomes less anomalous. In this light, size does not deserve to be a systematic factor in the Fama-French model and should be eliminated. Smaller stocks, on the other hand, have higher returns on average than larger stocks. As a result of the weak size effect, the asset owner should avoid preferring small stocks solely for the sake of a higher risk-adjusted return.

2.5 Value factor

A good example of an investment style factor is the value strategy. The price-to-book ratio is commonly used to determine the value of a stock. It is known as the ratio of a security's current share price to its book value. The market-to-book ratio is another name for this ratio. Asness and Frazzini (2013) demonstrate that the HML construction of Fama and French (1993), which uses lagged market prices in BE/ME calculations, implicitly induces positive covariance with momentum. When constructing an HML factor, which they call the HML devil, or HML-d for short, Asness and Frazzini (2013) suggest using the most recent, last month's price to measure the BE/ME ratio in order to analyze the value effect separately from the momentum. The following is a statistical description of the value factor:

$$\frac{\boldsymbol{P}}{\boldsymbol{B}} = \frac{\boldsymbol{Share\ price}}{\boldsymbol{Book\ value}}$$

The value premium, unlike the size premium, is robust (Davis, Fama, and French 2000). Since the 1930s, the advantages of a value approach have been recognized. Value stocks have historically outperformed growth stocks. Between 1975 and 1995, there was a 7.68 percent annual gap in the average return on global portfolios of high and low book-to-market stocks, and value stocks beat growth stocks in 12 of the 13 major markets (Fama and French 1998). During both bear markets and economic downturns since the Great Recession, value stocks have outperformed growth stocks (Campbell et al. 2008). On average, value investing pays off. Over the last half century, the predicted value premium has remained relatively constant at about 6.1 percent per year (Chen, Petkova, and Zhang 2008). However, some recent papers have shown that average out-of-sample value premiums for post-1991 value premiums are low and statistically indistinguishable from zero (Linnainmaa and Roberts 2018, and Fama and French 2020).

Value strategy may often result in a loss of money. The risk of a value strategy is that, while value stocks outperform growth stocks over time, value stocks can underperform growth stocks at times. According to Chen et al. (2008), the value premium is countercyclical, and value firms are riskier than growth firms in bad economic times. Value is also riskier than growth, according to Petkova and Zhang (2005), particularly in bad times when the cost of risk is high. Overall, investor can only be a value investor if investor is willing to lose money on businesses in bad times. The way investor invests in hard times determines whether investor is a value or growth investor.

The fundamental reasoning behind value strategy, like many other things in the financial literature, is largely divided into two camps, the rational and the behavioral. In a rational story of value, value stocks move along with other value stocks when market exposure is controlled and move in a different direction with growth stocks. Some value risk can be diversified by putting together stock portfolios, but since certain value fluctuations are impossible to diversify, the remaining risk must be priced in the equilibrium, resulting in a value premium. The Fama-French model does not explain why value stocks need a premium. As a result, the economic reasons for the value premium must be explored. A risk premium is included in the pricing kernel formula as compensation for losing money in bad times. So that value deserves its premium on average, rational stories of value must define their own meanings of bad times when value underperforms. Consumption of nondurable or luxury goods, labor income risk, and investment growth are examples of factors that have been found to influence the value premium. As marginal utility rises sharply, as it does at business cycle troughs when durable consumption falls sharply compared to nondurable consumption, stocks produce unexpectedly low returns (Yogo 2006). The asset's beta, according to Santos and Veronesi (2006), is determined by a proxy for the share of consumption funded by labor income. The beta of value stocks rises during hard times determined by some of these variables, making value stocks especially risky. Lewellen and Nagel (2006), for example, discovered that betas differ significantly from year to year, with relatively large variations in frequency.

Berk, Green, and Naik (1999) offered a key picture of the behavior of value and growth firms. Berk et al. (1999) demonstrated that when market returns are poor, managers make the best use of investment options, which are dynamically related to the company's book-to-market ratio, resulting in a value premium. Lu Zhang has written a series of papers that justify the value premium by claiming that value companies are risky due to their simple production technologies. Zhang's (2005) paper is important, and it is focused on Cochrane's (1991,1996) production-based asset pricing paradigm. The production-based model of Cochrane (1991) is used to look at stock return projections based on business-cycle variables and the relationship between stock returns and economic activity. According to Zhang (2005), costly reversibility and the countercyclical cost of risk limit value firms' ability to cut capital, making them riskier than growth firms, especially during bad times when the cost of risk is large. As a result, value businesses are intrinsically riskier than growth companies, necessitating a long-term premium. Overall, if an investor can go against the crowd, value investing is a successful strategy.

According to the behavioral story, value stocks will earn a large additional return if behavioral biases are not arbitraged away. The majority of value premium behavioral theories are concerned with overreacting investors or extrapolating recent news. Value stocks are cheap since investors underestimate their growth prospects, whereas growth firms are costly because investors overestimate their growth prospects, according to behavioral theories. From a behavioral theory standpoint, the important question for an asset owner to consider is whether they behave like the market or are willing to not overextrapolate or overreact. Value effect may also be caused by other psychological biases. A high book-to-market ratio stock, for example, has reached its relatively low price due to some previous poor results.

The central question posed by behavioral models is why more buyers do not purchase value stocks, increasing their prices and removing the value premium, as investors seem to have done with the size premium, according to Grossman and Stiglitz (1980). To put it another way, why aren't there any more value investors? Investors may believe that value investing is too difficult. Perhaps it is a hangover from the 1970s', efficient markets theory, but successful managers have never truly believed in efficient markets, and scholars are no longer convinced either. Perhaps many organizations do not have long enough investment horizons to successfully execute value investing. The value effect needs a three- to six-month investment period, which might be too long for most long-term investors.

2.6 Momentum factor

Momentum is another common investment factor and trend investing is another name for momentum investing. In the same year that Fama and French captured size and value factors, Jegadeesh and Titman (1993) burst onto the academic scene. According to Jegadeesh and Titman (1993), strategies that purchase previously well-performing stocks and sell underperforming stocks over 3- to 12-month holding periods produce substantial positive returns. De Bondt and Thaler (1985, 1987) discovered a reversal effect on long-term returns, which means that stocks with low long-term past returns have higher potential returns. This result was interpreted by De Bondt and Thaler (1987) as supporting the behavioral hypothesis of investor overreaction. The weekly and monthly returns of extreme winners and losers have also shown reversal activity, according to Lo and MacKinlay (1990).

Momentum investing is a technique that includes purchasing stocks that have increased in value in the last six months and selling stocks that have had the lowest returns in the same time span. Within an asset class, momentum is mainly a cross-sectional technique. A cross-sectional approach, such as size and value, compares one stock category to another in cross-section rather than looking at a single stock over time. The momentum strategy is focused on three-month to one-year relative returns. Rebalancing should be performed primarily at the asset class or strategy level, as rebalancing necessitates the existence of assets or strategies over time, whereas individual stocks can vanish. The return on momentum outperforms all size and value returns. The study finds clear and consistent proof of momentum in the United States and Europe, but poor and negligible evidence in Japan (Haugen and Baker 1996). After risk is corrected, a globally diversified portfolio of past medium-term winners outperforms a portfolio of past medium-term losers by more than one percent per month between 1980 and 1995 (Rouwenhorst 1998).

While Momentum returns are not the inverse of value returns, there is a small negative correlation between HML and momentum (UMD). Depending on the study, UMD or WML may be used as an abbreviation. Momentum is a positive feedback strategy, and positive feedback strategies are inherently unstable, exposing them to collapses on a regular basis. These have also been high-volatility periods. For example, Daniel and Moskowitz (2016), investigated the timing of volatility associated with a momentum collapse. They conclude that, despite high positive average returns across a variety of asset classes, momentum strategies may sometimes experience sustained negative returns, but that these drops are partly predictable (Daniel and Moskowitz 2016). Ilmanen and Kizer (2012) also stress the benefits of volatility-timing on the performance of cross-sectional equity momentum and other factor premia.

Momentum is often applied to the Fama-French model as an investment factor. Carhart was the first to do so in 1997:

$$E(r_i) = r_f + \beta_{i,MKT}E\left(r_m - r_f\right) + \beta_{i,SMB}E(SMB) + \beta_{i,HML}E(HML) + \beta_{i,WML}E(WML)$$

The same intuition applies as in the Fama-French three-factor model. Winning stocks have a positive momentum beta and risk premiums that are balanced upwards according to the previous equation, whereas losing stocks have negative momentum betas and risk premiums that point downwards. Fama and French (2018) expand their five-factor model with the momentum factor UMD of Jegadeesh and Titman (1993), resulting in a six-factor model.

The persistence of short-term returns or momentum is an example of a phenomenon that defies logical explanation and market efficiency (Chordia and Shivakumar 2002). According to the literature, at least some of the momentum returns are associated with macro variables. Asset owners should analyze how they behave with various sources of macro-risk in a rational story that is still far from making full use of the literature. Behavioral models are at the core of the most commonly cited theories. The momentum is either an overreactive phenomenon or an underreactive phenomenon, according to behavioral theories. Barberis, Shleifer, and Vishny (1998), as well as Daniel et al. (1998), have established important models of overreaction. According to Barberis et al. (1998), continuous parallel news, such as a string of positive earnings reports, represent very powerful but not very useful information. This assumption, on the other hand, predicts that stock markets will overreact to a continuous stream of good or bad news. On the other hand, Daniel et al. (1998) establish a hypothesis focused on investors' self-esteem and shifts in confidence as a result of skewed self-attribution of investment outcomes. As a result, investors can overreact to private information signals while underreacting to public information signals, according to this theory. Investors are overreacting and raising stock prices above their fundamental prices as a result of their increased self-confidence, generating momentum.

An article by Hong and Stein (1999) is the standard reference for under reaction theory. If information gradually spreads among the population, prices do not respond in the short run, according to Hong and Stein (1999), and underreaction means that momentum investors will profit from chasing the trend. In other words, news audiences receive information with a pause, and it is only partly reflected in prices when it is first revealed to the investor, resulting in underreactions. Prices ultimately reverse in both the under- and over-reaction models as they return to fundamentals in the long run.

It was also investigated if the calculation of investors' net selling propensity could be used to describe price momentum. An's (2016) study showed that stocks with significant unrealized gains and losses perform better in the following month than stocks with smaller unrealized gains and losses, with a monthly alpha of 0.5-1 percent and a Sharpe ratio of 1.5. An (2016) finds that the measure of net selling propensity that recognizes unrealized gains cannot explain price momentum since investors' selling propensity increases in the magnitude of both gains and losses.

Overall, every asset owner should look into his or her own psychological biases. For example, do an investor's biases vary from an average investor's biases, or can an investor even define all of his biases? At the very least, the investor should be able to withstand significant losses in their investments due to momentum strategies.

2.7 Low risk factor

The average return that exceeds a benchmark tells us more about the factors that went into forming the benchmark than it does about the ability required to beat it. If the benchmark is risk adjusted, academics refer to tracking error as idiosyncratic volatility. Instead, tracking error refers to the excess return's standard deviation, which determines how dispersed the manager's returns are in comparison to the benchmark. In comparison to traditional market-weighted indexes, value-growth, momentum, and other dynamic variables, the risky phenomenon that stocks with low beta and low volatility have high returns appears to be a good source of alpha. Stocks with low risk, as calculated by past volatility or past beta, are said to have higher returns than stocks with high risk. This contradicts widely held financial theory, such as the capital asset pricing model, which notes that risk and return must have a positive relationship. There is a long history of a negative relationship between risk and returns, at least as calculated by market beta and volatility. In 1975, Haugen and Heins published research that found that in the long run, equity portfolios with lower monthly volatility had higher average returns than more risky equity portfolios.

The low-risk anomaly is made up of three effects, one of which is caused by the other two. The first effect is that predicted returns are negatively linked to uncertainty. Another effect is that realized beta is linked to potential returns in a negative way. The third effect is that portfolios with the lowest volatility outperform the market. Clarke, De Silva, and Thorley (2006), for example, found that minimum variance portfolios that are not based on any particular estimated return principle or return estimate have a better chance of outperforming a market-weighted benchmark. The risk paradox is that the risk, as calculated by the market's beta or volatility, is inversely proportional to the return.

Ang, Hodrick, Xing, and Zhang published a paper in 2006 that served as a springboard for this new risk anomaly literature. Ang et al. (2006) found that stocks with high sensitivity to advances in aggregate volatility have low average returns, which is consistent with the theory. Instead, they discovered that high-volatility stocks had a disciplined low return. Higher volatilities are correlated with higher risk premiums in models with noise traders who trade for reasons unrelated to fundamental valuation. De long, Shleifer, Summers, and Waldmann (1990) proposed a simple overlapping generations asset market model in which irrational noise traders with erroneous stochastic beliefs control both prices and deserve higher expected returns. Barberis and Huang (2001) also predict that stocks with higher idiosyncratic volatility would have higher expected returns. Ang et al. (2006), on the other hand, found the exact opposite. The strength of the negative relationship between idiosyncratic and complete volatility and returns is noteworthy. Ang, Hodrick, Xing, and Zhang (2009) demonstrated that a volatility effect exists in every G7 nation and in all developed stock markets in their subsequent work. This suggests that stocks with high idiosyncratic volatility recently have had low global average returns.

The first CAPM experiments, performed in the 1970s, discovered positive relationships between beta and expected returns but found that pure CAPM models did not work. For example, Jensen, Black, and Scholes (1972) discovered that the relationship between beta and expected returns was too flat in comparison to what the CAPM predicted, but it was still positive. Fama and French published a prestigious paper in 1992 that addressed the CAPM's core issues. In short, Fama and French (1992) found that the Sharpe-Lintner-Black model's primary prediction that average stock returns are positively linked to market beta was no longer supported. Worse still, the point estimates revealed a negative relationship between beta and return.

The low beta factor betting against beta (BAB), according to Frazzini and Pedersen (2014), goes long on low-beta shares and shorts high-beta shares, producing substantial positive risk-adjusted returns. In small stocks, the beta anomaly is more pronounced. Volatility anomalies, on the other hand, are more prevalent in large stocks, which are usually easier to trade due to their higher liquidity. One of the most prestigious studies of the last decade, the betting against beta factor, has piqued academic interest due to its outstanding performance. However, its efficiency is influenced by atypical construction procedures that efficiently, but not transparently, equalize stock returns. BAB is likely to offer much too much weight to micro- and nano-shares as a result of the atypical beta-creation approach used in the Frazzini and Pedersen (2014) report, and thus the investor will not be able to realize BAB's projected results (Novy-Marx and Velikov 2018).

According to empirical evidence, low volatility securities reap higher risk-adjusted returns than highly volatile assets (Blitz and van Vliet 2007). A typical approach for capturing volatility is to measure the standard deviation over a period of one to three years. The standard deviation of weekly total stock returns calculated over the three years prior to the current month is characterized as low volatility. If three years of weekly return data are not available, a shorter history is used, with a one-year minimum duration. Blitz and van Vliet (2007) suggested this factor concept.

The quest for a systematic explanation for the risk anomaly continues. The real reason may be a mixture of all of the hypotheses mentioned below, as well as other theories in the works. Some reports correctly suggest that data mining could have harmed Ang's et al. (2006) initial findings. Idiosyncratic volatility, according to Chen, Jiang, Xu, and Yao (2012), is a common stock phenomenon that is not caused by microstructural or liquidity biases. Chen et al. (2012) discovered that predicted return and idiosyncratic volatility have a negative relationship. The strongest argument against data mining is that the low-risk effect can be seen in a variety of other settings. Low-risk situations are normal.

Many investors are limited by their leverage; they want to take more risks but are unable to do so. Black (1972) was the first to propose a CAPM theory under which investors are unable to leverage. Black's (1972) model assumes the existence of a risk-free asset and that long positions in risk-free assets are permissible, but short positions are not. However, the leverage restriction story just describes the overpricing of high beta stocks, not the underpricing of low beta stocks compared to the market. Institutional investors tend to underweight high-risk equities, despite the fact that they should be drawn to them, and private investors are primary holders and traders in equities with high idiosyncratic volatility. Han and Kumar (2013) found that speculative, risk-seeking, and gambling-motivated traders explain why high idiosyncratic volatility can entice private investors.

Many institutional managers are unable to exploit the risk anomaly. The use of market-weighted indexes, in particular, can result in a low volatility anomaly. The low beta-high alpha and high beta-low alpha scenarios, according to Baker, Bradley, and Wurgler (2011), are due to the fact that most institutional investors want to beat a benchmark, and in order to do so, they select high-beta stocks. High beta stocks, on the other hand, have been shown to have low risk-adjusted returns (Baker et al. 2011). Borrowing restrictions, including a long-only mandate, make arbitrage between low beta-high alpha and high beta-low alpha stocks impossible. Because of the arbitrage, this risk anomaly will vanish in a perfect world with no borrowing restrictions. When considering an investor who can only go long and is subject to tracking error constraints that restrict how much he can deviate from the benchmark. The use of tracking errors with these benchmarks then makes betting against low volatility or low beta difficult.

If equity owners actually want high-volatility, high-beta securities, they will bid on them before the price falls below a certain threshold. This risk anomaly could be explained by hopes and aspirations, which are reflected by high volatility and high beta stocks. Equities with high idiosyncratic volatility have had low returns, but it has been discovered that the beta effect is also true when managing idiosyncratic risk, but it vanishes when controlling the maximum daily return for the previous month (Bali, Cakici, and Whitelaw 2011). Hou and Loh (2016) have looked into a number of possible causes for the low volatility phenomenon. Many existing hypotheses, according to Hou and Loh (2016), clarify less than 10% of the idiosyncratic volatility puzzle. Individual lottery preference stories illustrate nearly half of the low-volatility puzzle when put together. Some of the risk anomaly may be caused by agents who disagree with each other, i.e., have heterogenous preferences, coupled with an inability to short. A sufficiently large disagreement makes the relationship between beta and returns declining. Other interpretations of the idiosyncratic volatility puzzle appear to concentrate on market failures that could contribute to such a relationship, such as short selling constraints or disclosure of lack of knowledge, perhaps because the negative risk-return relationship is difficult to reconcile with investor utility assumptions (Jiang, Xu, and Yao 2009). Jiang et al. (2009) concluded that companies with a history of high volatility are more likely to have negative unexpected earnings surprises in the future, resulting in low returns.

Overall, low-risk strategies tend to have a major alpha advantage over traditional market capitalization benchmarks and advanced factor benchmarks that use competitive value-growth and momentum variables in addition to the market portfolio to mitigate risk. In reality, the asset management industry's general constraints on tracking errors may have contributed to this risk anomaly. But what will happen to this risk anomaly in the future? Will it be able to survive? The current low-risk anomaly investors would make major capital gains if the risk anomaly disappeared. In essence, the fact that the low risk anomaly can be found in a wide range of markets, including stocks, bonds, commodities, currency, and derivatives, means that the effect is long-term and needs further investigation.

2.8 Quality factor

This section introduces the quality factor's theory and empirical proof. Quality as an investment strategy aims to capture the excess returns of businesses that are operationally productive, earnings and cash flow stable, have low debt, are highly profitable, and have low operating risk. Careful capital management, for example, decreases the risk of overcapitalization or overindebtedness, which has a positive impact on the stock price later. Piotroski (2000) is an example of a study that uses fundamental analysis to predict future earnings and stock returns, i.e., it is a market efficiency test. According to Piotroski (2000), a simple accounting-based fundamental analysis will adjust the distribution of a portfolio's return based on a broad book-to-market measure. Piotroski (2000) demonstrated that by choosing financially strong high BM firms, a high book-to-market investor's average return can be increased by at least 7.5 percent per year, while the overall distribution of realized returns changes to the right.

In accounting, there are two types of cross-sectional return predictability measures. The test used by Piotroski (2000) in his analysis evaluates the performance of multivariate metrics, such as a company's fundamental value compared to its market value. According to Piotroski (2000), the conclusion about the market's sluggish adjustment to the information ratio is bolstered by the fact that potential abnormal returns tend to be concentrated on earnings announcement dates when the analyses' earnings estimates are realized. The first quality ideas were based on the idea that companies that are underpriced or undervalued and meet certain requirements should have higher expected returns. As a result, Piotroski (2000) devised an F-score based on the sum of nine binary variables to calculate a firm's financial strength:

$$F_{Score} = F_{ROA} + F_{\Delta ROA} + F_{CFO} + F_{Accrual} + F_{\Delta Margin} + F_{\Delta Turn} + F_{\Delta Lever} + F_{\Delta Liquid} + F_{EQ-Offer}$$

Where F_{ROA} is given 1 point if the return on assets is positive in the current year and 0 if it is negative, $F_{\Delta ROA}$ is given 1 point if the change in return on assets is greater in the current year than in the previous year and otherwise 0, F_{CFO} is given 1 point if the cash flow from operating activities is positive in the current year and 0 if it is negative. $F_{Accrual}$ is given 1 point if accruals were positive in the previous year and 0 if they were negative; $F_{\Delta Margin}$ is given 1 point if the improvement in the growth margin is greater in the current year than in the previous year and otherwise 0, and $F_{\Delta Turn}$ is given 1 point if the asset turnover ratio is higher in the current year than in the previous year and otherwise 0. $F_{\Delta Lever}$ receives 1 point if the leverage ratio is lower this year than last year, otherwise 0, $F_{\Delta Liquid}$ receives 1 point if the current ratio is higher this year than last year, otherwise 0, and $F_{EQ-Offer}$ receives 1 point if no new shares are issued during the previous year, otherwise 0.

Fast-growing businesses have been shown to outperform slow-growing companies (Mohanram 2005). Unlike Piotroski (2000), Mohanram (2005) investigated the impact of financial statement analysis on low book-to-market portfolios, also known as growth stock portfolios, where a low book-to-market was described as a ratio of less than 20% in the overall market, and Mohanram (2005) conducted financial statement analysis using three types of signals. One of these groups, for example, looked at signals related to naive extrapolation, and Mohanram (2005) calculated earnings variability relative to all low book-to-market firms in the same sector, as well as revenue growth variability relative to all low book-to-market firms in the same industry. To build the GSCORE index, Mohanram (2005) merged conventional fundamental factors like earnings and cash flow with measures targeted to growth firms like earnings stability, growth stability, R&D intensity, investments, and advertising.

Sloan (1996) was one of the first to merge high earnings quality stocks with excess returns, using accruals as a proxy for earnings quality. According to Sloan (1996), the relative magnitudes of the cash and accrual components of current earnings will determine whether current earnings performance continues in the future. Sloan (1996) also claims that firms with high current accrual components have negative future abnormal stock returns, whereas firms with low current accrual components have positive future abnormal stock returns. Fama and French (2006) investigated book-to-market stocks, as well as projected profitability and investment levels. Given the book-to-market equity ratio and projected profitability, higher expected investment rates mean lower expected returns, according to Fama and French (2006). Fama and French (2006) also find a shaky but statistically significant connection between investment and average return.

Financially troubled stocks have generated extremely low returns. Financial distress, as measured by trailing financial ratios, is correlated with lower returns, according to Dichev (1998), Griffin and Lemmon (2002), and Vassalou and Xing (2004). The risk of bankruptcy, according to Dichev (1998), is a natural proxy for firm distress. Dichev (1998) looked into the connection between bankruptcy risk and systemic risk. According to Griffin and Lemmon (2002), the gap in returns between high and low book-to-market securities among firms with the highest distress risk is more than twice that of other firms. For this reason, Griffin and Lemmon (2002) argued that the book-to-market effect must be due to mispricing as a result of this. The size effect is a default effect, according to Vassalou and Xing (2004), and this holds true for the book-to-market effect as well. Vassalou and Xing (2004) used Moody's KMV to calculate the distance to default. Vassalou and Xing (2004) find some evidence that distressed stocks with a small distance to default have higher returns, but this evidence comes entirely from small-value stocks. A one-month reversal and bid-ask bounce, however, have skewed the returns on the distressed shares upwards, according to Vassalou and Xing (2004). Surprisingly, the profitability of momentum is strong and significant among low-quality businesses, but there is no connection between high-quality businesses and momentum (Avramov, Chordia, Jostova, and Philipov 2007).

Overall, quality stocks are those that have a high return-on-equity (ROE) and a low debt-to-equity ratio. Quality is described by Asness, Frazzini, and Pedersen (2019) as characteristics for which investors should be willing to pay a premium. The quality factor is determined by the company's balance sheets and accounts. Since determining the quality of stocks is difficult, one or more variables are often used to determine a company's profitability, safety, and earnings quality (Asness et al. 2019). The protective nature of a subset of values is described by the quality factor. According to Asness et al. (2019), high-quality stocks, which are described as stable, profitable, rising, well-managed, and efficient, outperform low-quality stocks, which are risky, unprofitable, shrinking, and poorly performing. The quality factor identifies high-quality, less cyclical, and less leveraged businesses that outperform the market. These are defensive stocks that can underperform in a bull market but provide stronger security in downturns. Furthermore, Asness et al. (2019) discovered a negative association between size and the quality factor, which is due to the fact that smaller stocks are riskier.

2.9 Time-varying factor performance

Over time, style factors have been important drivers of equity returns. Factor premia, on the other hand, have changed over time and behaved differently at various points in the macro cycle. The following are the top-performing factors in major macro regimes, according to research. Value was the best performer during a "recovery" process, while low volatility and momentum were the worst. Momentum and value were top performers during a "expansion" period, while low volatility and quality were laggards. Low volatility, momentum, and quality were top performers during a "slowdown" era, while size and value were laggards. Low volatility and quality were the best performers during a "contraction" period, while momentum was the worst.

The value and momentum premia measured in the mixed four-factor model indicate a great deal of variation over time and across countries, according to Chaieb, Langlois, and Scaillet (2018). All factors have positive premia through developed markets, with the exception of momentum, which has negative premia during and after the global financial crisis (Chaieb et al. 2018). During the global financial crisis, value and market premia skyrocketed (Chaieb et al. 2018). Periods with higher value premiums also have lower momentum premiums (Chaieb et al. 2018). This trend is consistent with the fact, that value and momentum have a negative relationship (Asness et al. 2013).

A counter-cyclical trend can be seen in the risk premia for market, size, and value factors (Gagliardini, Ossola, and Scaillet 2016). These risk premia do indeed rise during economic downturns and fall during economic booms (Gagliardini et al. 2016). The risk premium for the momentum factor, on the other hand, is pro-cyclical (Gagliardini et al. 2016). Furthermore, time-varying measures of the value premium are usually negative, with the exception of recessions, where they take positive values (Gagliardini et al. 2016). In boom times, growth firms are riskier due to their in-the-money growth options; in recessions, value firms are riskier due to default risk (Gagliardini et al. 2016). The other empirical evidence for this interpretation, however, is mixed. Distress is linked to size and book-to-market effects in some studies (Vassalou and Xing 2004), but not in others (Campbell, Hilscher, and Szilagyi 2008). Most of the time, time-varying estimates of the size premium are marginally positive (Gagliardini et al. 2016).

In almost every asset class over the last century, Ilmanen, Israel, Moskowitz, Thapar, and Lee (2021) find that return premia for value, momentum, carry, and defensive are robust and meaningful, and that they differ significantly over time. Part of the variation stems from the original studies' poorer out-of-sample results, which is consistent with overfitting biases (Ilmanen et al. 2021).

In terms of low volatility, Garcia-Feijoo, Kochard, Sullivan, and Wang (2015) discovered that, like any quantitative investment approach, low-risk investing's historical success differs over time. Garcia-Feijoo et al. (2015) also discovered that low-risk strategies are dynamically exposed to well-known value, size, and momentum factors, as well as being affected by the overall economic environment. Their findings indicate that the approach to building low-risk portfolio strategies, as well as the market environment and related valuation premiums, affect low-risk strategy performance over time.

The price of quality fluctuates over time, hitting a low during the internet bubble, and a low price of quality indicates that QMJ will return a high future return (Asness, Frazzini, and Pedersen 2019). When the stock prices fall, Asness et al. (2019) characterize a "race to quality", in which investors flock to high-quality stocks, increasing their returns. To conclude, the findings support the hypothesis that price variation is not random noise, but rather represents shifts in market pricing of quality characteristics, resulting in variation in QMJ returns (Asness et al. 2019).

2.10 Macroeconomic exposure

In today's world of volatile earnings growth and high market uncertainty, investing is more difficult than ever. Given the historically strong correlation between the performance of a typical 60/40 balanced approach and stock markets, even a well-diversified portfolio could still be exposed to significant risk. As a consequence, seeking the diversification that investors need can be challenging. Many investors diversify their portfolio through stocks and bonds to address these issues. Factor diversification, according to Ilmanen and Kizer (2012), is the best solution for many investors whose portfolio risk is dominated by stock market directionality and who are willing to learn about the strategy and its potential benefits. The good news is that factor investing has the ability to provide more efficient diversification, which can help investors meet their investment objectives. Macro factors allow the development of risk and reward-diversified investment strategies. An easy but effective way to realize the possible diversification advantages of this strategy is to use an equal-weighted mix of macroeconomic factors.

Given the variation in factor return premia per unit of risk, previous literature suggests that macroeconomic sources of variation may be driving these dynamics. However, due to the short time series, previous attempts to relate factors to economic risks have proven difficult. Measures of macroeconomic activity are examined in an attempt to relate factor returns to macroeconomic models (Campbell and Cochrane 1999, Lettau and Ludvigson 2001, and Bansal and Yaron 2004). The timing of certain macroeconomic factors is also a critical consideration.

With today's developments in data and technology, factor investing has reached new heights, enabling investors to gain a better understanding of their assets and, as a result, pursue a better mix of those return drivers in their portfolios. According to multiple studies, six key drivers of returns, or causes, can explain much of the returns across asset classes. The most important drivers of returns across asset classes are economic growth, real rates, and inflation; credit, emerging markets, and liquidity are also important drivers to recognize and manage, particularly during periods of crisis. For example, Ilmanen et al. (2021) have used global GDP growth and global CPI inflation rate, two variables that Chen, Roll, and Ross (1986) find important for stock returns. A factor-based approach cuts through investment constructs to concentrate on the underlying drivers of returns, and it transforms what can be nuanced into easy-to-understand factor exposures. Focusing on these macroeconomic return drivers concentrates portfolios on the most relevant fundamentals and allows for greater diversification against market volatility. Market dynamics can also influence allocations: as volatility increases and returns fall, many investors seek flexible allocations that can adjust to changing market conditions. Furthermore, factor investment will reveal possible overlapping risks in investor's portfolio.

The finding that both domestic and foreign risk factors play a significant role in stock pricing supports recent evidence presented by Eun et al. (2010) on the risk-return trade-off of global investors. Asness et al. (2013) found that there are common global risks, which they categorize using a three-factor model. Overall, individual asset groups are influenced by a variety of variables. The issue is that even seemingly unrelated assets can be exposed to common sources of risk, such as inflation, central bank policy changes, or a weakening global economy. Equities are primarily influenced by economic growth, with a small premium for inflation and interest rate risk. Many of these models, which are equity-centric theories, are challenged by the presence of the same factor premia in other asset classes besides equities. Given the abundance of theories linking factor returns to macroeconomic variables in stocks and the lack of theory linking macroeconomic variables to factor premia in other asset classes, Ilmanen et al (2021) conduct an empirical investigation of factor exposures across asset classes to a variety of macroeconomic variables.

Individual asset prices can be affected by a broad range of unanticipated events, and some events have a more pervasive impact on asset prices than others, according to Chen et al. (1986). Rare catastrophe theories (Tsai and Wachter 2015, and Gabaix 2012) claim that factor returns fall with the likelihood of tail incidents, while expected returns increase. Tsai and Wachter (2015) have reviewed recent catastrophe risk models that explain the equity premium puzzle, volatility puzzle, return predictability, and other characteristics of the overall stock market. According to, Gabaix (2012) the fundamental value of an asset falls by a time-varying amount during a catastrophe. Hou, Xue, and Zhang (2015) connect asset pricing factors to economic shocks that affect firm investment, such as the business cycle, interest rates, growth, and even political uncertainty. Economic growth is the reward for taking on the possibility of economic uncertainty. Economic rationale is that growth-sensitive assets depend on economic expansion to produce high returns, and they will suffer if the global economy weakens. Surprise in GDP, i.e., the difference between expected and actual growth, is a metric for economic growth. For taking on the possibility of a possible economic downturn, investors could be compensated with a long-term premium.

The sentiment index developed by Baker and Wurgler (2006) describes changes in value, momentum, and other equity factor returns over time. Small stocks, young stocks, high volatility stocks, unprofitable stocks, non-dividend-paying stocks, severe growth stocks, and distressed stocks all have relatively high subsequent returns when beginning-of-period proxies for sentiment are poor, according to Baker and Wurgler (2006). However, with low r-squares and negligible coefficient, the evidence for economic news predicting factor returns is as poor as contemporaneous behavior (Ilmanen et al. 2021). Ilmanen et al. (2021) also found no evidence that factors change in response to interest rate environments.

Some studies link value to long-run consumption growth (Parker and Julliard 2005, and Malloy, Moskowitz, and Vissing-Jörgensen 2009). Malloy et al. (2009), for example, show that long-run stockholder consumption risk better captures cross-sectional variance in average asset returns than aggregate or nonstock holder consumption risk, implying more likely risk aversion estimates, using microlevel household consumption data. Although contemporaneous consumption risk explains only a small portion of the variance in average returns across the 25 Fama-French portfolios, the calculation of ultimate consumption risk across a three-year period explains a significant portion of it (Parker and Julliard 2005). Campbell and Cochrane (1999) present a consumption-based model that describes a broad range of dynamic asset pricing phenomena, including procyclical stock price variation, long-horizon predictability of excess stock returns, and countercyclical stock market volatility variation. The conditional consumption CAPM may explain the difference in returns between portfolios with low and high book-to-market portfolios, with little evidence of residual size or book-to-market impact (Lettau and Ludvigson 2001). Consumption and dividend growth rates are modelled also by Bansal and Yaron (2004) as having a small long-run predictable variable and fluctuating economic uncertainty otherwise known as consumption volatility.

Global funding liquidity risk can be one cause of these trends, which can only be seen by looking at both value and momentum across markets (Asness et al. 2013). The reward for keeping illiquid assets is liquidity. Individual stock momentum is exposed to liquidity risk, as Pástor and Stambaugh (2003) and Sadka (2006) prove, and Asness et al. (2013) show some evidence that value and momentum across all asset classes are oppositely exposed to liquidity shocks. Small-cap equities have a higher liquidity premium because they are less liquid and more costly to sell. Expected stock returns are linked cross-sectionally to the sensitivity of returns to aggregate liquidity fluctuations, according to Pástor and Stambaugh (2003). What is the global demand for liquidity is a key fundamental question regarding this variable? Within the sense of momentum and post-earnings-announcement-drift portfolio returns, unexpected market-wide fluctuations of the variable component rather than the fixed component of liquidity are seen to be priced (Sadka 2006). Investors that hold less liquid assets recognize the risk that they will not be able to sell their investment immediately under some circumstances. Investors may be compensated for delaying consumption and bearing that cash strain by foregoing immediate access to capital.

It can be concluded that successfully managing today's markets necessitates a well-balanced blend of macro factors. Overall, there is no evidence that factor returns are related to macroeconomic variables in a significant way, either in the present or in the future. Factor investing does not tend to be affected by the same macroeconomic uncertainties that affect general equity and bond markets, and as a result, conventional asset allocation strategies are diversifying. We can create robust portfolios and aim to better meet desired investment results with a better understanding of portfolio risk and return.

3 DATA AND METHODOLOGY

3.1 Data and methodology

The aim of this section is to clarify how data is collected and how it is used. The performance of factors in the Nordic stock markets is investigated in this thesis. To investigate the variations in factor performance in different factor portfolios, cross-sectional and time-series tests are used. The growing body of evidence that the size (SMB), book-to-market (HML), and momentum (UMD) factors, in combination with the market factor, adequately explain international stock returns, as well as the direct link between investors' portfolio choice problems and international asset pricing theories and tests, have prompted me to take this approach. The data sources and sample preparation are listed first in this section. The methods for creating factor portfolios, as well as the cross-sectional and time-series tests that were used, are then presented.

3.2 Data sources and sample preparation

This research is based on AQR Library's international monthly returns on factor portfolios. Betting against beta (BAB), high minus low (HML), the market risk factor (MKT), quality minus junk (QMJ), small minus big (SMB), and up minus down (UMD) are six distinct factors extracted from cross-sectional data used in this analysis. Fama and French (1992, 1993, and 1996), Asness and Frazzini (2013), and Asness, Frazzini and Pedersen (2019) are used to build the portfolio.

All securities in a country are listed in ascending order based on their estimated beta value, and the ranked securities are assigned to one of two portfolios, the low beta portfolio or the high beta portfolio, to create each BAB factor. Securities are weighted in each portfolio based on their ranked betas, with lower beta securities receiving higher weights in the low beta portfolio and higher beta securities receiving higher weights in the high beta portfolio. Both portfolios are rescaled so that beta is one in portfolio creation to create the BAB factor. BAB is a self-financing zero-beta portfolio that invests in low-beta portfolio while short-selling high-beta portfolio.

Value weighting is used to establish the remaining factors. The majority of factor model studies use value weighting rather than equal weighting of returns because value weighting reduces the effect of extreme returns on small stocks. The value-weighted return on all available stocks minus the one-month Treasury bill rate is the market factor MKT. To calculate the four remaining factors (HML, QMJ, SMB and UMD), the companies at time t-1 were sorted by their book-to-market (B/M) ratio, overall quality score, size (total stock market capitalisation) and by momentum (lagged cumulative return in months t-12 to t-2). QMJ and UMD are measured in the same way as HML, but instead of using the B/M ratio to sort stocks, they use momentum and overall quality ranking. The value factor HML^{devil} is calculated using Asness and Frazzini's (2013) process. The average return of two value portfolios minus the average return of two growth portfolios equals the HML^{devil}:

$$HML^{devil} = ½ \text{ (Small Value + Big Value)} – ½ \text{ (Small Growth + Big Growth)}$$

The securities are divided into two size-sorted portfolios based on their market capitalization at the end of each calendar month. The size breakpoint for securities in the Nordic stock market is the 80th percentile by country. For value and growth breakpoints, the 30th and 70th percentiles are used. The average return of the three small portfolios minus the average return of the three big portfolios is the size factor SMB:

$$SMB = 1/3 \text{ (Small Value + Small Neutral + Small Growth)} – 1/3 \text{ (Big Value + Big Neutral + Big Growth)}$$

The research was conducted using stock market returns from four Nordic countries: Denmark, Finland, Norway, and Sweden. Monthly returns were chosen because they provide enough data to ensure the statistical efficacy of the experiments and prevent the tests from being subjected to unnecessary microstructural issues. The factor portfolio returns sample period is from January 1986 to October 2020, with 418 monthly observations available. To ensure a stable and accurate outcome, the time window selection aims to obtain the largest possible sample. All of the returns are in US dollars. Since the data is Nordic and the four countries' currencies differ, all currency-denoted data must be obtained in the same currency.

3.3 Time-variation in the commonality of factor performance

Then there's the issue of how the integration of factor returns changes over time in this sample. The degree of comovement of returns between countries is used as a measure of factor return commonality. The variance of the monthly cross-section at time t ($DISP_t$) is determined for each factor using the equation below:

$$DISP_t = \mathrm{var}(R_t)$$

where R_t is the vector of all countries' factor excess returns. The return dispersion is equal to $\sqrt{DISP_t}$. This is a widely used metric in the literature (Rangvid, Santa-Clara, and Schmeling 2016; Angelidis, Sakkas, and Tessaromatis 2015), based on the assumption that as countries become more integrated, stock returns become more similar. The key indicator of global financial market integration, according to Rangvid et al. (2016), is the dispersion of equity returns across countries. Angelidis et al. (2015), on the other hand, show that dispersion and value and momentum returns have a major relationship. Return dispersion is also closely associated with the business cycle and economic growth, according to Angelidis et al. (2015), and greater dispersion contributes to a higher likelihood of recession, increased unemployment, and a potential downturn in economic activity. Factor returns are more integrated during times when return dispersion between countries is minimal, according to this measure of return dispersion. In the sense that it is not dependent on an asset pricing model or explicit exposures to common variables, the metric is model-free.

3.4 Effectiveness of factor diversification versus country diversification

In this section we are interested in both static country-class premia and more dynamic style premia in Nordic countries. Returns are not easy to come by, even with the most tried and tested factors like value and momentum, which can go through long stretches of underperformance, such as over ten years. It's the same as holding a single country's assets, such as stocks or bonds.

Main aim in this section is to compare the efficacy of two different diversification strategies. In this section, the aim is to answer two questions. Should factors outperform country diversification in terms of expected returns and if it is true that factor diversification reduces volatility more than country diversification? Country diversification has been a standard investment strategy in recent decades to reduce risk, often political risk. For example, if the government of one country reports a larger-than-normal budget deficit or the central bank increases interest rates, this may impact security prices in that country but not necessarily in other countries that did not take similar measures. Some observers argue that in an age of globalization, country diversification is less effective, but others disagree. Diversification into different dynamic factors is the second method.

If factor returns are projected to be higher than country-diversified returns and to be more diversifying, investors can invest heavily in these sources of return. Factor returns, on the other hand, are at best replacements for country exposure if they are no better than country diversification on a risk-adjusted basis and often strongly correlated. If this were the case, one might simply leverage up a less complicated country diversification to achieve the same portfolio impact as owning the factor exposure.

This is tested by establishing 1) a country-diversified portfolio with four evenly weighted country building blocks using data dating back to 1995, and 2) a dynamic factor-diversified portfolio with betting against beta, momentum, quality style premia, and equity premia using data dating back to 1995. This design allows comparing whether it was better to diversify out of some Nordic county's stocks into other Nordic countries or into style factors, or whether static or dynamic factors were more successful diversifiers.

This country-diversified portfolio is made up of four different components: 25% Danish equities, 25% Finnish equities, 25% Norwegian equities, and 25% Swedish equities. Every Nordic country's factor-diversified portfolio includes three style premia: betting against beta (Frazzini and Pedersen 2014), momentum (Asness et al. 2013), and quality (Asness et al. 2019). For symmetry with the four-component country-diversified portfolio the three style premium components are weighted equally and combined with a 25% allocation to that country's equity premium proxy. That is also the reason why size and value factors were left out from this test.

3.5 Time series tests of risk exposures

Potential variables that could contribute to common variation in momentum, quality, and betting against beta strategies across markets are investigated in this section. This research uses a dataset that only includes data from the last three decades, but it is thought to be adequate for identifying these relationships and determining what similar features exist in the factor performance of Nordic countries.

The results of time series regressions of momentum, quality, and betting against beta returns for Nordic equities based on some macroeconomic variables and liquidity risks, are presented. Macroeconomic explanatory variables include TED spread, change in stock market volatility and VIX, Baker-Wurgler sentiment, change in local and global industrial production, change in M2, change in real exchange rate index, change in short interest rate, change in term spread, change in economic policy uncertainty, change in consumer credit, inflation, lagged inflation, default spread, dividend yield, geopolitical risk index, LIBOR-term repo, global Pástor-Stambaugh liquidity measure, and local recession dummy.

Betting against beta, momentum, and quality returns are regressed on liquidity shocks to determine liquidity risk exposure. Both funding liquidity shocks and market liquidity shocks are considered similar to Asness et al. (2013). The Treasury-Eurodollar (TED) spread (the monthly difference between local 3-month interbank LIBOR rate and the local 3-month government rate) and the global LIBOR minus term repo spread (the difference between the global 3-month LIBOR rate and the global term repurchase rate) are the funding liquidity variables. The funding series are eligible from January 1999 to October 2020.

As a proxy for arbitrage costs and market instability, change in local stock market volatility (realized volatility of the local equity market over the previous 36 months) is also included almost similarly to Ilmanen et al. (2021). Another indicator is the volatility index VIX, which measure global market instability. A rise in the VIX indicates a deterioration in financial conditions. Chang, Christoffersen, and Jacobs (2013), for example, show that aggregate volatility (as calculated by the shift in the VXO or VIX index) is significant in explaining cross-section of stock returns. According to Chang et al. (2013), stocks with more exposure to innovations in implied market volatility have lower average returns.

Political uncertainty (Caldara and Iacoviello 2018), liquidity risk (Pástor and Stambaugh 2003), and investor sentiment (Baker and Wurgler 2006) are also examined. Ilmanen et al. (2021) also attempted to relate factor variation to these economic sources in order to generate return dynamics and find if they can explain variation in factor premia.

The change of local and global industrial production is also investigated. Since GDP growth data is only available quarterly, change in industrial production is used to calculate economic growth in this thesis. Asness et al. (2013) used GDP growth to explain value and momentum premia. The growth rate of industrial production has also been used by Belo, Gala, and Li (2013) as a macroeconomic business cycle variable.

The change in M2 is also looked at. The global financial development is measured using the broad global money growth (M2) metric. Flannery and Protopapadakis (2002), for example, claim that stock market returns are associated with inflation and money growth, and they provide evidence that a monetary aggregate M1 is the candidate for priced factors, affecting both stock returns and conditional volatility. Narrow money M1, on the other hand, excludes holdings of such financial instruments such as money market funds and short-term marketable financial instruments that can be converted into cash easily and with minimal frictions. Investors' liquidity and portfolio composition are affected by changes in their holdings of such financial instruments, which in turn influence stock prices. When evaluating the relationship between stock returns and changes in the money supply, it is important to use broad money M2 rather than M1.

The change in the real exchange rate is also taken into consideration. According to classical economic theory, there is a connection between stock market performance and exchange rate activity. For example, "flow focused" models of exchange rate determination (Dornbusch and Fisher 1980) assert that currency fluctuations affect international competitiveness and the balance of trade status, and therefore the country's real production, which affects corporations' current and future cash flows and stock prices. Some researchers have discovered a connection between stock markets and exchange rates. The real exchange rate, for example, is positively linked to the domestic stock market, according to Phylaktis & Ravazzolo (2005). Chow, Lee, and Solt (1997), on the other hand, found no association between monthly excess stock returns and real exchange rate returns using monthly data from 1977 to 1989. According to Chow et al. (1997), the real exchange rate is used instead of the nominal exchange rate because it better represents an economy's competitive position with the rest of the world.

The short interest rate fluctuation and the change in term spread are also taken into account. The term spread and short interest rate, also known as the risk-free rate, are two predictors that are often used by researchers to estimate future stock returns. The term spread is the difference between long- and short-term interest rates or yields. In the study period 1952-2002, Campbell and Yogo (2006) use the long-short term spread as a control variable, and their test shows that the standard t-test is true for the term spread variable since there is little correlation between the term spread and stock returns; as a result, they find that the term spread produces good evidence of future stock return predictability. According to Hjalmarsson (2010) short interest rates and term spread are reasonably reliable predictors of potential stock returns in developed markets.

The fluctuation in economic policy uncertainty is also taken into account. Baker, Bloom, and Davis (2016) created a new economic policy uncertainty (EPU) index focused on the frequency of media coverage. Baker et al. (2016) use firm-level data to show that policy uncertainty is linked to higher stock price volatility and lower investment and jobs in policy-sensitive industries such as security, health care, banking, and infrastructure construction. Economic policy uncertainty, according to You, Guo, Zhu, and Tang (2017), should be considered when constructing portfolios and diversification strategies because it has a huge impact on equity markets. According to You et al. (2017), the effect of economic policy uncertainty on stocks is almost always negative.

Global consumer credit fluctuation is also taken into account. The role of credit markets in driving business cycles varies a lot depending on which model investor uses. Some models suggest that these markets are only marginally relevant for business cycle dynamics, while others attribute a major role to financial sector shocks. Credit market developments, which are simply reflected by asset price fluctuations, may affect consumption by affecting household income, and investment by affecting a firm's net worth and the market value of its capital stock compared to its replacement value. Credit shocks seem to be able to explain U.S. market cycles, and they do play a significant role during financial crises, but they play a smaller role during "normal" business cycles. Credit shocks in the United States have been instrumental in driving global growth dynamics, according to Helbling, Huidrom, Kose, and Otrok (2011), and they have also played a key role in influencing the evolution of U.S. market cycles during the 1991 recession.

Inflation is taken into consideration as well. While some studies find a weak or positive association between stock returns and inflation, most empirical studies find that inflation (anticipated and/or unanticipated) has a negative impact on (real or nominal) stock returns. For example, Chen et al. (1986) found that the CPI inflation rate has an effect on stock returns. Several economic variables, most notably industrial production, shifts in the risk premium, yield curve twists, and, somewhat weaker, indicators of unanticipated inflation and changes in expected inflation during times when these variables were highly volatile, were found to be important in explaining expected stock returns (Chen et al. 1986). Cohen, Polk, and Vuolteenaho (2005) found that when inflation is high (low), stock returns are higher (lower) than justified by an amount that is constant across stocks, regardless of the riskiness of the specific stock. If investors have a money illusion, steady and low inflation is more likely to lead to a less mispriced stock market than unpredictable and high inflation (Cohen et al. 2005). According to Frazzini and Pedersen (2014) inflation is equivalent to the one-year US CPI inflation rate, which is included to account for possible effects of money illusion, though they find no evidence of this impact. Ilmanen et al. (2021) also present findings of a time-series regression of each factor's returns on the CPI inflation rate over the last century. I use a one-month lagged local CPI inflation rate and a local monthly CPI inflation rate.

The global default spread is also taken into account. Belo et al. (2013), for example, used the default spread as a business cycle variable. Asness et al. (2013) looked into the relationship between default spread and a few investment factors. The default spread is negatively related to momentum, while DEF is positively related to value. The default premium (DEF) is the yield spread between Moody's seasoned Baa corporate bond yield and Federal Reserve Economic Data's (FRED) 10-year treasury constant maturity yield.

In addition, the dividend yield is considered. Dividend yield, also known as the dividend-price ratio, is calculated by dividing the annual dividend per share by the stock's price per share. Over the period 1926-1991, Kothari and Shanken (1997) find credible evidence that dividend yield tracks time-series variation in expected real stock returns. Also, Rapach and Wohar (2005) find that the price-dividend ratio has considerable potential to forecast real stock price growth at long, though not short, horizons, using annual data from 1872 to 1997 and in line with the existing literature.

The local recession dummy is also taken into account. A recession dummy is used to represent the state of the economy. For example, Asness et al. (2013) report the time series regression coefficients of U.S. value and momentum returns on U.S. macroeconomic variables, one of which is a recession indicator. Ex post peak (=0) and trough dates (=1) from the FRED are used to calculate the recession predictor. Recessions have a small negative relationship with value and momentum, but none of these relationships are statistically important (Asness et al. 2013).

Ordinary Least Squares regression (OLS) is used in this analysis as the regression model to examine the relationship between investment factors and macroeconomic variables. The OLS model allows for the investigation of linearity, or the relationship between the dependent variable (Y) and the independent variable (X). The following is a simple regression model:

$$y_i = \beta_0 + \beta_1 x_i + \varepsilon_i$$

in which y_i is the dependent variable, x_i is the independent variable, and ε_i is the error term of observation unit i. β_0 is the intercept of the regression line's population, and β_1 is the slope of the regression line in question. The OLS estimator chooses the appropriate regression coefficients such that the regression line is as similar to the observed data as possible. Before OLS regression is run the stationarity condition is fulfilled by running the augmented Dickey-Fuller test and by possibly making changes to series if it is not stationary already.

Using OLS estimators β_0 and β_1 has a number of advantages. The OLS estimator is a system that is impartial and consistent, among other things. The OLS regression model, on the other hand, has been criticized for its shortcomings. First, when certain points in the data set have overly large or small values for the dependent variable relative to the rest pf the data set, least squares regression will perform poorly. Second, all linear regression methods (including, of course, least squares regression) have the significant flaw that most processes are not linear in fact. Finally, while it may seem intuitively that the more knowledge we have about a system, the simpler it is to make predictions about it, this is not always the case for many (if not all) widely used algorithms. As a result, in this study, each variable is looked at separately in order to avoid including too many independent variables in the model, which would cause serious problems. The following are some of the main reasons for choosing this method. First, it is simple to implement on a computer using widely available linear algebra algorithms. Second, compared to many other regression methods, it is easier to test mathematically. Finally, it generates solutions that are simple to comprehend.

4 RESULTS AND ANALYSIS

4.1 Summary statistics

This section presents summary statistics for each factor portfolio and a discussion of these before continuing with the analysis of the results and exploring potential reasons for the results as an initial examination of the possible occurrence of factor effects in the Nordic markets. The first research question concerns the time variation in the development of factor excess returns in the Nordic stock market. The second question is how does commonality in factor performance vary over the sample period? The last question is what are the common features of factor performance in different Nordic stock markets? These are the questions that this result section is trying to answer.

In this section the mean, standard deviation, Sharpe ratio, t-statistics, skewness, and kurtosis were calculated to examine the overall performance of five different portfolios (value, momentum, betting against beta, size, and quality) and market excess return in different countries. A t-statistic here is used to test the null hypothesis that the alpha is insignificant against the two-sided alternative that it is not. In addition, the tables show the correlation for each factor in different countries and the correlation between different countries.

Beginning with Table 1, the equity premium for stocks in the Nordic markets is measured as annual returns using monthly return data from 1986 to 2020. Denmark's equity premium is 10.3%, Finland's is 10.9%, Norway's is 9.3%, and Sweden's is 11.1%. So, on average, this is around 10.4% a year. The equity premium estimate is subject to high uncertainty, with an annual standard deviation of 18.4% in Denmark, 26.6% in Finland, 24.9% in Norway and 24.0% in Sweden. So, on average, this is about 23.5% a year. Nonetheless, the equity premium calculation, along with its standard deviation, yields significant t-stats in all Nordic countries after being measured on a sample of 418 months. In other words, based on the 95% confidence 1.96 hurdle-rate, the equity premium calculation is substantially different from zero. The statistical evidence for the equity premium on the value weighted market for Nordic common stocks supports the idea that investing in equities yields a higher, albeit riskier, return than risk-free assets. This is a significant implication in support of the idea that there should be some systematic risk factor exposures underlying differences in asset returns.

When it comes to factor premia, the outcomes of factor portfolios vary significantly between factors and Nordic countries. With t-stats high enough, only betting against beta (2.83) and momentum (5.25) can be statistically shown to be significant at a satisfactory level of confidence in Denmark. Quality, size, and value factors, on the other hand, fail to pass the t-test. During this sample period, the only significant factors in Finland were betting against beta (3.26) and momentum (3.28). Quality, size, and value, on the other hand, are unable to obtain significant t-statistics in Finland. In Norway, betting against beta (3.46) and momentum (3.91) are significant, but quality factor (2.3) can also pass the test hurdle. In Norway, size and value are insignificant. In Sweden, the situation is similar to that in Norway, with betting against beta (3.56), momentum (2.82) and quality (3.12) being significant.

This means that betting against beta and momentum factors are significant in all Nordic countries, quality is significant in half of them, and size and value factors are insignificant in all of them. Furthermore, from 1990 to 2020, the SMB size effect premium is estimated to be negative across the Nordic zone. In addition, during the same time span, the value effect premium was negative in Denmark and Norway. To put it another way, going long small cap or value stocks and short big cap or growth stocks from 1990 to 2020 would have resulted in a negative annual average return of approximately -1.1% for size strategy and approximately -3% for Danish and Norwegian value strategy. Fama and French (2012) found no evidence of a size premium in comprehensive international data from recent years. Following its discovery in the early 1980s and subsequent exploitation, the size effect is thought to have vanished, which seems to be the case for the Nordics as well, based on this study. The value factor, comparable to size, yields a negative premium in Norway and Denmark, but a marginally positive premium of approximately 2.7% annually in Finland and Sweden. However, due to the high sample standard deviation, the resulting t-statistics provide little faith in the estimate. Since the book-to-market representation of the value-effect has traditionally had the most traction in the literature, the lack of significance for the value premium may seem surprising, but recent research has shown that average out-of-sample value premiums for post-1991 value premiums are low and statistically indistinguishable from zero (Linnainmaa & Roberts 2018, Fama & French 2020).

When it comes to the UMD factor, the momentum effect has shown to be the most promising so far. From 1987 to 2020, investing in the best-performing stocks over the previous 12 months, except the most recent month, and shorting the worst-performing stocks would have yielded an average annual return of 12.4% across the Nordic countries. The UMD factor premium is clearly significant, with annual factor volatility of 19.4% on average, which is lower than the broad market's 23.5%. These findings are encouraging for factor models involving UMD and trades on the momentum proposition, but due to higher turnover, UMD factor returns are more susceptible to transaction costs.

Significant results are obtained for betting against beta factor. Despite the fact that the estimated standard deviation is high, averaging 19.4% annually across Nordic countries, the relatively high returns of the BAB factor, averaging 11.3% annually across Nordic countries, gives the BAB premium estimate a statistically significant t-statistic in each Nordic country. The t-stat is well above the 95% confidence level of 1.96, and with the sample size of 381 monthly observations, it's safe to assume that betting against beta has produced substantial risk-adjusted returns from 1989 to 2020. When these five factors are compared, the quality factor is in the center. In Norway and Sweden, it generates large premiums, but in Denmark and Finland, it generates positive but insignificant returns. A statistically significant t-statistics of 2.3 and 3.12, respectively, are based on relatively solid average monthly returns of 6.9% in Norway and 7.7% in Sweden annually, as well as lower sample standard deviation compared to other factors of 15% in Norway and 12.5% in Sweden annually. The quality factor in Denmark has yielded annual returns of 3.7%, and with a standard deviation of 13%, the t-statistics is unable to clear the hurdle rate.

Table 1: Descriptive statistics (annual)

Asset class	**Factor**	**Mean**	**Stdev**	**Sharpe**	**t-stat**	**Skew**	**Kurt**	**Start date**	**End date**
Danish stocks	Betting against beta	8.5%	16.9%	0.50	**2.83**	0.2	5.4	Feb-1989	Oct-2020
	Value	-3.7%	15.4%	-0.24	1.32	0.2	3.9	Jul-1990	Oct-2020
	Market	10.3%	18.4%	0.56	**3.31**	-0.4	5.2	Jan-1986	Oct-2020
	Quality	3.7%	13%	0.29	1.44	0.0	4.6	Jul-1995	Oct-2020
	Size	-0.8%	12.1%	-0.06	0.34	-0.2	3.4	Jul-1990	Oct-2020
	Momentum	14.0%	15.5%	0.90	**5.25**	-0.8	5.6	Jan-1987	Oct-2020
Finnish stocks	Betting against beta	12.4%	21.5%	0.58	**3.26**	0.5	5.6	Feb-1989	Oct-2020
	Value	4.0%	21.7%	0.18	1.01	0.9	7.2	Jul-1990	Oct-2020
	Market	10.9%	26.6%	0.41	**2.42**	0.1	4.7	Jan-1986	Oct-2020
	Quality	0.6%	16.7%	0.03	0.17	-0.2	4.3	Jul-1995	Oct-2020
	Size	-1.1%	15.1%	-0.07	0.40	0.2	4.9	Jul-1990	Oct-2020
	Momentum	11.8%	21.0%	0.56	**3.28**	-0.3	6.8	Jan-1987	Oct-2020
Norwegian stocks	Betting against beta	12.3%	20.0%	0.62	**3.46**	0.2	4.2	Feb-1989	Oct-2020
	Value	-2.2%	18.1%	-0.12	0.66	0.1	4.1	Jul-1990	Oct-2020
	Market	9.3%	24.9%	0.38	**2.22**	-0.7	4.9	Jan-1986	Oct-2020
	Quality	6.9%	15.0%	0.46	**2.3**	0.3	4.3	Jul-1995	Oct-2020

	Size	-0.5%	12.3%	-0.04	0.21	-0.2	3.8	Jul-1990	Oct-2020
	Momentum	14.0%	20.9%	0.67	**3.91**	-0.2	3.8	Jan-1987	Oct-2020
Swedish stocks	Betting against beta	12.1%	19.2%	0.63	**3.56**	-0.2	5.8	Feb-1989	Oct-2020
	Value	1.4%	18.5%	0.08	0.42	0.3	9.3	Jul-1990	Oct-2020
	Market	11.1%	24.0%	0.46	**2.74**	-0.3	4.3	Jan-1986	Oct-2020
	Quality	7.7%	12.5%	0.62	**3.12**	-0.7	6.9	Jul-1995	Oct-2020
	Size	-2.0%	12.4%	-0.16	0.89	-0.5	6.8	Jul-1990	Oct-2020
	Momentum	9.7%	20.1%	0.49	**2.82**	-0.6	7.5	Jan-1987	Oct-2020

Despite the quality factor's overall good performance in other Nordic countries, it has not provided nearly any positive returns in Finland, with an average annual return of only 0.6% and a t-statistic of only 0.17. It is fascinating to see how the quality factor behaves so differently in Finland than in other Nordic countries. It is something to watch for in upcoming experiments to see whether this behavior can be clarified in some way. As it is clear that value and size factors were unable to provide investors excess returns during the sample period, and the aim of this study is to discover time-varying differences between different factors and to identify variables that may explain these results, it is preferable to concentrate only on the significant factors in the upcoming time series tests.

Tables 2-5 below show correlations between different factors, while tables 6-11 show correlations between nations. The correlations between factors are an important thing to consider when diversifying. Combining factors into multifactor portfolios increases the risk-returns relationship when they are not perfectly correlated. The main feature that results in substantial diversification benefits over long investment horizons is the low, or even negative, correlation between factors.

According to Asness et al. (2014), there is a negative relationship between size and quality, which is due to smaller stocks being riskier in general. This is true in all Nordic countries where the correlation between size and quality factors is negative. In Denmark, Norway, and Sweden, the quality factor has the strongest correlation with the momentum factor, as shown in tables 2 to 5. In Finland, however, the correlation between quality and momentum is actually negative. Quality has the strongest correlation with market factor in Finland, which is in turn negatively correlated with quality factor in any other Nordic country. This poses the intriguing question of which companies actually make up Finland's quality stock portfolio. There must be some fundamental discrepancies between Finland and the other Nordic countries that justify why Finland's quality strategy works so differently. However, this is something that will have to be studied further in the future. In each Nordic country, the quality factor has a negative correlation with the value factor.

In Denmark and Sweden, the size factors have the lowest correlations with the quality portfolios. The size factor has the lowest correlation with market factor in Finland and Norway. The size factor has the highest correlations with betting against beta portfolios in all Nordic countries. The correlation between market excess returns and momentum as a long-short strategy is negative. Market excess return, on the other hand, have the lowest correlations with quality portfolios in every Nordic country except Finland. In Finland, on the other hand, market excess return has the lowest correlation with size and value portfolios. Market excess return has the highest correlation with value portfolios in Norway and Sweden, while it has the highest correlation with betting against beta factor in Denmark and quality factor in Finland.

Asness et al. (2013) investigate the correlations between value and momentum strategies across eight asset classes and markets. Within and through asset classes, there are negative correlations between value and momentum (Asness et al. 2013). In my Nordic data set, I also discovered negative correlations between value and momentum everywhere but Finland, where the correlation is exactly zero. In Denmark and Sweden, value factor has the highest correlation with betting against beta portfolios, while in Norway and Finland, it has the highest correlation with market excess return and size factor, respectively. Value factor has the lowest correlation with quality portfolios in Denmark and Finland, and the lowest correlation with momentum factor in Norway and Sweden.

In Denmark and Finland, betting against beta factor has the highest correlation with size portfolios, and in Norway and Sweden, it has the highest correlation with momentum factor. Betting against beta factor has the lowest correlation with market excess return in Finland and Sweden, while it has the lowest correlation with quality in Denmark and value factor in Norway.

In every Nordic country except Finland, the momentum factor has the highest correlation with quality portfolio, and it has the highest correlation with betting against beta factor in Finland. The momentum factor has the lowest correlation with value portfolio in every Nordic country except Finland, and it has the lowest correlation with market excess return in Finland. With a correlation of 0.55, quality and momentum factors in Sweden have the highest single correlation of all. To summarize, factor performance appears to be very well integrated in Denmark, Norway, and Sweden, but Finland appears to be a bit of an outlier, and factor performance appears to be somewhat different in Finland compared to other Nordic countries.

Table 2: Correlation Denmark

	BABDNK	HMLDNK	MKTDNK	QMJDNK	SMBDNK	UMDDNK
BABDNK	1					
HMLDNK	0,08	1				
MKTDNK	0,06	0,00	1			

QMJDNK	0,05	-0,40	-0,29	1		
SMBDNK	0,19	-0,01	-0,11	-0,20	1	
UMDDNK	0,18	-0,28	-0,19	0,43	-0,13	1

Table 3: Correlation Finland

	BABFIN	HMLFIN	MKTFIN	QMJFIN	SMBFIN	UMDFIN
BABFIN	1					
HMLFIN	0,16	1				
MKTFIN	-0,22	-0,44	1			
QMJFIN	0,02	-0,52	0,09	1		
SMBFIN	0,34	0,17	-0,44	-0,09	1	
UMDFIN	0,28	0,00	-0,27	-0,04	0,09	1

Table 4: Correlation Norway

	BABNOR	HMLNOR	MKTNOR	QMJNOR	SMBNOR	UMDNOR
BABNOR	1					
HMLNOR	-0,11	1				
MKTNOR	0,05	0,16	1			
QMJNOR	0,21	-0,37	-0,40	1		
SMBNOR	0,16	0,07	-0,22	-0,15	1	
UMDNOR	0,24	-0,42	-0,21	0,42	-0,14	1

Table 5: Correlation Sweden

	BABSWE	HMLSWE	MKTSWE	QMJSWE	SMBSWE	UMDSWE
BABSWE	1					
HMLSWE	0,07	1				
MKTSWE	-0,19	0,01	1			
QMJSWE	0,37	-0,22	-0,43	1		
SMBSWE	0,11	-0,07	-0,07	-0,26	1	
UMDSWE	0,41	-0,45	-0,31	0,55	-0,06	1

The similarities in factor performance between nations are shown in tables 6-11. Table 6 shows that the highest correlation in betting against beta factor is between Finland and Denmark, and Finland and Sweden. Denmark and Norway have the lowest correlation in betting against beta factor. Table 7 reveals that Finland and Sweden have the highest value factor correlation. Denmark and Finland, as well as Denmark and Sweden, have the lowest value factor correlation.

According to Table 8, Denmark and Sweden have the highest market excess return correlation of 0.79, which is considered high. With a value of 0.63, Finland and Norway have the lowest market excess return correlation, but this is still a mild correlation. Table 9 shows that Norway and Sweden have the highest quality factor correlation of 0.38, indicating a low positive correlation. Finland and Norway have the lowest quality factor correlation, with a value of 0.01, and this indicates no correlation at all between Finland and Norway.

Table 10 indicates that the size factor correlation between Norway and Finland is 0.27, suggesting a negligible correlation. With a value of 0.08, Finland and Denmark have the lowest size factor correlation, indicating that there is no correlation between the two countries. The momentum factor correlation between Norway and Sweden is 0.56, indicating a moderate positive correlation, according to Table 11. Finland and Denmark have the lowest momentum factor correlation, with a value of 0.32, suggesting a low correlation between the two countries.

All in all, because of these correlations, it can already be expected that factor diversification will beat country diversification in the upcoming factor diversification versus country diversification section. This is because none of the country correlations were negative, while multiple factor correlations were heavily negative, implying greater diversification benefits.

Table 6: Correlation Betting against beta

	BABDNK	BABFIN	BABNOR	BABSWE
BABDNK	1			
BABFIN	0,37	1		
BABNOR	0,26	0,31	1	
BABSWE	0,33	0,37	0,33	1

Table 7: Correlation Value

	HMLDNK	HMLFIN	HMLNOR	HMLSWE
HMLDNK	1			
HMLFIN	0,25	1		
HMLNOR	0,32	0,32	1	
HMLSWE	0,25	0,38	0,33	1

Table 8: Correlation Market

	MKTDNK	MKTFIN	MKTNOR	MKTSWE
MKTDNK	1			
MKTFIN	0,65	1		
MKTNOR	0,76	0,63	1	
MKTSWE	0,79	0,78	0,76	1

Table 9: Correlation Quality

	QMJDNK	QMJFIN	QMJNOR	QMJSWE
QMJDNK	1			
QMJFIN	0,24	1		
QMJNOR	0,28	0,01	1	
QMJSWE	0,27	0,03	0,38	1

Table 10: Correlation Size

	SMBDNK	SMBFIN	SMBNOR	SMBSWE
SMBDNK	1			
SMBFIN	0,08	1		
SMBNOR	0,13	0,27	1	
SMBSWE	0,21	0,24	0,23	1

Table 11: Correlation Momentum

	UMDDNK	UMDFIN	UMDNOR	UMDSWE
UMDDNK	1			
UMDFIN	0,32	1		
UMDNOR	0,39	0,39	1	
UMDSWE	0,42	0,53	0,56	1

4.2 Time-varying factor performance

In this thesis, time-varying factor performance is one of the points of concern, in addition to overall factor performance. As a result, factors have been divided into three sub-periods, with each sub-period's performance being analyzed in greater detail. First, time-varying market excess returns are looked at. The market excess returns are divided into three cycles, the first of which runs from January 1986 to July 1997, the second of which runs from August 1997 to February 2009, and the third of which runs from March 2009 to September 2020. Overall, as shown in Figure 1 market excess returns have developed in a very similar manner across Nordic countries. During the first sub-period, the trend was fairly consistent, with only a slight decline during the early 1990s recession. Except in Sweden, as shown in Table 12, where the annual average return was 14.8%, annual average returns have been about 10%. However, since the first sub-period's standard deviations are also high, Sweden is the only Nordic country with significant t-statistics.

By far, the second sub-period has been the most difficult. This is attributed to the financial crisis, which resulted in a significant drop in market excess returns. During this second sub-period, market excess returns were about 5% per year, and standard deviations were at their highest levels. As shown in Figure 1, the most recent sub-period produced the best market excess returns. Even though the eurozone sovereign debt crisis in 2011 and the corona virus crisis in the spring of 2020 triggered some stock market volatility, it was mostly uphill during this sub-period. Despite the crises, average annual market excess returns in Denmark, Finland, and Sweden were about 15%, with t-statistics that were significant. The average annual return in Norway was 10.3%, and the t-statistic was insignificant.

Table 12: Time-varying market factor performance

	Market	Mean	Stdev	Sharpe	t-stat	skew	Kurt
Danish stocks	1/1986-7/1997	8.9%	17.9%	0.50	1.62	0.3	4.4
	8/1997-2/2009	5.1%	19.5%	0.26	0.86	-1.2	6.2
	3/2009-9/2020	17.1%	17.7%	0.97	**3.15**	0.1	3.8
Finnish stocks	1/1986-7/1997	12.5%	24.7%	0.51	1.65	0.3	3.8
	8/1997-2/2009	7.5%	32.5%	0.23	0.75	0.0	4.2
	3/2009-9/2020	13.3%	21.7%	0.61	**1.98**	0.2	4.7
Norwegian stocks	1/1986-7/1997	12.8%	23.6%	0.54	1.76	-0.6	3.7
	8/1997-2/2009	5.6%	27.4%	0.20	0.67	-1.1	5.8
	3/2009-9/2020	10.3%	23.6%	0.44	1.42	-0.1	3.8
Swedish stocks	1/1986-7/1997	14.8%	23.8%	0.62	**2.03**	-0.4	3.9
	8/1997-2/2009	2.6%	26.6%	0.10	0.32	-0.4	4.0
	3/2009-9/2020	16.5%	21.4%	0.77	**2.52**	0.4	4.8

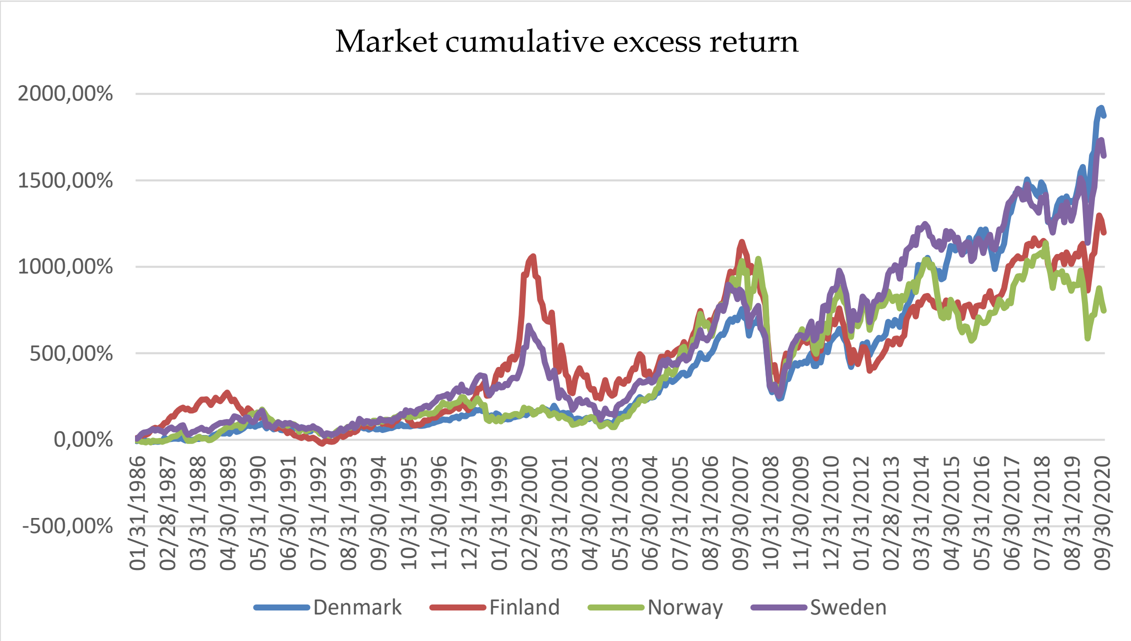

Figure 1: Cumulative excess returns of market factor

The betting against beta factor is split into three cycles: the first runs from February 1989 to August 1999, the second from September 1999 to March 2010, and the third from April 2010 to October 2020. When we look at the three sub-periods of betting against beta factor in Table 13, we can see that there were no significant excess returns for this strategy in the first sub-period. In reality, the betting against beta strategy in Denmark has generated negative average annual returns of -1.3% over this time period. In all of the Nordic countries, the betting against beta strategy performed best in the second sub-period. In this sub-period, this factor has a significant t-statistic in every Nordic country, with average annual excess returns of over 20% in Denmark, Finland, and Sweden. The average excess return in Norway was just 16.8%. In Finland, investors who used this strategy in the second sub-period would have earned huge excess returns of 29.7% per year.

Figure 2 shows that this strategy operated similarly across Nordic countries until 2005-2006, but then something changed. In the most recent sub-period, this strategy still generated significant excess returns in Norway and Sweden, with average annual returns of 19.5% and 8.2%, respectively, and t-stats of 3.96 and 2.30. However, in Denmark and Finland, betting against beta factor has been no longer a viable strategy. In this sub-period, betting against beta factor has yielded positive returns of 4.7% annually in Denmark, but negative returns of -1% annually in Finland. Figure 2 shows that accumulated excess returns in Finland have not yet returned to the amount they were prior to the eurozone sovereign debt crisis. Certain stock market anomalies are less anomalous after they are released, according to McLean and Pontiff (2016). This is also possible in Denmark and Finland. After Frazzini and Pedersen's work on betting against beta was published in 2014, it is likely that investors in Denmark and Finland were able to exploit this anomaly and its impact was lost.

Table 13: Time-varying betting against beta factor performance

	Betting against beta	Mean	Stdev	Sharpe	t-stat	Skew	Kurt
Danish stocks	2/1989-8/1999	-1.3%	13.5%	-0.10	0.32	-0.1	3.0
	9/1999-3/2010	22.1%	21.7%	1.02	**3.30**	-0.3	4.1
	4/2010-10/2020	4.7%	13.3%	0.36	1.16	1.1	9.6
Finnish stocks	2/1989-8/1999	8.5%	23.7%	0.36	1.17	0.3	4.8
	9/1999-3/2010	29.7%	24.7%	1.20	**3.91**	0.4	4.9
	4/2010-10/2020	-1.0%	13.5%	-0.07	0.24	0.3	3.3
Norwegian stocks	2/1989-8/1999	0.5%	24.6%	0.02	0.06	0.5	3.9
	9/1999-3/2010	16.8%	18.1%	0.93	**3.03**	0.2	2.9
	4/2010-10/2020	19.5%	16.0%	1.22	**3.96**	-0.2	5.2
Swedish stocks	2/1989-8/1999	3.9%	19.6%	0.20	0.65	-0.7	4.7
	9/1999-3/2010	24.2%	23.9%	1.01	**3.29**	-0.2	4.8
	4/2010-10/2020	8.2%	11.7%	0.71	**2.30**	0.3	2.7

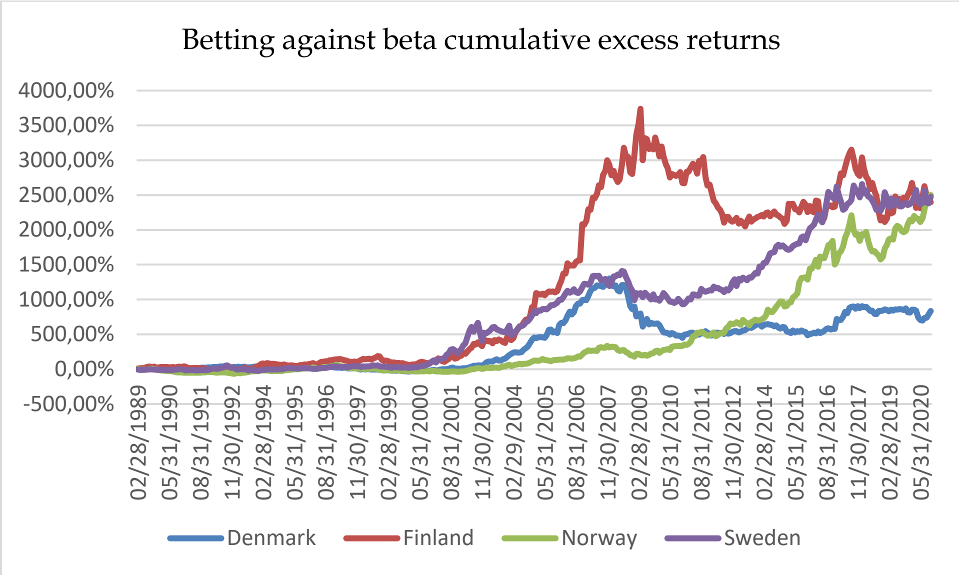

Figure 2: Cumulative excess returns of betting against beta factor

The value factor is divided into three cycles: the first begins in July 1990 and ends in July 2000, the second in August 2000 and ends in August 2010, and the third in September 2010 and ends in September 2020. When comparing the output of value factor in different Nordic countries, Figure 3 shows that value factor appears to perform equally in all Nordic countries, indicating that there are no significant variations between countries. Table 14 show that in the first sub-period, value factor produced negative average returns of around -5% per year in every Nordic country.

Value stocks have given positive returns in the second sub-period, with significant positive returns in Finland and Sweden. The average annual return in Finland was 18.2%, while the average annual return in Sweden was 14.3%. In the second sub-period, average annual returns in Denmark were 7%, while in Norway they were 8.8%. The second sub-period starts shortly after the dotcom bubble exploded, when investors found a more stable place to put their money and turned to value stocks. Therefore, the low starting point and the good performance of value strategy during the financial crisis largely explain why value stocks performed well during this period. Value stocks performed poorly once again in the third sub-period, with average returns in every Nordic country being negative. Worse, the negative returns in Denmark and Norway were statistically significant, with t-values of -2.59 and -2.44, respectively. In the third sub-period, average annual excess returns in Denmark equaled -12.2%, while in Norway they equaled -13.2%. Overall, it appears that the value strategy works during economic downturns because investors choose to invest in businesses with stronger balance sheets and companies that are undervalued during volatile periods.

Table 14: Time-varying value factor performance

	Value	Mean	Stdev	Sharpe	t-stat	skew	Kurt
Danish stocks	7/1990-7/2000	-6.4%	15.1%	-0.42	1.35	0.1	3.2
	8/2000-8/2010	7.0%	15.8%	0.44	1.40	0.5	4.8
	9/2010-9/2020	-12.2%	14.9%	-0.81	**2.59**	-0.1	3.2
Finnish stocks	7/1990-7/2000	-5.0%	23.1%	-0.22	0.71	0.0	3.3
	8/2000-8/2010	18.2%	26.1%	0.70	**2.27**	1.4	7.1
	9/2010-9/2020	-0.9%	13.6%	-0.07	0.22	-0.3	4.5
Norwegian stocks	7/1990-7/2000	-2.4%	19.9%	-0.12	0.38	-0.1	3.8
	8/2000-8/2010	8.8%	16.7%	0.53	1.68	0.8	4.6
	9/2010-9/2020	-13.2%	17.3%	-0.77	**2.44**	-0.0	3.3
Swedish stocks	7/1990-7/2000	-4.7%	24.8%	-0.19	0.60	-0.2	6.1
	8/2000-8/2010	14.3%	17.6%	0.81	**2.58**	1.6	7.7
	9/2010-9/2020	-5.3%	9.2%	-0.58	1.83	-0.8	6.9

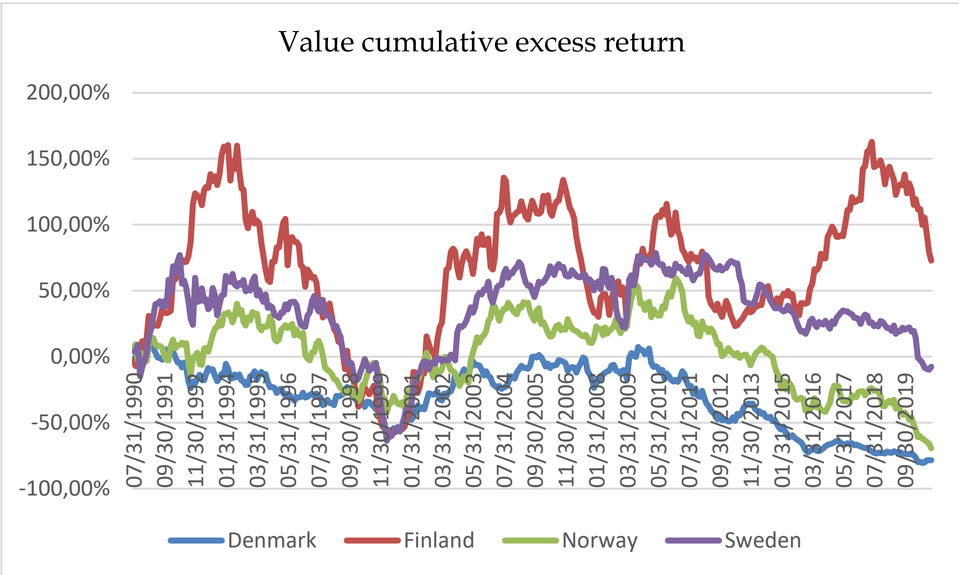

Figure 3: Cumulative excess returns of value factor

The quality factor is split into three cycles: the first runs from July 1995 to November 2003, the second from December 2003 to April 2012, and the third from May 2012 to September 2020. When looking at Figure 4, there is a lot of difference to note. Among the factors studied, it appears that the quality factor has the most variation. First and foremost, as shown in Table 15, Swedish quality stocks have had the most consistent results, with positive average returns in each sub-period. Swedish stocks, on the other hand, have only had significant average annual returns of 9% in the last sub-period. In addition, quality stocks in Norway have performed well in the third sub-period, with annual returns averaging 15.4% and a t-stat of 3.48. In the most recent sub-period, Finland had a positive average return of 2.3% annually, while Denmark had a negative average return of -1% annually.

The Nordic countries' quality factor performance is the most similar in the first sub-period. In Denmark, Norway, and Sweden, average returns have been positive around 5%. The average return in Finland has been just 1.6%. There is a lot of variation in excess returns in the second sub-period. The Danish and Swedish quality strategies have yielded positive but insignificant results, with average returns of around 8%. However, quality strategies in Finland and Norway both generated negative returns at the same time. Finland's average annual excess returns were -2.5%, while Norway's were -0.7%. In addition, Figure 4 reveals one noteworthy observation. In Finland, the accumulated excess returns have been completely negative, and the most recent observation is below the starting mark, implying that the quality strategy is failing miserably.

Table 15: Time-varying quality factor performance

	Quality	Mean	Stdev	Sharpe	t-stat	skew	Kurt
Danish stocks	7/1995-11/2003	5.0%	13.1%	0.38	1.10	-0.1	3.6
	12/2003-4/2012	7.8%	15.1%	0.52	1.51	-0.3	4.7
	5/2012-9/2020	-1.0%	10.3%	-0.10	0.29	0.4	4.8
Finnish stocks	7/1995-11/2003	1.6%	21.5%	0.07	0.24	-0.1	2.8
	12/2003-4/2012	-2.5%	14.8%	-0.17	0.54	-0.8	5.6
	5/2012-9/2020	2.3%	12.7%	0.18	0.58	0.4	5.2
Norwegian stocks	7/1995-11/2003	6.2%	18.1%	0.34	0.99	0.7	4.0
	12/2003-4/2012	-0.7%	13.4%	-0.05	0.14	-0.4	4.0
	5/2012-9/2020	15.4%	12.8%	1.20	**3.48**	0.0	3.0
Swedish stocks	7/1995-11/2003	5.8%	15.7%	0.37	1.07	-0.3	6.0
	12/2003-4/2012	8.3%	12.4%	0.67	1.94	-1.2	5.6
	5/2012-9/2020	9.0%	8.4%	1.08	**3.13**	-0.3	2.7

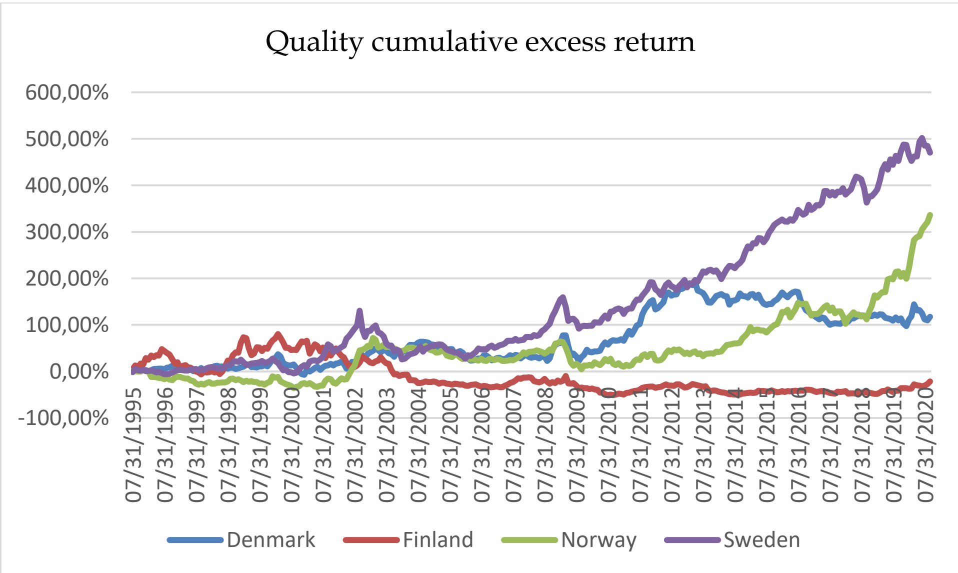

Figure 4: Cumulative excess returns of quality factor

The size factor is divided into three cycles: the first begins in July 1990 and ends in July 2000, the second in August 2000 and ends in August 2010, and the third in September 2010 and ends in September 2020. When we look at Figure 5, which depicts the evolution of accumulated excess returns of size factor, we can see that although, there are some differences along the way, the end result appears to be very similar across Nordic countries. Table 16 show that this is right. Nothing here is significant. As a result, it can be concluded that the size factor does not provide significant excess returns for investors, a trend that has been observed in previous studies as well. In addition, Figure 5 shows that the cumulative development in every Nordic country has been negative.

Table 16: Time-varying size factor performance

	Size	Mean	Stdev	Sharpe	t-stat	skew	Kurt
Danish stocks	7/1990-7/2000	-0.4%	12.5%	-0.03	0.10	0.0	3.4
	8/2000-8/2010	-2.0%	12.2%	-0.16	0.52	-0.1	3.5
	9/2010-9/2020	0.1%	11.9%	0.01	0.04	-0.5	3.4
Finnish stocks	7/1990-7/2000	-0.6%	18.5%	-0.03	0.11	0.2	4.1
	8/2000-8/2010	0.4%	15.1%	0.02	0.08	0.0	4.7
	9/2010-9/2020	-3.8%	10.5%	-0.36	1.17	0.1	3.2
Norwegian stocks	7/1990-7/2000	4.4%	13.7%	0.32	1.02	-0.5	3.8
	8/2000-8/2010	-0.9%	13.8%	-0.07	-0.21	0.0	3.2
	9/2010-9/2020	-4.7%	8.7%	-0.54	1.72	-0.2	2.9
Swedish stocks	7/1990-7/2000	-2.7%	13.3%	-0.2	0.65	-0.9	10.2
	8/2000-8/2010	-5.1%	13.5%	-0.38	1.21	-0.2	4.1
	9/2010-9/2020	1.8%	10.1%	0.18	0.57	0.2	2.8

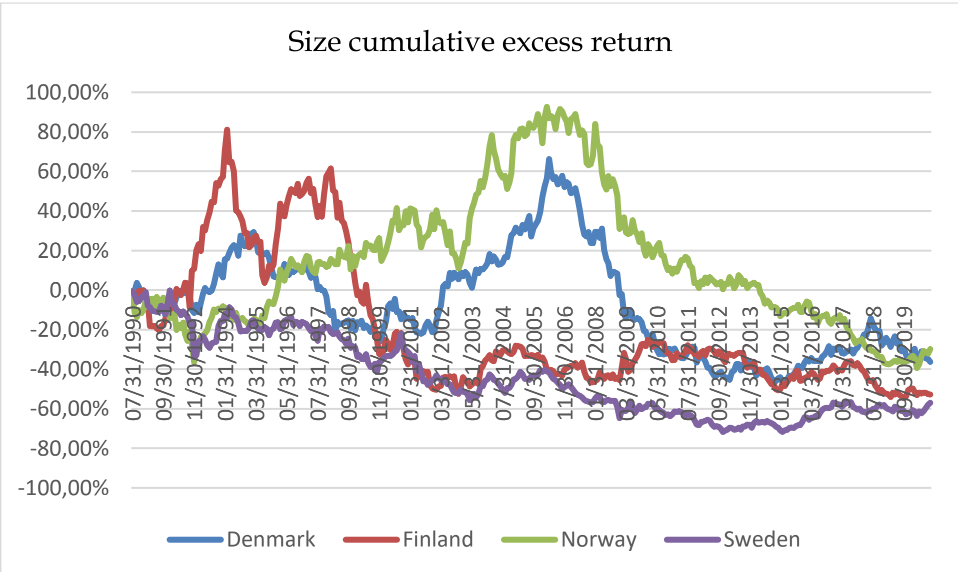

Figure 5: Cumulative excess returns of size factor

The momentum factor is divided into three cycles, the first of which starts in January 1987 and ends in March 1998, the second of which starts in April 1998 and ends in June 2009, and the third of which starts in July 2009 and ends in September 2020. As previously stated and documented in the literature, the momentum factor has given the best overall results. Despite the fact that certain crashes will occur in the future, this factor consistently produces positive results. The average returns in every sub-period in every country have always been positive, as shown in Table 17 below. In Finland, Norway, and Sweden, however, there is some evidence of periodic changes since standard deviation was extremely high in the second sub-period. It has been about 25% annually. As a result, even though the average annual return in Finland has been 14%, the middle sub-period t-statistic is not significant.

So, while the overall momentum factor has worked well in every country, there are some variations between countries when we look at the sub-periods. In the first sub-period only in Denmark the average excess returns have been significant 9.0% annually with t-statistics being 2.03. Instead, in Sweden, the average excess returns were just 2.6% per year, with t-statistic of just 0.48.

Denmark and Norway have significant excess returns in the second sub-period, while Finland and Sweden have insignificant excess returns. Finally, in the most recent sub-period, every Nordic country's average excess returns were significant, and every country's momentum t-statistics were at their highest levels. Denmark is also worth noting because it is the only country with significant momentum t-statistics in each sub-period. Overall, momentum is obviously the factor in the Nordic countries that has provided investors with the most consistent positive excess returns, as shown in Figure 6 below, with Denmark and Norway providing much higher excess returns than Finland and Sweden.

Table 17: Time-varying momentum factor performance

	Momentum	Mean	Stdev	Sharpe	t-stat	Skew	Kurt
Danish stocks	1/1987-3/1998	9.0%	15.0%	0.60	**2.03**	-0.3	3.1
	4/1998-6/2009	14.4%	18.4%	0.78	**2.62**	-1.1	6.3
	7/2009-9/2020	18.4%	12.6%	1.46	**4.90**	-0.3	3.7
Finnish stocks	1/1987-3/1998	10.5%	22.6%	0.47	1.52	-0.9	8.1
	4/1998-6/2009	14.0%	24.9%	0.56	1.83	0.2	4.4
	7/2009-9/2020	10.9%	14.0%	0.78	**2.54**	-0.1	3.4
Norwegian stocks	1/1987-3/1998	5.8%	21.6%	0.27	0.90	-0.3	2.9
	4/1998-6/2009	16.0%	24.5%	0.66	**2.20**	-0.1	3.7
	7/2009-9/2020	20.3%	15.8%	1.29	**4.32**	-0.2	4.0
Swedish stocks	1/1987-3/1998	2.6%	18.4%	0.14	0.48	0.2	5.1
	4/1998-6/2009	11.8%	27.5%	0.43	1.43	-0.6	5.3
	7/2009-9/2020	14.6%	10.6%	1.37	**4.61**	-1.1	7.6

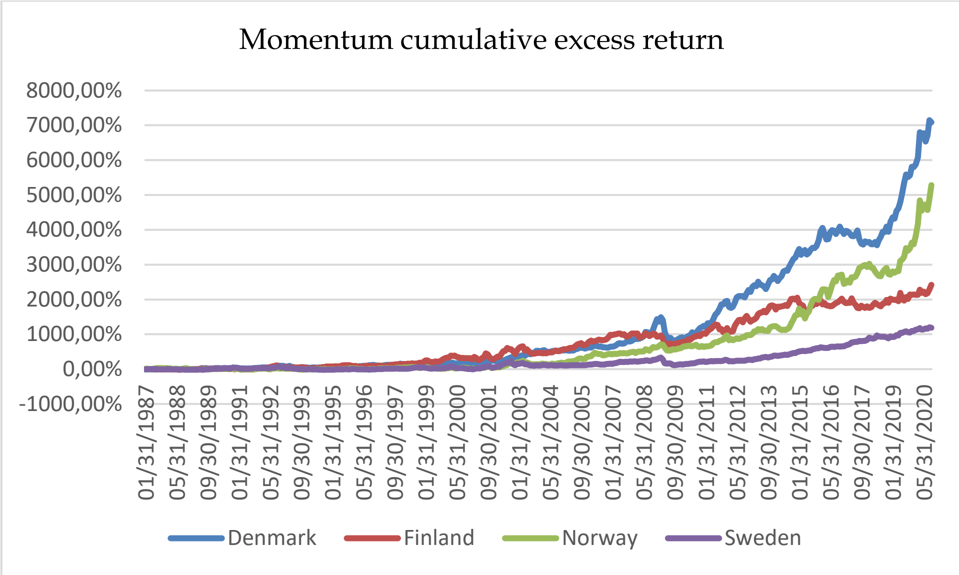

Figure 6: Cumulative excess returns of momentum factor

It is also fascinating to see how various factors provide returns during times of high volatility from the perspective of investors. Therefore, I looked at one more particular time frame, the financial crisis period, and the findings are in the appendix. This is due to the fact that the financial crisis lasted just 29 months, making it impossible to draw any meaningful conclusions. However, we can see from Appendices B1-B6 that there is a great deal of difference in factor performance between countries. This is something that should be investigated further in the future by integrating all the recession times in order to obtain adequate data to draw economically relevant conclusions.

4.3 Macroeconomic exposure

Given the variation in factor return premia discovered in section 4.2, it is now necessary to determine why this variation exists and what causes of variation may be driving these dynamics. As a result, a broad variety of economic shocks and news inspired by various asset pricing theories are investigated in this section. Previous attempts to link factors to economic risks have been hampered by a lack of time series, and this is a problem in my research as well due to the scarcity of data in Nordic markets. The variety of asset classes can also help reduce noise that can obscure these relationships, but this is a limitation of this study since equity is the only asset class examined. Furthermore, since size and value factors have previously been shown to be insignificant in Nordic markets, they are not investigated here. This is because it makes more sense to concentrate solely on factors that have produced significant excess returns, since these are the factors that investors care about. In addition, macroeconomic variables, listed in the data section, are tested with all the factors. However only significant variables are presented in the tables 18-20 below. As the significant variables vary between factors, different macroeconomic variables are found in the tables. All insignificant determinants are reported in the appendix.

Table 18 displays the results of the betting against beta factor. To begin with, in every Nordic country, changes in the local real exchange rate index positively and significantly explain the betting against beta factor excess returns. This means that as the real exchange rate index rises, low beta stocks outperform high beta stocks. International competitiveness will be harmed by an increase in the real effective exchange rate. According to previous literature, competitive economies have higher stock market growth. The relationship between stock prices and the real exchange rate is negative, since a deterioration in a country's competitiveness should be reflected in deteriorated domestic company output and lower stock prices. Even though any previous research on the relationship between the real exchange rate index and long-short betting against beta portfolios was not found, I suppose that if a country's competitiveness declines, low-risk stocks would outperform high-risk stocks.

In Finland and Sweden, Baker and Wurgler (2006) sentiment index has a positive and significant effect on the betting against beta factor. The relationship between these two variables is not significant in Denmark and Norway. Investor sentiment, according to Baker and Wurgler (2006), explains variation in value, momentum, and other equity factor returns over time. When sentiment is strong, defensive low-beta stocks appear to have higher returns, similar to Ilmanen et al. (2021).

In two of the four Nordic countries, the Vix index, Ted spread, and dividend yield have a negative and significant effect on betting against beta factor. We can see that VIX has a negative and significant relationship with BAB returns in Denmark and Norway, so if the VIX index falls for any reason, the BAB strategy should then provide excess returns there. These findings are the opposite of what one would predict. Stocks with higher betas, by definition, shift more with the market than stocks with lower betas. As a result, it is reasonable to expect the BAB to benefit from peaks in market volatility – when uncertainty rises, the stock market tends to fall in value. High-beta stocks fall more rapidly than low-beta stocks under these situations, so BAB's short position in high-beta stocks should be profitable. Low-beta stocks will, of course, be affected by market losses, but they will not, by definition, fall to the same degree as high-beta stocks. As a result, the long position in low-beta stocks should not result in greater losses than the short side, and the strategy as a whole should be profitable in volatile market conditions. In high-VIX conditions, BAB was expected to perform better; however, the reason for the observed results is relatively clear. As previously stated, the excess returns on the betting against beta strategy are very high, especially during the low-volatility era prior to the financial crisis. Furthermore, rescaling portfolio betas entails leveraging the low-beta portfolio and deleveraging the high-beta portfolio, which increases the low-beta portfolio's impact on BAB returns while weakening the high-beta portfolio's effect. Since the low-beta side is leveraged, the returns on BAB are higher as low-beta stocks rise in value, as opposed to when profits are derived mostly from falling prices of shorted high-beta stocks.

Regression results regarding TED spread are like the results of Frazzini and Pedersen 2014. Frazzini and Pedersen (2014) said that a high TED spread can mean that banks are credit constrained, and that banks tighten other investors' credit constraints over time, causing BAB returns to deteriorate. The relationship between dividend yields and stock returns is a problem in finance that has yet to be solved. According to Lewellen (2004) estimated returns and dividend yields have a good positive relationship. However, Welch and Goyal (2008) found no evidence to support the connection. According to Maio and Santa-Clara (2015), the relationship between dividend yield and stock returns is favorable for the overall stock market, but not for small and value stock portfolios. No research regarding connection between long-short betting against beta portfolios and dividend yield was found, maybe because the impact mechanism of dividend yield to long-short portfolios is hard to determine. However, stocks that usually trade with a little less price volatility in the market pay dividends more regularly. In my analysis the relationship was negative implying that when dividend yield of certain country goes down betting against beta excess return increase.

Some of the macroeconomic variables explain betting against beta factor significantly only in one country. In Denmark, changes in global consumer credit, global industrial production, and the global geopolitical risk index are all significant. In Finland, global LIBOR-term repo is significant. In Norway, changes in local stock market volatility as well as lagged local inflation are significant. Finally, in Sweden, changes in the local short-term interest rate and the local term spread are significant.

Table 18: Macroeconomic exposure of betting against beta factor. Upper value is coefficient, middle value is t-value, and lower value is r-squared. Bolded values are significant with 5% statistical significance level.

Betting against beta	Denmark	Finland	Norway	Sweden
Change in global consumer credit	**0,0115**	0,0047	0,0054	0,0072
	(2,39)	(0,76)	(0,93)	(1,31)
	1,5 %	0,2 %	0,2 %	0,5 %
Change in global industrial production	**0,0034**	0,0009	0,0011	0,0016
	(2,31)	(0,48)	(0,66)	(0,95)
	1,5 %	0,1 %	0,1 %	0,3 %
Change in local equity market volatility	0,0004	-0,0004	**-0,0015**	0,0005
	(0,59)	(-0,75)	**(-2,45)**	(0,81)
	0,1 %	0,2 %	**1,6 %**	0,2 %
Change in local real exchange rate index	**0,0175**	**0,0077**	**0,0092**	**0,0048**
	(4,54)	**(2,14)**	**(4,98)**	**(2,29)**
	6,1 %	**1,4 %**	**7,2 %**	**1,6 %**
	0,0015	-0,0128	-0,0052	**0,0198**
	(0,39)	(-1,61)	(-1,12)	**(3,99)**

Change in local short-term interest rate	0,0 %	0,7 %	0,3 %	**4,07 %**
Change in local Term spread	-0,0086	0,0057	0,0102	**-0,0138**
	(-0,75)	(0,63)	(1,26)	**(-2,17)**
	0,2 %	0,1 %	0,5 %	**1,2 %**
Global Baker-Wurgler Sentiment	0,0035	**0,0119**	-0,0057	**0,0193**
	(0,83)	**(2,22)**	(-1,13)	**(4,08)**
	0,2 %	**1,4 %**	0,4 %	**4,5 %**
Global geopolitical risk index	**0,0001**	0	0	0
	(2,13)	(-0,66)	(0,86)	(-0,45)
	1,2 %	0,1 %	0,2 %	0,1 %
Global LIBOR-term repo	-0,0033	**0,0245**	-0,0151	0,0047
	(-0,34)	**(2,24)**	(-1,6)	(0,46)
	0,0 %	**1,9 %**	1,0 %	0,1 %
Global Vix	**-0,001**	-0,0006	**-0,001**	-0,0002
	(-2,9)	(-1,41)	**(-2,72)**	(-0,65)
	2,2 %	0,5 %	**2,0 %**	0,1 %
Lagged local inflation	-0,0033	-0,019	**-0,0165**	-0,0088
	(-0,46)	(-1,89)	**(-2,3)**	(-1,56)
	0,1 %	0,9 %	**1,4 %**	0,6 %
Local dividend yield	-0,0068	**-0,0061**	-0,0049	**-0,0128**
	(-1,05)	**(-2,36)**	(-1,67)	**(-3,46)**
	0,4 %	**2,1 %**	1,1 %	**4,4 %**
Local Ted spread	**-0,0396**	**-0,0324**	-0,0071	0,011206
	(-3,07)	**(-2,74)**	(-0,9)	(1,95)
	3,0 %	**2,8 %**	0,3 %	1,0 %

The results of the momentum component are shown in Table 19. To begin with, changes in local short-term interest rates positively and significantly explain momentum excess returns in every Nordic country except in Denmark. This means that as the short-term interest rate rises, the recently best-performing stocks outperform the recently worst-performing stocks. This differs from the findings of Ilmanen et al. (2021), which found no evidence that factors vary with interest rate environments. In addition, dividend yield, default spread, term spread, and short-term interest rates, according to Cooper, Gutierrez Jr, and Hameed (2004), do not capture the asymmetry in momentum earnings.

Changes in local term spread have a negative and significant impact on the momentum factor in every Nordic country except Norway. As a result, if the term spread narrows for some reason, the UMD strategy can generate higher excess returns. Asness et al. (2013), on the other hand, found no proof that the momentum factor varies with term spread. Also, Cooper et al. (2004) claim that term spread does not capture the asymmetry in momentum earnings as stated in the previous chapter.

Changes in the local exchange rate index produce interesting results, as it positively and significantly explains momentum returns in Finland, but negatively and significantly explains momentum returns in Sweden. This means that in Finland if country competitiveness decreases, the momentum strategy can generate higher profits whereas in Sweden the momentum strategy generates higher profits when country competitiveness increases. In Denmark and Norway, however, the findings are statistically insignificant.

Some macroeconomic variables only explain the performance of the momentum factor in one country. Global VIX is significant in Denmark, whereas change in global economic policy uncertainty and local Ted spread are significant in Sweden. All in all, it seems to be that in Nordic countries short-term interest rate and term spread are the only macroeconomic variables play a role in explaining the variation in momentum factor excess returns. This is in line with the previous literature, for example Ilmanen et al. (2021), who state that overall, there is no evidence that momentum returns are related to macroeconomic variables in a meaningful way, either in real time or in the future. This suggests that the main reasons for the variation in the momentum returns comes from the behavioral explanations side. In addition, momentum seems to be the investment factor that correlates the least with macroeconomic variables.

Table 19: Macroeconomic exposure of momentum factor. Upper value is coefficient, middle value is t-value, and lower value is r-squared. Bolded values are significant with 5% statistical significance level.

Momentum	Denmark	Finland	Norway	Sweden
Change in global economic policy uncertainty	0,0001	0,0002	0,0001	**0,0003**
	(0,99)	(1,58)	(0,51)	**(2,48)**
	0,2 %	0,6 %	0,1 %	**1,5 %**
Change in local real exchange rate index	0,0055	**0,0118**	-0,0015	**-0,0049**
	(1,63)	**(3,28)**	(-0,7)	**(-2,15)**
	0,8 %	**3,3 %**	0,2 %	**1,4 %**
Change in local short-term interest rate	0,0047	**0,0326**	**0,0111**	**0,0172**
	(1,37)	**(4,41)**	**(2,34)**	**(3,37)**
	0,5 %	**4,6 %**	**1,4 %**	**2,8 %**
Change in local Term spread	**-0,0249**	**-0,0334**	-0,0112	**-0,0176**
	(-2,55)	**(-3,86)**	(-1,24)	**(-2,73)**
	2,1 %	**4,1 %**	0,5 %	**1,8 %**
Global Vix	**0,0007**	-0,0003	0,0005	0,0001
	(2,31)	(-0,8)	(1,15)	(0,3)
	1,4 %	0,2 %	0,4 %	0,0 %
Local Ted spread	0,0107	-0,0159	-0,0037	**0,0174**
	(0,96)	(-1,35)	(-0,42)	**(3)**
	0,3 %	0,7 %	0,1 %	**2,2 %**

Table 20 shows the results of the quality factor. To begin, with the exception of Finland, global VIX positively and significantly explains quality excess returns in every Nordic country. As the global VIX index increases, this means that high-quality stocks outperform low-quality stocks. Rise in VIX index means deterioration in financial conditions. So, it is intuitive that when financial conditions worsen, high-quality stocks perform better than low-quality stocks. This is because low-quality should be expected to be more sensitive to worsening financial conditions.

In Finland and Sweden, change in global economic policy uncertainty has a positive and significant effect on the quality factor, while the relationship is still positive but insignificant in Denmark and Sweden. Economic policy uncertainty is related to higher stock price volatility, according to Baker et al. (2016). Therefore, economic policy uncertainty should have the same impact on quality factor performance as the VIX index, which it does. So, when economic policy uncertainty increases, increases also high-quality stock returns compared to low-quality stock returns.

In Finland and Norway, change in the global Pástor-Stambaugh liquidity measure has a negative and significant effect on the quality factor, while the impact is negative but insignificant in Denmark and Sweden. As a result, the QMJ strategy will produce higher excess returns if the Pástor-Stambaugh liquidity measure declines for some reason. It is thus intuitive that, if market-wide liquidity goes down, it produces the flight-to-quality effect, where investors move to high-quality stocks and push the price of those shares up.

Changes in the local exchange rate index yield interesting results in terms of the quality component, as it explains quality returns positively and significantly in Finland, but negatively and significantly in Sweden. This is actually completely similar to the effect of real exchange rate regarding momentum factor performance. This means that when country competitiveness falls in Finland, the quality strategy can generate higher profits, while when country competitiveness rises in Sweden, the quality strategy can generate higher profits. There are so many different channels of influence in the relationship between real exchange rate and stock market excess returns and the results from previous literature have also been conflicting, so it is impossible to say why the effects of real exchange rate on quality and momentum returns in Finland and Sweden are completely opposite. In addition, the results are statistically insignificant in Denmark and Norway.

Some macroeconomic variables can only explain the quality factor's performance in one country. Change in global consumer credit is significant in Denmark. The shift in global m2 in Finland is significant. Changes in the local term spread, the global geopolitical risk index, and the local recession dummy are all significant in Norway. Finally, global Baker-Wurgler sentiment and local inflation are both significant in Sweden.

All in all, only few macroeconomic variables can explain the cross-section of betting against beta, momentum, and quality returns. To name a few, real exchange rate appears to explain all the factors to some extent, even though results are mixed between Finland and Sweden. Also, VIX seems to explain both betting against beta and Quality returns, as well as momentum returns in Denmark. Otherwise most macroeconomic variables are insignificant in explaining the factor excess returns and all the rest insignificant macroeconomic variables can be found in the appendices B7-B9.

Table 20: Macroeconomic exposure of quality factor. Upper value is coefficient, middle value is t-value, and lower value is r-squared. Bolded values are significant with 5% statistical significance level.

Quality	Denmark	Finland	Norway	Sweden
	-0,0088	-0,0009	-0,0087	-0,0059
Change in global consumer credit	**(-2,11)**	(-0,16)	(-1,8)	(-1,48)
	1,5 %	0,0 %	1,1 %	0,7 %
	0,0001	**0,0002**	0,0002	**0,0003**
Change in global economic policy uncertainty	(1,62)	**(2,17)**	(1,64)	**(2,98)**
	0,9 %	**1,5 %**	0,9 %	**2,9 %**
	0,0065	**0,0189**	-0,0007	-0,0023
Change in global m2	(1,12)	**(2,55)**	(-0,11)	(-0,41)
	0,4 %	**2,1 %**	0,0 %	0,1 %
	0,0046	**0,0086**	-0,0022	**-0,0051**
Change in local real exchange rate index	(1,51)	**(2,59)**	(-1,38)	**(-3,48)**
	0,8 %	**2,2 %**	0,6 %	**3,9 %**
	-0,0029	-0,0147	**-0,0155**	-0,0107
Change in local Term spread	(-0,33)	(-1,18)	**(-2,16)**	(-1,31)
	0,0 %	0,5 %	**1,5 %**	0,6 %
	-0,0007	-0,0001	0,0013	**0,0091**
Global Baker-Wurgler Sentiment	(-0,19)	(-0,03)	(0,33)	**(2,78)**
	0,0 %	0,0 %	0,0 %	**2,7 %**
	0,0001	0	**0,0001**	0
Global geopolitical risk index	(1,72)	(0,51)	**(3,51)**	(0,75)
	1,0 %	0,1 %	**3,9 %**	0,2 %
	-0,011	**-0,1161**	**-0,87**	-0,0292
Global Pástor-Stambaugh liquidity measure	(-0,32)	**(-2,6)**	**(-2,15)**	(-0,85)
	0,0 %	**2,3 %**	**1,6 %**	0,3 %
	0,0012	0,0006	**0,001**	**0,0005**
Global Vix	**(4,76)**	(1,64)	**(3,32)**	**(2,12)**
	7,0 %	0,9 %	**3,5 %**	**1,5 %**
	0,001	-0,0086	-0,0051	**0,0111**
Local inflation	(0,16)	(-0,9)	(-0,87)	**(2,22)**
	0,0 %	0,3 %	0,3 %	**1,6 %**
	0,0048	-0,0031	**0,0126**	0,0061
Local recession dummy	(1,11)	(-0,54)	**(2,44)**	(1,39)
	0,4 %	0,1 %	**2,0 %**	0,7 %

4.4 Market integration

One of the research questions is to see how factor performance commonality differs over time, and the dispersion of equity returns across countries is used as a measure of market integration in this analysis. To put it another way, a lower degree of return dispersion across markets is reflecting a higher degree of equity market integration.

To better capture the trend in market integration, the return dispersion measure is divided into two graphs, each with a 12-month moving average. The return dispersion of betting against beta, market, and momentum factors is depicted in the first graph. First, as shown in Figure 7, today's market integration is higher than it was at the start of the sample period. This makes sense because globalization has brought financial markets closer together, and global activities have an effect on investors in every region. This has also had an impact in the Nordic markets, resulting in even further convergence.

Figure 7 acts in a similar way to what previous research indicates (for example, Angelidis et al. 2015). According to Angelidis et al. (2015), return dispersion follows a business-cycle trend, with lower levels during expansions and higher levels during recession. This can also be seen in Nordic results. Return dispersion peaked in the early 1990s and it was also strong in the early 2000s. I believe that the financial liberalization process in the Nordic countries in the late 1980s was the catalyst for the overheating that led to high return dispersion and the great depression in the early 1990s. In 1988 to 1992, Norway experienced a banking crisis, which could have resulted in a high return dispersion between Nordic countries. The financial crisis in the Nordic countries in the 1990s was particularly serious, particularly in Finland, Norway, and Sweden, as it became systemic. Stock prices in Finland and Sweden, in particular, experienced significant fluctuations. Furthermore, until the end of 1994, return dispersion remained strong, implying that market integration was at its lowest in the first years of the sample period.

After the dotcom bubble burst at the turn of the century, a wider bear market started in 2000, fueled by a rash of accounting scandals and the September 11 terrorist attacks in the United States. Instability spread to Europe, affecting asset markets and resulting in high return dispersion. Market integration began to rebound after the market's instability in the early 2000s, and it was very high until the financial crisis of 2009. Return dispersion peaks can be seen during financial and corona crises, though not to the same extent as during the 1990s downturn and early 2000s instability. In conclusion, market integration seems to be declining during bad times. This is consistent with previous research. Aside from bad times, market integration has been high during the recovery phase following the early 1990s downturn and the period following the financial crisis until today. Furthermore, as shown in Figure 7, the market excess returns have the highest commonality in factor performance, while the betting against beta factor has the lowest.

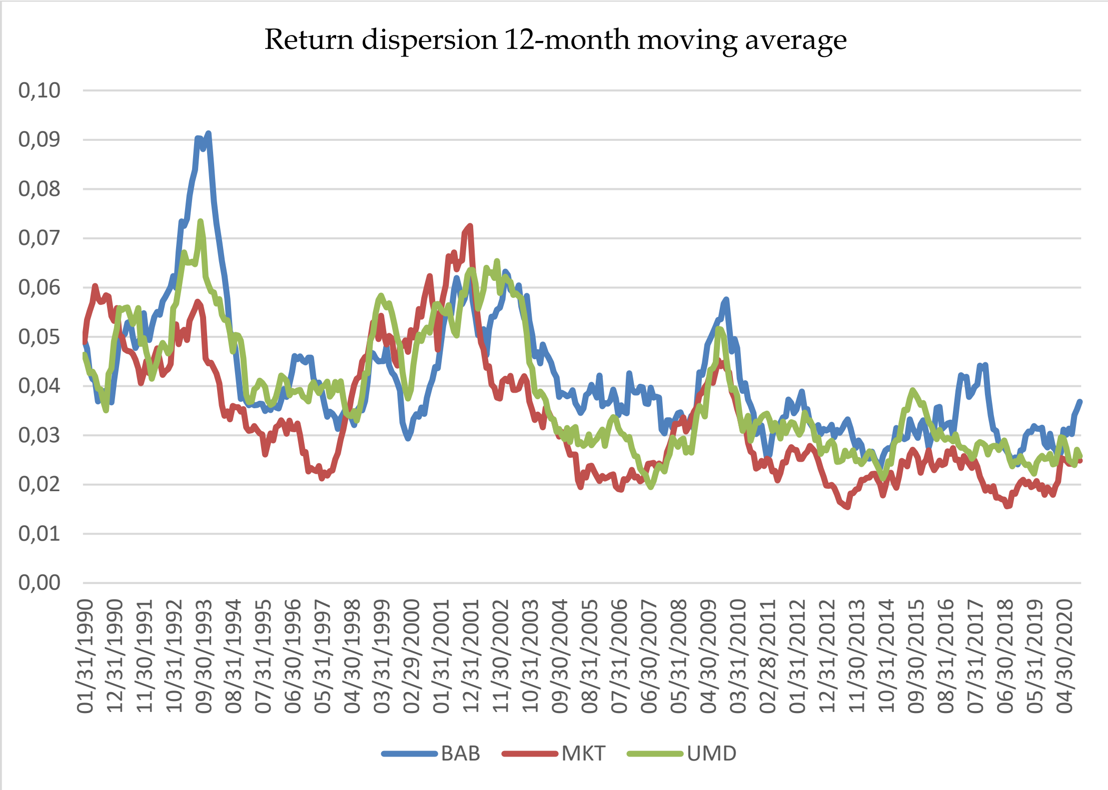

Figure 7: Return dispersion of betting against beta, market, and momentum factors

Next, return dispersion in the remaining factors in Figure 8 will be looked at. Since this time series is a little shorter, data from the early 1990s depression is missing. Still as shown in Figure 8, return dispersion has been low and market integration has been strong for the majority of the time similar to the previous case. The big peaks occurred at the turn of the century, in the early years of the new millennium, and during the financial crisis. In addition, there is a similar downward trend in return dispersion. We can also see that the return dispersion between various factors is very similar. However, it seems that commonality of the performance of the size factor is the highest, while commonality of the performance of the value factor is the lowest.

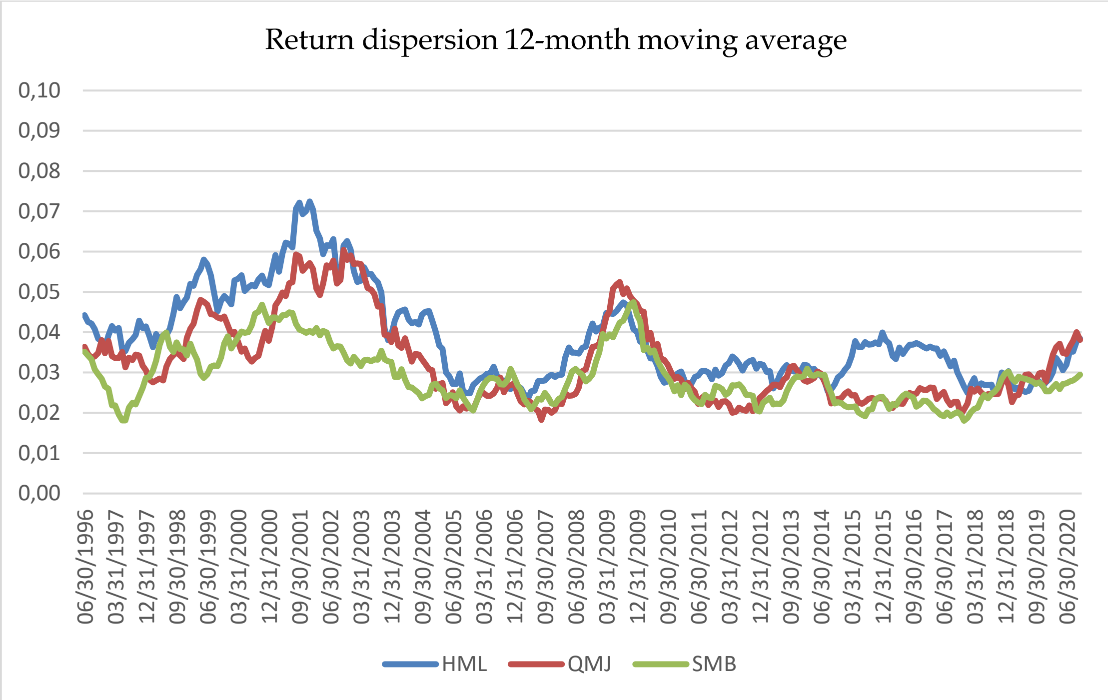

Figure 8: Return dispersion of value, quality, and size factors

4.5 Factor diversification

In this section the main aim is to figure out from investors point of view which of the two possible diversification methods is better. Country diversification is compared to factor diversification and then it is possible to determine, which one to prefer. First in Table 21 is listed the risk and return of country-diversified portfolio.

In Table 21 below country diversification can only increase the Sharpe ratio of a portfolio marginally. Nonetheless, the country-diversified portfolio has a Sharpe ratio of 0.5, compared to 0.4 for Finnish stocks and 0.45 for the average of the four constituents. This boost is due to portfolio volatility being 89 percent of the average volatility of the constituents.

Table 21: Country diversification

	Country-diversified portfolio	**Danish stocks**	**Finnish stocks**	**Norwegian stocks**	**Swedish stocks**	**Average across four countries**
Arithmetic mean	10,39 %	11,29 %	10,84 %	8,43 %	11,00 %	10,39 %
Geometric mean	8,19 %	9,63 %	7,20 %	5,26 %	8,18 %	7,57 %
Volatility	**20,80** %	18,03 %	26,96 %	24,70 %	23,66 %	**23,34** %
Skewness	-0,53	-0,73	-0,03	-0,75	-0,22	-0,43

Kurtosis	2,16	2,90	2,03	2,64	1,65	2,31
Sharpe ratio	**0,50**	0,63	0,40	0,34	0,46	**0,45**

Factor diversification is very successful in Finland, as shown in Table 22 below. Portfolio volatility is less than half of the average volatility of the constituents (9.92 percent versus 20.95 percent). As a result, the portfolio Sharpe ratio jumps from 0.44 to 0.92, more than double the average Sharpe ratio of the constituents. Tables 21 and 22 show that the factor-diversified portfolio's Sharpe ratio advantage over the country-diversified portfolio (0.92 versus 0.5) can be due to better diversification abilities, as there are no large variations in constituent Sharpe ratios and there is even more variation in Sharpe ratios in Finland, with the quality factor Sharpe ratio just marginally over zero. It is difficult not to draw the conclusion that smart investors should integrate cost-effectively sourced dynamic factor premia into long-term portfolio allocations rather than waste time on country diversification, at least among countries that are geographically close to one another.

Table 22: Factor diversification in Finland

Finland	**Factor-diversified portfolio**	**Equity premium**	**Betting against beta**	**Quality**	**Momentum**	**Average across four asset classes**
Arithmetic mean	9,18 %	10,84 %	13,41 %	0,46 %	11,99 %	9,18 %
Geometric mean	8,69 %	7,20 %	11,44 %	-0,95 %	10,03 %	6,93 %
Volatility	**9,92** %	26,96 %	20,12 %	16,74 %	19,98 %	**20,95** %
Skewness	0,21	-0,03	0,57	-0,15	0,26	0,16
Kurtosis	0,51	2,03	2,96	1,30	2,42	2,18
Sharpe ratio	**0,92**	0,40	0,67	0,03	0,60	**0,44**

As shown in Table 23, factor diversification is very successful in Denmark. The results are very similar to Finland. The volatility of the portfolio is about half that of the constituents (8.45 percent versus 16.03 percent). As a result, the portfolio Sharpe ratio rises from 0.63 to 1.19, almost double the constituents' average Sharpe ratio. The Sharpe ratio advantage of the Danish factor-diversified portfolio over the country-diversified portfolio (1.19 versus 0.5) is even greater than the Sharpe ratio gap between the Finnish factor-diversified portfolio and the country-diversified portfolio, as shown in Tables 21-23. This may be because the quality strategy in Finland has not provided any excess returns, while the quality strategy in Denmark has provided a Sharpe ratio of 0.3.

Table 23: Factor diversification in Denmark

Denmark	**Factor-diversified portfolio**	**Equity premium**	**Betting against beta**	**Quality**	**Momentum**	**Average across four asset classes**
Arithmetic mean	10,02 %	11,29 %	8,75 %	3,92 %	16,12 %	10,02 %
Geometric mean	9,67 %	9,63 %	7,17 %	3,08 %	14,94 %	8,71 %
Volatility	**8,45 %**	18,03 %	17,87 %	12,99 %	15,25 %	**16,03 %**
Skewness	-0,46	-0,73	0,19	-0,02	-0,94	-0,38
Kurtosis	1,42	2,90	2,28	1,67	3,93	2,69
Sharpe ratio	**1,19**	0,63	0,49	0,30	1,06	**0,63**

Factor diversification is also very successful in Norway, as shown in Table 24. The outcomes are strikingly similar to those of Denmark and Finland. The portfolio's volatility is roughly half that of its constituents (10.1 percent versus 19.44 percent). As a result, the portfolio Sharpe ratio increases from 0.62 to 1.19, almost double the average Sharpe ratio of the constituents. As shown in Tables 21, 23, and 24, the Norwegian factor-diversified portfolio's Sharpe ratio advantage over the country-diversified portfolio (1.19 versus 0.5) is identical to the Sharpe ratio difference between the Danish factor-diversified portfolio and the country-diversified portfolio.

Table 24: Factor diversification in Norway

Norway	**Factor-diversified portfolio**	**Equity premium**	**Betting against beta**	**Quality**	**Momentum**	**Average across four asset classes**
Arithmetic mean	12,01 %	8,43 %	14,58 %	6,96 %	18,08 %	12,01 %
Geometric mean	11,51 %	5,26 %	13,01 %	5,85 %	16,06 %	10,04 %
Volatility	**10,10 %**	24,70 %	17,82 %	15,04 %	20,18 %	**19,44 %**
Skewness	-0,07	-0,75	0,06	0,28	-0,14	-0,14
Kurtosis	1,05	2,64	0,69	1,29	1,38	1,50
Sharpe ratio	**1,19**	0,34	0,82	0,46	0,90	**0,62**

As shown in Table 25, factor diversification is also very successful in Sweden. The results are remarkably close to all the other Nordic countries' results. The volatility of the portfolio is about half that of its constituents (9.62 percent versus 18.61 percent). As a result, the portfolio Sharpe ratio rises from 0.61 to 1.17, almost double the constituents' average Sharpe ratio. The Sharpe ratio advantage of the Swedish factor-diversified portfolio over the country-diversified portfolio (1.17 versus 0.5) is nearly similar to the Sharpe ratio disparity between the Danish and Norwegian factor-diversified portfolios and the country-diversified portfolio, as shown in Tables 21, 23, 24, and 25.

Table 25: Factor diversification in Sweden

Sweden	Factor-diversified portfolio	Equity premium	Betting against beta	Quality	Momentum	Average across four asset classes
Arithmetic mean	11,28 %	11,00 %	14,04 %	7,70 %	12,38 %	11,28 %
Geometric mean	10,82 %	8,18 %	12,39 %	6,91 %	10,31 %	9,45 %
Volatility	**9,62 %**	23,66 %	18,26 %	12,51 %	20,00 %	**18,61 %**
Skewness	-0,12	-0,22	0,10	-0,65	-0,84	-0,40
Kurtosis	2,28	1,65	3,30	3,99	5,92	3,72
Sharpe ratio	**1,17**	0,46	0,77	0,62	0,62	**0,61**

The mean-variance efficient frontier is plotted in Figure 9 with a country-diversified portfolio as well as four factor-diversified portfolios. The graph clearly shows that factor diversification provides investors with the most effective risk-return trade-off. To be more specific, the Danish factor-diversified portfolio produces the most efficient result, with the highest return when assuming a certain level of risk. Overall, as already predicted in the section 4.1, the empirical evidence provided in this section supports the hypothesis that factor diversification increases investment performance significantly more than mere country diversification.

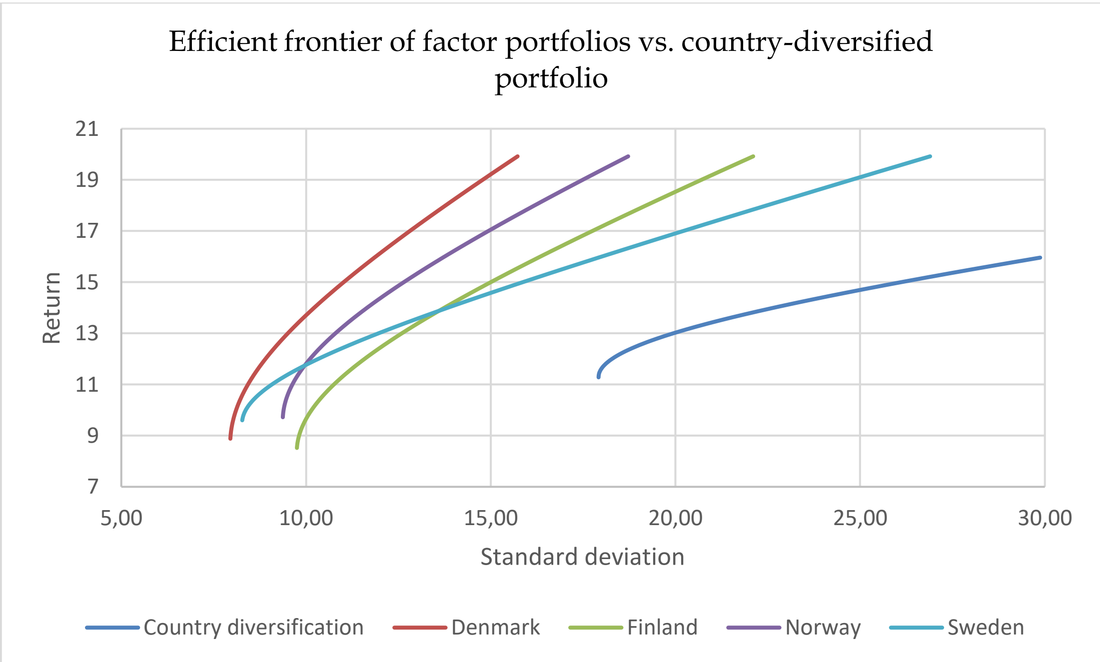

Figure 9: Efficient frontiers for country-diversified portfolio and for factor-diversified portfolios

5 CONCLUSIONS

Factor investing is currently one of the most common investment principles. On the Nordic stock markets compelling evidence for the existence of factor effects has been discovered. The key reason for researching the commonalities and return drivers of time-varying factor performance in the sparsely researched Nordic stock market is the global and rapid advent of factor investing methodology, as well as a lack of more detailed information about factor performance in the Nordic stock market. The aim of the thesis was to dig deeper into the behavior of investment factors in the Nordic stock markets and to see how the performance of the most well-known investment factors varied over time, as well as commonality in the factor performance. In addition, aim was to see whether macroeconomic variables could explain this variation in factor excess returns and if factor diversification can provide diversification benefits compared to country diversification.

The findings show that, on average, betting against beta and momentum strategies provided significant excess returns in every Nordic country, quality factor provided significant excess returns in two out of four countries, and size and value factors were insignificant in all Nordic countries. The results are consistent with a large body of previous studies. For example, some recent papers have shown that average out-of-sample value premiums for post-1991 value premiums are low and statistically indistinguishable from zero (Linnainmaa and Roberts 2018, Fama and French 2020.) Asness et al. (2013) discovered momentum in international returns.

The first hypothesis was that factor premia could change over time and behave differently at different stages of the macrocycle. Risk premia for market, size, and value factors, for example, have shown a counter-cyclical pattern (Gagliardini et al. 2016). All in all, the results show that all the factors in the Nordic stock markets show time-varying behavior and they seem to behave differently in every stage of macrocycle. The market factor premia were positive in all three periods, with the second period showing the worst results and the third period showing best performance. The premium for betting against beta factor is positive in the majority of periods, with the worst results in the first period and the best performance in the second, with just two periods of decade-long underperformance for a factor. Value factor premia have been negative in both the first and second periods, with the second period showing the only positive results. It seems to be that investing in growth stocks is generally better strategy in the Nordic countries than investing in value stocks. With three periods of decade-long underperformance for a factor, the premium for quality factor is positive in the majority of periods, with the worst results in the second period and the best performance in the third. However, quality factor returns are the ones that vary the most between different Nordic countries, so it is difficult to draw much general conclusions about time-varying quality factor performance. In all countries, size factor premia have been negative in two out of three periods, with no period outperforming the others. The performance has been poor in all the periods. Momentum shows positive performance in every period but the first showing the weakest results, whereas third being the best. Every period shows good momentum performance, with the exception of the first, which has the worst results and the third, which has the highest. Overall, value factor seems to be working better during bad times, whereas momentum, and quality factors seem to provide good results in good times. Betting against beta factor is able to provide excess returns in both bad and good times but the effect is greater in good times and this is due to its ability to short high-beta stocks weakening the high-beta portfolio's effect on BAB returns.

Based on previous research, the next hypothesis was that rational reasons should play a minor or non-existent role in the time-variation of factor returns. Overall, there is no proof that factor returns are significantly linked to macroeconomic variables, either now or in the future (Ilmanen et al 2021). This remains true for almost every macroeconomic variable that was studied. However, changes in the local real exchange rate index positively and substantially explain the betting against beta factor excess returns in every Nordic country. This is due to the effect of changes in country competitiveness reflecting to domestic company performance and stock prices. In terms of the momentum factor, changes in the local short-term interest rate explain momentum excess returns positively and significantly in three out of four countries, while changes in the local term spread explain momentum excess returns negatively and significantly in three out of four countries. Thus, in the Nordic countries interest rates environment seems to play a role in explaining momentum excess returns. However, this is not in line with previous literature, which found no evidence that momentum factor varies with interest rate environments (Cooper et al. 2004, Asness et al. 2013, Ilmanen et al. 2021). However, those other studies have been conducted mainly in U.S. and also in United Kingdom, continental Europe and Japan. Because this study is done in Nordic countries, the different economic environment might explain the difference in results. In terms of quality factor, global VIX explain quality excess returns positively and significantly in three out of four countries. It is straightforward that when financial conditions worsen, high-quality stocks outperform low-quality stocks. This is in line with previous research, for example, Chang et al. (2013) stated that stocks that are more exposed to volatility have lower average returns.

Return dispersion should follow a business-cycle pattern, with lower levels during expansions and higher levels during recession, according to the next hypothesis. The results show that in conclusion, market integration appears to be decreasing during bad times and rising during good times. This is in line with previous studies like the one of Angelidis et al. (2015). Market integration has also been increasing over time. Commonality in factor performance seems to be highest in the performance of market and size factor, whereas commonality in factor performance is lowest with betting against beta and value factors.

Factor diversification is also proven to be more efficient than country diversification. The empirical evidence clearly states that factor diversification increases investment performance significantly more than country diversification. Country diversification can only slightly enhance the Sharpe ratio of the average of the constituents, whereas factor diversification almost doubles the Sharpe ratio of the average of the constituents. This result highlights the importance of factor investing approach when deciding investment strategies.

Overall, the findings of this study are useful in understanding the risk and return characteristics of various factors, as well as how they behave over time and what logical explanations might explain this behavior. Future research might look at whether factor returns can predict market returns, for example. Furthermore, researching betting against beta and quality portfolios in Finland in greater depth by analyzing the firms that were included in those portfolios after 2003 may be an interesting and novel area of future research, since the performance of these strategies has evolved in totally opposite directions since that time. Finally, future studies should look at whether behavioral reasons, rather than rational ones, might explain factor excess returns better in Nordic stock markets.

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APPENDIX A Data sources

Change in global consumer credit:
Total Consumer Credit Owned and Securitized, Outstanding (TOTALSL), retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/TOTALSL is used.

Change in global economic policy uncertainty:
Baker, Bloom, and Davis' (2016) Economic Policy Uncertainty measure is used. The measure can be found at www.PolicyUncertainty.com.

Change in global and local industrial production:
For two types of markets (global and local), two industrial production variables are produced. Data is retrieved from Thomson Reuters DataStream.

Change in global m2:
Thomson Reuters DataStream is used retrieve monthly changes in the sum of European m2 money.

Change in local equity market volatility:
To proxy for equity market volatility, the 36-month realized volatility of each stock market index is determined. Stock market index values are retrieved from Thomson Reuters DataStream.

Change in local real exchange rate index:
FRED, the Federal Reserve Bank of St. Louis, provides monthly local real broad effective exchange rates for each country.

Change in local short term interest rate:
The data for local short-term interest rates, which dates back to 1978, is used. Thomson Reuters DataStream was used to obtain the data.

Change in local term spread:
To calculate term spread, the 3-month government bill returns are subtracted from the 10-year government bill returns and the data is obtained from Thomson Reuters DataStream.

Global Baker-Wurgler sentiment:
Baker and Wurgler's (2006) Sentiment index is used. http://people.stern.nyu.edu/jwurgler/ contains the index.

Global default spread:
The default spread is used to see if it has an affect on the stock market. The monthly Moody's seasoned Baa corporate bond yield relative to yield on 10-year

treasury constant maturity is the variable definition and it is retrieved from FRED, the Federal Reserve Bank of St. Louis.

Global geopolitical risk index:
This variable was retrieved from Dario Caldara and Matteo Iacoviello's "Measuring Geopolitical Risk" at https://matteoiacoviello.com/gpr.htm#data.

Global LIBOR-term repo:
The data was obtained from Thomson Reuters DataStream and the variable was generated by subtracting term repo from short term interest rate.

Global Pástor-Stambaugh liquidity measure:
The data series is from Robert Stambaugh's website, http://finance.wharton.upenn.edu/~stambaug/, and the variable is from Pástor and Stambaugh (2003).

Global VIX:
The monthly VIX variable is retrieved using Thomson Reuters DataStream.

Local inflation and lagged local inflation:
The monthly CPI inflation rate is used as a proxy for inflation in each country. The CPI figures come from Thomson Reuters DataStream.

Local dividend yield:
For each country, Thomson Reuters DataStream provides monthly dividend yields.

Local recession dummy:
The economy's realization of recession is proxied by a dummy variable. If the economy is in a recession, the variables is 1; otherwise, it is 0. FRED, the Federal Reserve Bank of St. Louis, provides OECD-based recession indicators for each nation from the following the peak to the trough.

Local Ted spread:
The data is based on local short-term interest rates and 3-month government bill returns. To construct ted spread 3-month government bill returns are subtracted from short-term interest rate. The data is retrieved from Thomson Reuters DataStream.

APPENDIX B Supplemental tables

Table B1: Market factor performance during financial crisis

Financial crisis period	Market	Mean	Stdev	Sharpe	t-stat
6/2007-10/2009	Danish stocks	-11.7%	31.4%	-0.37	0.58
6/2007-10/2009	Finnish stocks	-15.5%	35.5%	-0.44	0.68
6/2007-10/2009	Norwegian stocks	-5.5%	41.8%	-0.13	0.21
6/2007-10/2009	Swedish stocks	-7.4%	36.5%	-0.20	0.32

Table B2: Betting against beta factor performance during financial crisis

Financial crisis period	Betting against beta	Mean	Stdev	Sharpe	t-stat
6/2007-10/2009	Danish stocks	-18.7%	23.1%	-0.81	1.26
6/2007-10/2009	Finnish stocks	14.5%	21.2%	0.68	1.06
6/2007-10/2009	Norwegian stocks	1.0%	20.6%	0.05	0.08
6/2007-10/2009	Swedish stocks	-9.8%	16.1%	-0.61	0.94

Table B3: Value factor performance during financial crisis

Financial crisis period	Value	Mean	Stdev	Sharpe	t-stat
6/2007-10/2009	Danish stocks	7.1%	18.8%	0.38	0.59
6/2007-10/2009	Finnish stocks	2.9%	24.8%	0.12	0.18
6/2007-10/2009	Norwegian stocks	8.3%	14.3%	0.58	0.90
6/2007-10/2009	Swedish stocks	5.9%	21.2%	0.28	0.43

Table B4: Quality factor performance during financial crisis

Financial crisis period	Quality	Mean	Stdev	Sharpe	t-stat
6/2007-10/2009	Danish stocks	4.0%	21.2%	0.19	0.30
6/2007-10/2009	Finnish stocks	-2.7%	20.9%	-0.13	0.20
6/2007-10/2009	Norwegian stocks	-2.2%	17.2%	-0.13	0.20
6/2007-10/2009	Swedish stocks	8.4%	14.8%	0.57	0.88

Table B5: Size factor performance during financial crisis

Financial crisis period	Size	Mean	Stdev	Sharpe	t-stat
6/2007-10/2009	Danish stocks	-22.0%	13.0%	-1.69	-2.63
6/2007-10/2009	Finnish stocks	8.8%	17.2%	0.51	0.80
6/2007-10/2009	Norwegian stocks	-13.5%	15.2%	-0.89	1.38
6/2007-10/2009	Swedish stocks	-5.5%	16.8%	-0.33	0.51

Table B6: Momentum factor performance during financial crisis

Financial crisis period	Momentum	Mean	Stdev	Sharpe	t-stat
6/2007-10/2009	Danish stocks	7.9%	26.9%	0.30	0.46
6/2007-10/2009	Finnish stocks	-9.9%	18.9%	-0.52	0.81
6/2007-10/2009	Norwegian stocks	8.8%	17.3%	0.51	0.79
6/2007-10/2009	Swedish stocks	-9.7%	26.1%	-0.37	0.58

Table B7: Insignificant macroeconomic variables to explain betting against beta factor

Betting against beta	**Denmark**	**Finland**	**Norway**	**Sweden**
	-0,0001	0,0001	0	0,0001

Change in global economic policy uncertainty	-0,56	0,61	0,29	1,4
	0,1 %	0,1 %	0,0 %	0,5 %
	-0,0069	-0,0001	-0,0137	-0,0112
Change in global m2	-1,13	-0,02	-1,9	-1,62
	0,3 %	0,0 %	0,9 %	0,7 %
	0,0008	-0,0011	0,0013	0,0005
Change in local industrial production	0,81	-0,81	1,28	0,36
	0,3 %	0,2 %	0,5 %	0,1 %
	-0,0066	-0,0046	0,0007	-0,003
Global default spread	-1,94	-1,06	0,17	-0,76
	1,0 %	0,3 %	0,0 %	0,2 %
	0,0239	-0,0626	-0,0653	-0,0409
Global Pástor-Stambaugh liquidity measure	0,54	-1,11	-1,23	-0,81
	0,1 %	0,3 %	0,4 %	0,2 %
	0,0079	-0,0168	-0,0039	0,0008
Local inflation	1,11	-1,66	-0,54	0,15
	0,3 %	0,7 %	0,1 %	0,0 %
	0,0039	-0,0085	-0,0059	0,01
Local recession dummy	0,77	-1,29	-0,91	1,68
	0,2 %	0,5 %	0,2 %	0,8 %

Table B8: Insignificant macroeconomic variables to explain momentum factor

Momentum	**Denmark**	**Finland**	**Norway**	**Sweden**
	0,0014	0,0032	-0,0105	-0,0018
Change in global consumer credit	0,32	0,54	-1,8	-0,32
	0,0 %	0,1 %	0,8 %	0,0 %
	-0,0011	0,0017	-0,0009	0,0011
Change in global industrial production	-0,83	0,94	-0,54	0,6
	0,2 %	0,3 %	0,1 %	0,1 %
	0,0035	-0,0003	0,0017	-0,0029
Change in global m2	0,63	-0,04	0,22	-0,4
	0,1 %	0,0 %	0,0 %	0,0 %
	-0,0005	0	-0,0001	0,0004
Change in local equity market volatility	-0,82	0,08	-0,14	0,66
	0,3 %	0,0 %	0,0 %	0,1 %
	0,001	0,001	0,0019	-0,001
Change in local industrial production	1,17	0,8	1,76	-0,69
	0,6 %	0,2 %	0,8 %	0,2 %
	0,0013	0,0035	0,0054	0,0078
Global Baker-Wurgler Sentiment	0,35	0,68	1,06	1,58
	0,0 %	0,1 %	0,3 %	0,7 %
	0,0011	-0,0082	0,0024	-0,0049
Global default spread	0,37	-1,96	0,57	-1,23
	0,0 %	0,9 %	0,1 %	0,4 %
	0	0	0,0001	0
Global geopolitical risk index	0,62	-0,99	1,46	0,12
	0,1 %	0,2 %	0,5 %	0,0 %

	0,0078	0,0023	0,0008	0,0021
Global LIBOR-term repo	0,91	0,21	0,07	0,19
	0,3 %	0,0 %	0,0 %	0,0 %
	0,0422	-0,0346	-0,0373	-0,0421
Global Pástor-Stambaugh liquidity measure	1,12	-0,67	-0,74	-0,86
	0,3 %	0,1 %	0,1 %	0,2 %
	-0,0038	-0,011	0,0037	-0,008
Lagged local inflation	-0,60	-1,18	0,52	-1,4
	0,1 %	0,3 %	0,1 %	0,5 %
	0,0018	-0,0034	0,0025	-0,0006
Local dividend yield	0,32	-1,33	0,72	-0,15
	0,0 %	0,7 %	0,2 %	0,0 %
	-0,0049	0,0075	-0,008	-0,0002
Local inflation	-0,77	0,8	-1,13	-0,04
	0,2 %	0,2 %	0,3 %	0,0 %
	0,0009	0,0044	0,0003	-0,00038
Local recession dummy	0,21	0,7	0,05	-0,06
	0,0 %	0,1 %	0,0 %	0,0 %

Table B9: Insignificant macroeconomic variables to explain quality factor

Quality	Denmark	Finland	Norway	Sweden
	-0,0018	-0,002	-0,001	-0,0003
Change in global industrial production	-1,57	-1,38	-0,76	-0,26
	0,8 %	0,6 %	0,2 %	0,0 %
	-0,0011	0	-0,001	-0,0006
Change in local equity market volatility	-1,93	0,1	-1,8	-1,29
	1,4 %	0,0 %	1,1 %	0,5 %
	-0,0003	-0,0008	-0,0005	-0,0015
Change in local industrial production	-0,47	-0,71	-0,53	-1,75
	0,1 %	0,2 %	0,1 %	1,2 %
	0,0051	-0,103	0,0123	-0,0052
Change in local short term interest rate	0,43	-0,56	1,42	-0,49
	0,1 %	0,1 %	0,7 %	0,1 %
	0,0046	-0,0004	0,0033	0,0027
Global default spread	1,63	-0,11	1	0,99
	0,9 %	0,0 %	0,3 %	0,3 %
	0,0059	-0,0025	-0,0035	0,0097
Global LIBOR-term repo	0,79	-0,29	-0,42	1,36
	0,2 %	0,0 %	0,1 %	0,7 %
	-0,0046	0,0135	0,003	-0,0027
Lagged local inflation	-0,75	1,42	0,52	-0,53
	0,2 %	0,7 %	0,1 %	0,1 %
	0,0022	0,0036	0,0022	0,0034
Local dividend yield	0,44	1,79	0,84	1,3
	0,1 %	1,2 %	0,3 %	0,7 %
Local Ted spread	0,0155	0,0136	0,0001	0,0032

	1,61	1,45	0,02	0,43
	0,9 %	0,8 %	0,0 %	0,1 %