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Does seasonal affective disorder affect ESG stock performance?

Evidence from Nordic markets

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ABSTRACT:

Seasonal affective disorder (SAD) has been discussed in the behavioral finance literature as a factor that may influence investors' attitudes toward risk during periods with limited daylight. Reduced sunlight during autumn and winter has been associated with changes in mood that may increase risk aversion and potentially affect financial decision-making. At the same time, environmental, social, and governance (ESG) investing has become increasingly important in equity markets and is often viewed as a comparatively stable or lower-risk investment alternative.

Against this background, this thesis analyzes whether seasonal mood variation related to SAD is reflected in stock market returns in the Nordic countries. Particular attention is given to the possibility that firms with ESG ratings may respond differently to seasonal shifts in investor sentiment than companies without such classifications. By examining this question, the study contributes to research that combines insights from behavioral finance with the growing field of sustainable investment. The empirical analysis is based on weekly stock return data from Finland, Sweden, Norway, and Denmark covering the period from 2014 to 2024. Regression models are used to investigate the relationship between seasonal factors and equity returns. To capture the potential influence of SAD, the analysis employs two alternative measures: a seasonal indicator reflecting SAD periods and a continuous proxy based on changes in daylight hours.

Overall, the empirical evidence does not reveal a strong or consistent link between SAD-related seasonal variation and stock returns in the Nordic equity markets. Estimated effects remain small and statistically insignificant, and their economic magnitude is minor compared with general market volatility. In addition, the results do not indicate that ESG stocks perform differently from non-ESG stocks in response to seasonal mood variation. Overall, the results suggest that while behavioral factors may influence individual decision-making, their aggregate impact on stock returns in developed markets appears limited.

KEYWORDS: Seasonal affective disorder, ESG investing, Stock returns, Behavioral finance, Nordic countries

VAASAN YLIOPISTO
Laskentatoimen ja rahoituksen yksikkö

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TIIVISTELMÄ:

Tämän tutkielman tavoitteena on tarkastella, vaikuttaako kaamosmasennus (seasonal affective disorder, SAD) osaketuottoihin ja vastuulliseen sijoituskäyttäytymiseen Pohjoismaiden osakemarkkinoilla. Erityisesti tutkielmassa analysoidaan, reagoivatko ESG-luokitellut yritykset eri tavoin kausiluonteisiin mielialavaihteluihin verrattuna ei-ESG-yrityksiin. Tutkimus sijoittuu käyttäytymistaloustieteen ja vastuullisen sijoittamisen rajapintaan ja yhdistää näkökulmia sijoittajapsykologiasta sekä ESG-tekijöiden kasvavasta merkityksestä rahoitusmarkkinoilla.

Käyttäytymistaloustiede kyseenalaistaa oletukset täysin rationaalisista sijoittajista korostamalla psykologisten ja emotionaalisten tekijöiden roolia päätöksenteossa. Aiempi tutkimus on osoittanut, että mielialan vaihtelut, sääolosuhteet ja vuodenaikaisvaihtelut voivat vaikuttaa riskinottohalukkuuteen ja omaisuuserien hintoihin. Kaamosmasennuksen, joka liittyy vähentyneeseen päivänvaloon syys- ja talvikuukausina, on havaittu lisäävän sijoittajien riskinkarttamista. Samanaikaisesti ESG-sijoittaminen on saanut merkittävää huomiota, sillä vahvat ympäristöön, yhteiskuntaan ja hyvään hallintotapaan liittyvät ominaisuudet yhdistetään usein vakaampiin ja vähemmän riskialttiisiin yrityksiin. Empiirinen analyysi perustuu viikoittaisiin osaketuottoihin Suomesta, Ruotsista, Norjasta ja Tanskasta ajanjaksolla 2014–2024 ja analyysissä hyödynnetään regressiomalleja, joissa käytetään sekä SAD-kausimuuttujaa että päivänvaloon perustuvaa jatkuvaa mittaria.

Tulokset tarjoavat vain rajallista näyttöä siitä, että kaamosmasennus vaikuttaisi systemaattisesti osaketuottoihin Pohjoismaiden markkinoilla. SAD-muuttujien vaikutukset ovat pääosin pieniä ja tilastollisesti merkitsemättömiä useimmissa mallispesifikaatioissa, ja niiden taloudellinen merkitys jää vähäiseksi suhteessa markkinoiden kokonaisvolatiliteettiin. Lisäksi tulokset eivät tue hypoteesia, jonka mukaan ESG-osakkeet olisivat vähemmän herkkiä kausiluonteisille mielialavaihteluille kuin muut osakkeet. Kokonaisuutena tulokset viittaavat siihen, että vaikka käyttäytymistekijät voivat vaikuttaa yksittäisten sijoittajien päätöksentekoon, niiden yhteenlaskettu vaikutus osaketuottoihin kehittyneillä markkinoilla on rajallinen.

KEYWORDS: Kaamosmasennus, ESG-sijoittaminen, Osaketuotot, Käyttäytymistaloustiede, Pohjoismaat

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Abbreviations

CAPM	Capital Asset Pricing Model
CML	Capital Market Line
CSR	Corporate Social Responsibility
DMI	Danish Meteorological Institute
EMH	Efficient Market Hypothesis
ESG	Environmental, Social, and Governance
FMI	Finnish Meteorological Institute
MET Norway	Norwegian Meteorological Institute
NEPSE	Nepal Stock Exchange
NYSE	New York Stock Exchange
OLS	Ordinary Least Squares
OR	Onset and Recovery
PANAS-X	Positive and Negative Affect Schedule – Expanded Form

SAD	Seasonal Affective Disorder
SMHI	Swedish Meteorological and Hydrological Institute
SML	Security Market Line
TRESGS	Thomson Reuters ESG Score

1 Introduction

Both sustainable investing and behavioral finance have become central and rapidly expanding areas of modern financial research. Research in behavioral finance has increasingly demonstrated that financial markets are not driven solely by fully rational decision-making. Instead, investor behavior is often influenced by psychological and emotional factors that can lead to systematic biases. Examples include loss aversion, herd behavior, mood-driven decisions, and limitations in cognitive processing, all of which may cause deviations from the predictions of traditional finance theory (Barberis and Thaler, 2003). Empirical evidence further suggests that even seemingly unrelated environmental variables, such as weather conditions or fluctuations in daylight, can affect investor sentiment and behavior (Saunders, 1993; Hirshleifer and Shumway, 2003). These insights imply that changes in collective mood may contribute to recurring seasonal patterns in financial markets, including variations in returns and shifts in risk-taking.

One psychological mechanism that may link environmental conditions to financial outcomes is seasonal affective disorder (SAD). This condition is associated with reduced exposure to natural daylight during autumn and winter and is commonly linked to symptoms such as lower energy levels, pessimism, and heightened risk aversion (Kramer and Weber, 2011). Building on this behavioral explanation, Kamstra et al. (2003) present evidence that fluctuations in daylight across the year correspond with systematic movements in stock market returns. Their findings suggest that reduced daylight may increase investors' aversion to risk, leading them to demand higher compensation for holding risky assets and thereby contributing to lower market returns. Subsequent studies indicate that such seasonal effects are more pronounced in regions located at higher latitudes, where the annual variation in daylight is particularly large (Dolvin and Pyles, 2007).

At the same time, investment practices themselves have undergone significant transformation with the rapid expansion of sustainable investing. Environmental, social, and governance (ESG) considerations are no longer limited to a specialized segment of the market but have become widely integrated into mainstream portfolio management. This development has been supported by stronger regulatory frameworks, increasing demand for transparency, and a growing awareness among investors regarding sustainability-related risks and opportunities. The trend has been especially visible in Europe and in the Nordic countries, where institutional structures and regulatory initiatives have facilitated the incorporation of ESG criteria into investment decision-making processes (Friede et al., 2015). As a result, ESG-related information is now regularly included in both institutional and retail investment strategies.

The Nordic region provides a particularly relevant setting for examining potential links between seasonal mood variation and financial markets. Countries such as Finland, Sweden, Norway, and Denmark experience substantial fluctuations in daylight over the course of the year, ranging from very dark winters to long summer days. This pronounced seasonal variation creates a natural environment for studying how changes in daylight may influence investor sentiment and behavior. Although earlier research has documented seasonal patterns in Nordic stock market returns (Floros, 2011), relatively little attention has been given to how such behavioral effects might influence the valuation of different types of firms. In particular, the potential interaction between seasonal mood changes and ESG-oriented companies remains largely unexplored.

Despite growing interest in both areas, the connection between seasonal affective disorder and ESG investing remains largely understudied. Firms with strong ESG characteristics are typically associated with lower perceived risk, as they tend to exhibit solid governance practices, long-term strategic orientation, reputational strength, and greater transparency. However, these same firms can also be viewed from a different perspective, which is as growth-oriented investments that may involve greater uncertainty in terms of short-term financial outcomes. Importantly, investor demand for ESG assets is shaped not only by financial considerations but also by prosocial preferences and identity-related motives (Riedl and Smeets, 2017). If seasonal mood variation influences risk perception and time preferences, it may also alter the relative attractiveness of sustainability-oriented assets.

Examining whether seasonal affective disorder affects the relative performance of ESG stocks, therefore, contributes to both behavioral finance and sustainable investing literature. It extends mood-based asset pricing research beyond aggregate indices and trading volume to the cross-section of stocks, and it evaluates whether sustainability characteristics moderate seasonal risk-aversion effects in a high-latitude setting where such mechanisms should be most pronounced.

1.1 Purpose of the study

The purpose of this thesis is to examine whether Seasonal Affective Disorder (SAD), a psychological condition linked to seasonal fluctuations in daylight, affects sustainable investment behavior. Specifically, the study examines whether ESG stocks in Nordic countries exhibit seasonality in performance or investor demand that can be attributed to SAD-related changes in mood or risk preferences. Prior research suggests that SAD increases risk aversion among investors, potentially impacting asset pricing and portfolio allocation decisions (Kamstra et al., 2003; Dolvin et al., 2009). Despite this, the role of SAD in shaping behavior within the context of sustainable investing has received limited attention. To contribute to this unexplored area, this thesis examines how SAD may influence returns associated with sustainable investment strategies.

Seasonal changes in daylight have been proposed as a factor that can influence financial market behavior through their impact on investor psychology. Kamstra et al. (2003) document that market activity tends to decrease during the darkest months of the year, a pattern they associate with heightened investor risk aversion. Their explanation is linked to seasonal affective disorder (SAD), a condition related to reduced daylight exposure that may alter mood and risk preferences. The authors argue that these mood fluctuations can systematically influence financial decisions, suggesting that seasonal psychological factors may contribute to observable patterns in stock market behavior.

Although Kamstra et al. (2003) primarily examine aggregate market activity and returns, the underlying mechanism may extend beyond trading behavior. If investor risk preferences change seasonally, these shifts could also affect how different investment strategies or asset classes are evaluated. In particular, sustainable investments may be sensitive to such changes in sentiment. These assets are frequently associated with longer investment horizons and broader non-financial objectives, and their short-term financial performance may sometimes be perceived as uncertain. As a result, the attractiveness of sustainable assets may vary depending on prevailing investor risk tolerance.

Periods characterized by higher risk aversion could therefore influence the demand for ESG-related investments in different ways. If such assets are perceived as uncertain or strongly linked to long-term growth, investors may become less willing to allocate capital to them during darker periods. Conversely, if ESG-oriented firms are viewed as relatively stable or aligned with risk-management considerations, increased risk aversion could strengthen their appeal. In this sense, seasonal mood changes may influence capital allocation even when the underlying fundamentals of the assets remain unchanged.

Empirical evidence from Fernandez-Perez et al. (2022) further illustrates how investor sentiment can affect sustainable investment behavior. Their study shows that during periods associated with lower mood, investors tend to increase their allocations to highly sustainable mutual funds. This pattern is interpreted as reflecting heightened risk aversion, which may lead investors to favor ESG-oriented assets. While the present study does not directly analyze fund flows, it builds on these findings by investigating whether comparable behavioral mechanisms are visible in the relative return performance of ESG and non-ESG equities.

A broader body of behavioral finance research also supports the idea that emotional and psychological factors influence risk-taking in financial markets. Kamstra et al. (2003)

provide evidence that fluctuations in daylight exposure coincide with seasonal variation in stock returns, consistent with changes in investor risk attitudes. Related work by Dolvin et al. (2009) strengthens this interpretation by showing that investors appear less willing to hold risky assets during darker periods of the year. Together, these findings highlight the potential role of SAD-related psychological mechanisms in shaping investment decisions. Based on this literature on seasonal mood variation, investor risk preferences, and sustainable investment behavior, the first hypothesis of this study is formulated as follows:

H1: Seasonal affective disorder increases investor risk aversion.

If SAD leads to a general increase in risk aversion, assets perceived as relatively risky may underperform compared with those considered safer. Conversely, investments that are viewed as more stable could experience relatively stronger performance. Evidence from Fernandez-Perez et al. (2022) suggests that highly sustainable investments may be interpreted as safer options during periods characterized by negative mood. This interpretation is consistent with earlier literature indicating that ESG-oriented firms are often associated with lower perceived risk due to factors such as stronger governance structures, long-term strategic orientation, and reputational advantages. Consequently, ESG stocks may exhibit relatively different return behavior during periods associated with SAD. Based on this reasoning, the second hypothesis is stated as follows:

H2: Seasonal affective disorder increases the relative return performance of ESG stocks compared to non-ESG stocks.

1.2 Contribution

This thesis contributes to the intersection of behavioral finance and sustainable investing by integrating seasonal mood effects into the analysis of ESG asset pricing. While previous literature has documented that seasonal affective disorder influences aggregate stock market returns and investor risk-taking behavior (Kamstra et al., 2003; Fernandez-

Perez et al., 2022), little empirical evidence exists on whether such mood-driven risk aversion systematically affects the relative pricing of ESG versus non-ESG equities. By explicitly examining the interaction between seasonal mood variation and sustainability characteristics at the firm level, this study extends the behavioral asset pricing literature into the domain of sustainable finance.

First, the thesis provides a theoretical contribution by linking two largely separate research streams, mood-driven anomalies in financial markets and ESG-related risk perception and asset pricing. Prior SAD research primarily focuses on aggregate index returns, trading volume, or capital flows, whereas ESG literature typically examines long-term performance, risk characteristics, or investor preferences. By combining these perspectives, this study investigates whether seasonal fluctuations in risk aversion translate into cross-sectional return differences between ESG and non-ESG firms. By approaching the question from this perspective, the study aims to clarify whether ESG characteristics are perceived as a source of safety when psychological risk aversion becomes elevated.

This thesis contributes empirically to the existing literature by analyzing firm-level data from four Nordic stock markets over the period 2014–2024. The Nordic region provides a particularly useful empirical setting because it experiences substantial seasonal variation in daylight. These pronounced changes in environmental conditions allow the study to investigate whether fluctuations in investor mood linked to daylight exposure are reflected in financial markets.

In contrast to many earlier studies that focus primarily on aggregate market indices, the empirical analysis in this thesis is conducted at the level of individual firms. This approach allows for a more detailed examination of potential differences across companies. In particular, the model includes interaction terms between firms' ESG classification and seasonal variables, enabling the analysis to assess whether sustainability characteristics affect the way seasonal mood variation is incorporated into stock prices.

To capture potential seasonal effects related to investor sentiment, the study applies two complementary methodological specifications. First, a binary indicator is used to identify periods associated with the SAD season. Second, a continuous variable based on daylight variation is employed, following the approach introduced by Kamstra et al. (2003). Using both measures strengthens the robustness of the analysis, facilitates comparison with previous research, and addresses methodological concerns that have been raised in subsequent critiques of the SAD hypothesis.

Beyond its empirical and methodological aspects, the study also has practical implications. The findings may offer useful insights for investors, asset managers, and policymakers by clarifying whether ESG-oriented firms respond differently to seasonal shifts in investor risk perception. Should such differences emerge, they would suggest that psychological influences may affect capital allocation toward sustainable assets even in the absence of changes in fundamental information. This question is particularly relevant in markets where ESG criteria are already widely incorporated into investment strategies and where investor sentiment may interact with long-term sustainability considerations.

1.3 Limitations

Several factors limit the extent to which the results of this study can be generalized. A central consideration concerns how seasonal affective disorder is represented in the empirical analysis. Because direct observations of investor mood or clinical SAD are not available, the study relies on environmental proxies, primarily variation in daylight. This approach follows the methodology introduced by Kamstra et al. (2003) and has been widely adopted in related literature. However, daylight exposure only approximates potential mood changes and does not measure the actual psychological state of investors. In addition, seasonal patterns in daylight may coincide with other recurring market phenomena, such as calendar anomalies or macroeconomic cycles. Although the empirical models include controls intended to mitigate these influences, it remains difficult to fully separate mood-related mechanisms from other seasonal effects.

Consequently, the analysis identifies relationships consistent with seasonal explanations rather than establishing clear causal effects.

Another aspect that should be considered relates to the classification of firms according to ESG characteristics. In this study, the categorization into ESG and non-ESG firms is based on ratings obtained from a single external data provider. While the use of ESG ratings is common in empirical finance research, these ratings are not fully standardized across providers. Differences in evaluation frameworks, weighting methods, and disclosure requirements may lead to inconsistencies in how firms are assessed. Such methodological variation can introduce measurement uncertainty into the ESG classification applied in the analysis and may weaken observable differences between ESG and non-ESG portfolios. The results should therefore be interpreted as conditional on the specific ESG rating framework used in this study.

The choice of data frequency also has implications for the interpretation of the findings. The empirical analysis relies on weekly stock return data, which helps reduce the influence of short-term market noise and microstructure effects that are often present in higher-frequency data. At the same time, the use of weekly observations limits temporal precision. Behavioral responses to changes in environmental conditions may occur within shorter time intervals, and these rapid adjustments may not be fully captured in weekly return data.

Finally, the sample period itself may influence the observed patterns. The dataset covers the years 2014–2024, a decade marked by several major global disruptions affecting financial markets. Events such as the COVID-19 pandemic, as well as subsequent geopolitical tensions and energy market shocks, significantly affected market volatility and investor risk perceptions. Because these developments occurred during the sample period, their effects may overlap with seasonal variation in returns. For this reason, the findings should be interpreted as context-dependent and indicative rather than as definitive evidence of seasonal behavioral effects.

1.4 Structure of the study

The thesis is organized into seven chapters, each addressing a specific component of the study. The first chapter begins with an introduction that presents the research topic, defines the purpose and key contributions, and outlines the main limitations. The second chapter develops the theoretical framework by examining market efficiency, behavioral finance, and asset pricing models, with particular emphasis on seasonal anomalies and seasonal affective disorder. The third chapter focuses specifically on SAD, describing both the concept itself and the ways in which it is measured and operationalized in financial research. The literature review is presented in the fourth chapter, where previous studies on mood-driven investor behavior, seasonal effects, and ESG-related risk perceptions are combined. Fifth chapter describes the data sources and empirical methodology used in the study. Sixth chapter reports the empirical findings, including descriptive statistics and regression results. The final chapter concludes the thesis by summarizing the key findings and discussing implications and directions for future research.

Regarding the use of artificial intelligence tools, Grammarly was used during the writing process for language editing and proofreading purposes, including grammar, spelling, and clarity improvements. The author is responsible for the final content, analysis, and conclusions presented in this thesis.

2 Market efficiency and asset pricing

The efficient market hypothesis has historically framed much of the academic understanding of financial markets. However, behavioral finance studies and empirical data have demonstrated that emotional states, heuristics, and cognitive biases can all systematically affect investing choices, resulting in predicted market anomalies. One such element that may intensify these behavioral impacts is seasonal affective disorder. A framework for comprehending how psychological and mood-related elements might influence investment behavior, including decisions about sustainable and ESG investing, is provided by this chapter's exploration of the theoretical underpinnings of market efficiency, behavioral biases, anomalies, and asset pricing models.

2.1 Efficient market hypothesis and behavioral finance

The efficient market hypothesis (EMH) posits that asset prices reflect all available information at any given time and that financial markets are informationally efficient. The idea that stock prices are difficult to predict has its roots in early empirical research. Kendall (1953) provides one of the first systematic examinations of price movements and finds that they do not follow stable or exploitable patterns but instead behave in a largely random manner. This observation later became central to the development of the random walk hypothesis in financial economics. According to this view, price changes are essentially unpredictable, which in turn implies that attempts to consistently outperform the market through forecasting or timing strategies are fundamentally limited.

If price changes follow a random walk, each movement occurs independently of previous ones, limiting the usefulness of historical data for forecasting future returns. Under this framework, attempts to achieve abnormal profits though market timing based solely on past price patterns are not expected to be systematically successful. The random walk intuition is closely related to weak-form efficiency, where current prices reflect all information contained in past prices and trading volumes. Importantly, however, the EMH extends beyond the random walk idea. It is fundamentally a statement about information incorporation and the absence of systematic profit opportunities after accounting for risk.

Fama (1970) expanded on this basis by formalizing the efficient market hypothesis into three different forms: weak, semi-strong, and strong efficiency. These forms are dependent on the amount of information that is absorbed into market pricing. All past price and volume data are reflected in present pricing in weak-form efficiency. According to the semi-strong form, current prices already consider all information that is accessible to the public, such as news articles and financial data. According to the strong form, there is no space for anomalous returns based on any kind of knowledge since asset prices fully reflect even insider or private information.

The three main assumptions of Fama's efficient market hypothesis are that investors are rational, irrational behavior is random and hence cancels out overall, and that arbitrage mechanisms effectively remove mispricing brought on by irrational behavior. However, these assumptions have been increasingly questioned. Behavioral finance research argues that departures from rationality can be systematic rather than random, and that limits to arbitrage may prevent mispricing from being fully corrected (Thaler, 1980; Barberis and Thaler, 2003). When large groups of investors exhibit similar biases or emotional responses, asset prices may systematically diverge from their fundamental values. Behavioral patterns such as overconfidence, herding behavior, loss aversion, and mood-driven decision-making provide evidence that these deviations can occur in a predictable manner.

Empirical research has increasingly identified return patterns that are difficult to reconcile with the assumption of strict market efficiency. Instead of behaving as purely random processes, asset returns have been shown to display systematic regularities in certain contexts. Examples such as momentum effects and calendar-based anomalies, including the January effect, suggest that predictability may exist over specific time horizons. These observations have contributed to a broader shift away from purely informational explanations of price formation and have encouraged the integration of behavioral and psychological mechanisms into financial theory.

A key development in this shift is the incorporation of insights from psychology into models of financial decision-making. Rather than assuming that investors process information in a fully rational and consistent manner, behavioral approaches emphasize the role of cognitive and emotional influences. One of the most influential contributions in this area is prospect theory by Kahneman and Tversky (1979), which redefines how individuals evaluate risky outcomes. Instead of assessing final wealth levels, individuals are assumed to evaluate gains and losses relative to a reference point. The theory further introduces loss aversion and non-linear weighting of probabilities, implying that preferences under risk are systematically distorted relative to standard expected utility theory.

Extending this perspective, behavioral finance challenges the core assumptions of classical finance by relaxing the requirement of fully rational agents. Investment decisions are instead understood as being shaped by cognitive constraints, emotional responses, and heuristic shortcuts. Investors may, for example, exhibit overconfidence in their own forecasts, place excessive weight on recent or salient information, or react differently to gains and losses despite equivalent magnitude. When such behavioral patterns are shared across a large number of market participants, they can generate persistent pricing distortions and aggregate market anomalies that are not easily eliminated through arbitrage. This also broadens the set of relevant explanatory variables in asset pricing, making it plausible that factors such as mood, environmental conditions, and seasonal variation can systematically influence financial outcomes through their effect on investor behavior.

An implication of this framework is that aggregate levels of risk aversion should not be assumed to remain constant over time. If investors' willingness to bear risk changes, then the compensation required for holding risky assets will also vary. This introduces a channel through which psychological factors may affect asset prices: fluctuations in mood-related states, including those associated with seasonal affective disorder, may lead to time variation in risk premia. As a result, return dynamics may partly reflect shifts in investor sentiment rather than only changes in underlying economic fundamentals.

2.2 Behavioral finance and heuristic biases

Behavioral finance departs from the assumption of fully rational decision-making by emphasizing that investor behavior is often shaped by cognitive constraints, emotional responses, and simplifying decision rules. These influences become particularly relevant in situations where mood conditions deteriorate, such as during periods associated with seasonal affective disorder. In such contexts, investment decisions may rely more heavily on intuitive processing, which increases the importance of understanding heuristic-based behavior in financial markets.

A key starting point for this literature is prospect theory by Kahneman and Tversky (1979). The theory explains risk-related decisions by showing that individuals do not evaluate outcomes in absolute terms, but instead relative to a reference point. This reference-dependent evaluation is combined with loss aversion, meaning that losses have a stronger psychological impact than equally sized gains. In addition, probabilities are not treated linearly: small probabilities tend to be overweighted, while larger probabilities are often underweighted. Together, these features imply that perceived risk is systematically distorted, particularly when individuals are in negative emotional states.

Building on this behavioral foundation, uncertainty in decision-making is often managed through heuristics rather than full analytical reasoning. Tversky and Kahneman (1974) show that these mental shortcuts simplify complex judgments but introduce predictable biases. Different heuristics affect financial judgment in distinct ways. The representativeness heuristic can lead investors to overemphasize similarity patterns and ignore statistical base rates. The availability heuristic makes recent or emotionally striking information more influential, which can amplify reactions to news and market events. Anchoring, in turn, causes judgments to be centered around an initial reference point, with insufficient adjustment even when new information becomes available.

When these behavioral mechanisms are applied in financial markets, they can produce systematic deviations in investor behavior. Price formation may be affected by overreaction to salient information, delayed response to gradual information flows, or excessive reliance on historical price levels when forming expectations. As these patterns occur across many market participants, they can contribute to persistent market inefficiencies and observable anomalies in trading behavior and asset pricing.

Seasonal affective disorder can be understood as a factor that may strengthen these behavioral tendencies. Reduced daylight during certain periods of the year is associated with lower mood, decreased motivation, and increased pessimism. These changes may reduce cognitive control and increase reliance on heuristic processing. As a result, investors may become more sensitive to negative information, more likely to anchor to past losses or reference prices, and more prone to interpreting future outcomes pessimistically. In combination, these effects suggest that SAD may amplify existing behavioral biases, leading to higher perceived risk and a reduced willingness to take on risk during darker periods. This mechanism may be especially relevant in sustainable investing, where decisions are not based solely on financial returns but also on non-financial considerations, potentially making them more sensitive to shifts in mood and risk perception.

2.3 Anomalies

In financial markets, anomalies refer to systematic patterns in returns or investor behavior that are difficult to reconcile with a strict interpretation of EMH and fully rational pricing. Behavioral finance interprets many anomalies as equilibrium outcomes when investors exhibit systematic biases and when limits to arbitrage prevent mispricing from being fully eliminated. For this thesis, anomalies linked to mood and seasonality are particularly relevant because they provide a conceptual connection between environmental conditions, changes in risk tolerance, and variation in required risk premia. This section reviews key behavioral anomalies, since they help motivate how seasonal mood mechanisms, such as SAD, can translate into return patterns, including possible differences between ESG and non-ESG stocks.

2.3.1 Loss aversion

One of the most frequently seen behavioral abnormalities in finance is loss aversion, which is the propensity for people to believe that possible losses will have a greater psychological impact than comparable benefits. This idea, which has its roots in prospect theory, contends that investors feel greater pain when they lose money than when they make the same amount of money (Kahneman and Tversky, 1979). Empirical studies suggest that these behavioral biases are reflected in actual investment behavior. Investors may exhibit a tendency to avoid realizing losses, retain poorly performing assets for extended periods, or adopt overly conservative strategies even when alternative choices would likely lead to superior long-term outcomes (Shefrin and Statman, 1985; Odean, 1998). These patterns indicate that psychological frictions can systematically affect portfolio decisions in practice.

In periods associated with seasonal affective disorder, the role of loss aversion may become more pronounced. Deteriorating mood can increase sensitivity to potential losses and strengthen pessimistic expectations about future market developments. As highlighted by Kamstra et al. (2003), such seasonal mood effects may be reflected in financial markets through higher required compensation for bearing risk during periods of reduced daylight. From this perspective, heightened perception of downside risk can translate into increased aggregate risk aversion and, consequently, higher risk premia. This mechanism may also have implications for sustainable investing. If investors become more loss-averse during darker periods, they may perceive assets with uncertain short-term performance or long-term payoff structures as less attractive. This could reduce demand for such investments, even when they align with environmental or social objectives.

2.3.2 Mood-driven investing

Investor sentiment plays a systematic role in financial decision-making by shaping both risk preferences and market-level outcomes. When overall mood is positive, investors tend to exhibit greater optimism and a higher willingness to assume risk. In contrast, periods characterized by negative mood are typically associated with increased caution and a lower tolerance for risk (Hirshleifer and Shumway, 2003). Because mood can vary in predictable ways over time, these fluctuations may translate into recurring patterns in aggregate investment behavior when they affect a large number of market participants simultaneously.

Seasonal affective disorder provides a concrete example of how mood-related mechanisms can influence financial decisions. Empirical evidence indicates that during winter months, when symptoms of SAD are more prevalent, investors tend to reduce their exposure to risk. This is reflected in lower trading activity and a shift toward safer asset choices (Kamstra et al., 2003). Importantly, the influence of mood extends beyond short-term trading behavior and may also affect broader portfolio decisions, including perceptions of risk, stability, and long-term investment attractiveness.

These considerations are particularly relevant in the context of ESG investing. The perceived attractiveness of sustainability-oriented assets may vary depending on prevailing investor sentiment and risk tolerance. If ESG firms are interpreted as relatively stable or less exposed to downside risk, periods of heightened risk aversion may increase demand for these assets. Conversely, changes in mood that reduce willingness to take risk may also shift preferences toward investment options perceived as more resilient or predictable, thereby affecting the relative appeal of ESG investments over time. Conversely, if ESG is perceived as uncertain or growth-like, the same mood mechanism could depress ESG demand. This provides a basis for examining whether seasonal mood variation is reflected in differences in return performance between ESG and non-ESG stocks.

2.3.3 Disposition effect and overreaction/underreaction to information

Investor behavior often reflects systematic biases such as the disposition effect, where gains are realized too quickly while losses are held for too long. This pattern is commonly linked to loss aversion and the reluctance to recognize losses (Shefrin and Statman, 1985; Odean, 2002). Related behavioral responses include overreaction and underreaction to information. For instance, De Bondt and Thaler (1985) demonstrate that investors may overreach to news, resulting in subsequent price reversals, whereas Jegadeesh and Titman (1993) identify momentum effects that are consistent with delayed adjustment to information over intermediate horizons.

These behavioral tendencies can become more pronounced under changing mood conditions. In periods of low mood, investors may place greater emphasis on negative information while discounting positive signals, reinforcing pessimistic expectations and increasing the likelihood of mispricing (Kamstra et al., 2003; Hirshleifer and Shumway, 2003). As a result, participation in financial markets may decline or investment decisions may be postponed, particularly in the case of assets associated with longer time horizons or higher uncertainty. Therefore, SAD can be interpreted as a seasonal psychological factor that intensifies behavioral mechanisms underpinning anomalies, connecting investor-level biases to observable market patterns.

2.4 Valuation models

2.4.1 Capital asset pricing model

One of the fundamental concepts in modern finance is the capital asset pricing model (CAPM), which provides a straightforward framework for understanding the relationship between risk and expected return on financial assets. William Sharpe (1964), John Linter (1965), and Jan Mossin (1966) developed the CAPM in the 1960s, building on Harry

Markowitz's (1952) introduction of modern portfolio theory. The idea of diversification, which is essential to the CAPM's argumentation, was developed out of Markowitz's realization that portfolio risk is influenced by both the correlation between assets and the volatility of individual assets.

The capital asset pricing model assumes that investors are logical, risk-averse, and only consider variance and expected return when making decisions (mean-variance optimizers). Furthermore, the model is predicated on the idea that all investors have identical expectations for future asset returns and operate over the same single-period investment horizon. The market itself is thought to be frictionless, meaning there are no transaction fees or taxes, and that lending and borrowing are unrestricted at a consistent, risk-free rate. Every investor has equal access to relevant information, and every asset is perfectly divisible and tradable (Bodie et al., 2023). The beta coefficient, which quantifies the linear relationship between an asset's expected return and its exposure to systematic risk, is the central component of the model. The CAPM equation is:

$$E(r_i) = r_f + \beta_i[r_m - r_f], \tag{1}$$

where:
$E(r_i)$ = expected return on asset *i*
r_f = risk-free rate
β_i = beta of the asset (systematic risk)
$E(r_m)$ = expected return of the market portfolio
$[\mathrm{E}(r_m) - r_f]$ = the market risk premium

A key factor in CAPM is beta. It measures how much an asset's return reacts to shifts in the market. An asset is more volatile than the market if its beta is more than one, and less volatile if its beta is less than one. The only risk for which investors receive compensation, according to CAPM, is systematic risk, or market-wide variables that are impossible to diversify away. On the other hand, unsystematic or firm-specific risk does not carry a premium in risk and can be removed by portfolio diversification (Nikkinen et al., 2002). Bodie et al. (2023) define beta as

$$\beta_i = \frac{Cov(r_i, r_M)}{\sigma_M^2} \tag{2}$$

where:
β_i = the beta of an individual security
$Cov(r_i, r_M)$ = the covariance between stock I and market portfolio M
σ_M^2 = the variance of market portfolio M

The capital market line (CML) and the security market line (SML) are two essential illustrations in CAPM theory. In a world with risk-free assets, the CML is the efficient frontier, displaying the optimal trade-offs between return and risk, which is measured as standard deviation for efficient portfolios. In contrast, the SML illustrates the correlation between beta and projected return for specific stocks or portfolios. According to Bodie et al. (2023), assets below the SML are overpriced, while those above the line are undervalued and provide greater returns for their degree of risk.

The CAPM has been widely used in financial economics, but it has also faced criticism for depending on strong assumptions, such as fully rational investors and perfectly frictionless markets, which are often unrealistic in practice. Behavioral finance provides an alternative view by arguing that risk attitudes and perceptions are not fixed, but instead can shift with psychological states, including changes in mood. From the perspective of this thesis, a central feature of the CAPM is that expected returns represent compensation for bearing risk; however, this relationship becomes more complex if the level of aggregate risk tolerance varies over time. In such a case, the market price of risk may itself fluctuate across seasons. This creates a possible link between seasonal mood variation, including effects associated with seasonal affective disorder, and time-varying risk premia observed in asset returns.

2.4.2 Other asset pricing models

While the CAPM provides a parsimonious benchmark for understanding the pricing of systematic risk, extensive empirical research has documented that market beta alone does not fully explain cross-sectional variation in stock returns. In response to these limitations, multifactor asset pricing models have been developed to capture additional systematic return patterns associated with firm characteristics. The Fama-French three-factor model extends the CAPM by incorporating size and value factors in addition to the market factor (Fama and French, 1993). The model can be expressed as:

$$R_{it} - R_{Ft} = a_i + b_i Mkt_t + s_i SMB_t + h_i HML_t + e_{it}, \tag{3}$$

where:
R_{it} = returns on portfolio i for period t
R_{Ft} = risk-free rate for period t
a_i = intercept
Mkt_t = market factor
SMB_t = size factor
HML_t = value factor
e_{it} = error term of the regression

SMB (small minus big) captures the empirical tendency of small-cap stocks to outperform large-cap stocks on average, and HML (high minus low) reflects the value premium associated with high book-to-market firms. By including these factors, the model explains a larger share of return variation across firms than the single-factor CAPM. Subsequent research demonstrated that profitability and investment patterns also help explain expected returns. Fama and French (2015) therefore introduced the five-factor model, adding profitability RMW (robust minus weak) and investment CMA (conservative minus aggressive) factors:

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + e_{it}, \tag{4}$$

where:

R_{it} = returns on portfolio i for period t

R_{Ft} = risk-free rate for period t

a_i = intercept

SMB_t = size factor

HML_t = value factor

RMW_t = profitability factor

CMA_t = investment factor

e_{it} = error term of the regression

Empirical evidence shows that firms with stronger profitability and more conservative investment behavior tend to display distinct return patterns, which motivates the inclusion of these characteristics in asset pricing models. As a result, such models highlight that expected returns are influenced not only by market exposure but also by firm-specific attributes.

For this thesis, the relevance of the multifactor models lies not in estimating factor alphas, but in clarifying the cross-sectional logic of asset pricing. If ESG-classified firms differ systematically in size, valuation characteristics, profitability, governance quality, or investment behavior, they may load differently on underlying risk factors. Consequently, their relative return performance may respond differently to changes in the aggregate market price of risk. In a setting where aggregate risk aversion varies seasonally, such as during periods associated with seasonal affective disorder, the required compensation for risk may shift. If ESG firms are perceived as more resilient or less exposed to downside risk, they may be less penalized when risk aversion increases. If perceived as uncertain, they may underperform. Multifactor models, therefore, provide a theoretical basis for examining whether seasonal mood variation is reflected not only in aggregate returns but also in the relative performance of ESG versus non-ESG stocks.

3 Seasonal affective disorder in financial markets

Seasonal affective disorder has received increasing attention in financial research as a potential channel linking seasonal variation in daylight to investor mood and risk preferences. Early evidence suggests that seasonal mood deterioration may coincide with increased risk aversion and predictable seasonal patterns in returns, particularly in high-latitude countries where daylight variation is substantial (Kamstra et al., 2003). At the same time, the robustness and identification of SAD effects remain debated, motivating careful measurement choices and robustness tests. This chapter reviews the conceptual foundations of SAD, commonly used proxies in finance, and key critiques relevant for interpreting empirical results.

3.1 The concept of SAD

Experimental psychology research indicates that depressive states are associated with above-average risk aversion and behavioral withdrawal (Zuckerman, 1984; 2007). Reduced exposure to daylight, which characterizes seasonal affective disorder, has been linked to patterns typically associated with depression, including a lower willingness to take risks. From this perspective, it is plausible that periods affected by SAD are accompanied by a decline in risk-taking behavior. Biological explanations provide further support for this link, as they emphasize underlying neurochemical and neurological mechanisms, particularly those related to serotonin regulation. Consistent with this view, clinical and neurobiological evidence shows that depressive states under limited sunlight are associated with observable changes in brain activity (Cohen et al., 1992).

Seasonal affective disorder can be viewed in financial terms as a factor that contributes to time variation in risk aversion. When daylight decreases, increased pessimism and heightened sensitivity to potential losses may lead investors to require greater compensation for bearing risk. Empirical evidence supporting this mechanism is provided by Kamstra et al. (2003), who document that stock index returns tend to be lower during autumn and recover after the darkest period, indicating seasonal shifts in the market price of risk. Their findings also show that these effects are more pronounced in higher-latitude regions, where larger fluctuations in daylight may strengthen the underlying psychological mechanism.

This seasonal risk-aversion interpretation motivates empirical tests in settings with pronounced daylight changes, such as the Nordic region, and raises the question of whether SAD affects not only aggregate returns but also the relative pricing of specific asset characteristics, including ESG-related sustainability attributes.

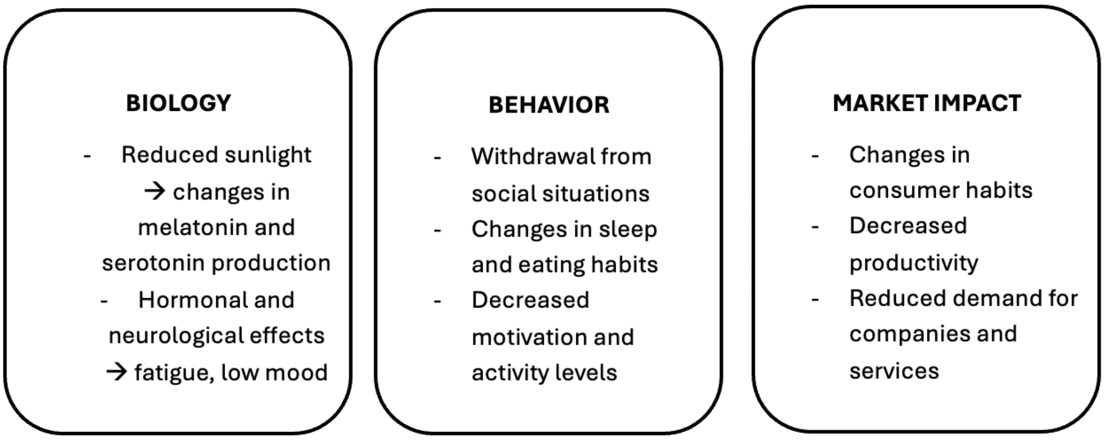

Figure 1 The effects of SAD across different dimensions

3.2 Measuring SAD

Kamstra et al. (2003) investigate the impact of SAD on stock market returns by estimating a time-series regression model for multiple countries using daily stock index data. Their approach runs separate regressions for each market and uses daylight-related variables as proxies for seasonal mood variation. The SAD proxy is operationalized as a function of night length, intended to capture seasonal variation in exposure to light. The underlying assumption is that longer nights correspond to lower daylight exposure and, therefore, higher prevalence or intensity of SAD symptoms at the population level.

To operationalize seasonal variation, Kamstra et al. (2003) approximate the sun's declination angle λ_t using the Julian day of the year. The Julian day counts calendar days from 1 to 365. The declination angle is defined as:

$$\lambda_t = 0{,}4102 * \sin\left[\left(\frac{2\pi}{365}\right)(julian_t - 80{,}25\right], \tag{5}$$

Given λ_t, the number of night hours H_t at latitude δ is computed as:

$$H_t = 24 - 7{,}72 * \arccos\left[-\tan\left(\frac{2\pi\delta}{360}\right)\tan\left(\lambda_t\right)\right], \tag{6}$$

The SAD variable is then defined as a seasonal measure that is active during the fall-winter period. In the original formulation, SAD intensity increases with longer nights relative to a 12-hour baseline. A common representation is:

$$SAD_t = \begin{cases} H_t - 12 \; for\ trading\ days\ in\ the\ fall\ and\ winter \\ 0 \qquad\qquad\qquad\qquad\qquad\qquad\qquad otherwise \end{cases}, \tag{7}$$

In this construction, larger values of the proxy correspond to longer nights (lower daylight exposure) during the fall-winter season, which is hypothesized to be associated with higher aggregate risk aversion. This approach has become one of the most widely used methods in finance for operationalizing SAD-related seasonality.

In the context of the Nordic region, the daylight-based SAD proxy is particularly relevant due to the substantial intra-annual variation in sunlight exposure at higher latitudes. Seasonal differences in daylight create a setting in which mood-related mechanisms can be examined through their potential effects on financial behavior. Rather than observing investor sentiment or clinical depression directly, the analysis relies on daylight variation as an external factor that may influence aggregate mood independently of market conditions. This indirect approach has led to the widespread use of daylight-based measures in empirical finance as proxies for seasonal changes in risk aversion. At the same time, such measures require careful interpretation, and their validity depends on appropriate robustness checks and awareness of their limitations.

Firm-level risk perceptions are not captured by the daylight-based SAD proxy, which instead reflects changes in aggregate risk aversion. To address this limitation, it is important to consider firm-specific characteristics, particularly corporate social responsibility (CSR). CSR is understood as a set of voluntary activities that extend beyond regulatory requirements and incorporate ESG-considerations. Its relevance for risk arises from multiple channels, for instance, stronger stakeholder relationships, reputational advantages, and accumulated goodwill can provide protection in adverse conditions, reducing the severity of negative market reactions (Godfrey et al., 2009). Consistent with this, empirical findings link CSR engagement to lower firm risk, especially in industries where reputational concerns are more pronounced (Jo and Na, 2012). Moreover, firms with stronger ESG profiles are often associated with a lower cost of equity capital, indicating that investors interpret sustainability characteristics as signals of reduced uncertainty and improved information quality (Ng and Rezaee, 2015).

The relationship between CSR and firm risk is not straightforward, as the underlying effects can operate in opposing directions. Greater transparency and stronger stakeholder trust associated with CSR may reduce perceived risk. CSR activities may also give rise to agency-related issues, as managerial incentives do not always align perfectly with shareholder value maximization. In some cases, corporate social responsibility initiatives may be pursued for reputational gains or personal managerial objectives rather than financial efficiency, as discussed by Barnea and Rubin (2010). This can lead to concerns about increased uncertainty regarding the true economic impact of such activities, as well as potential tensions between different groups of shareholders with diverging priorities. Consequently, whether CSR reduces or amplifies risk depends on how market participants interpret sustainability activities, providing a theoretical basis for examining whether seasonal mood variation translates into differential effects across ESG and non-ESG firms.

4 Literature review

Research in behavioral finance increasingly demonstrates that investor decisions are shaped not only by information and rational evaluation but also by psychological and environmental influences. Mood fluctuations, weather conditions, and biological cycles have been shown to affect risk perception, trading behavior, and asset pricing. At the same time, a growing body of literature examines how ESG-related characteristics influence perceived risk, downside protection, and investor preferences. This chapter integrates these two strands of research by first reviewing evidence on mood-driven market effects and seasonal anomalies and then examining how ESG characteristics interact with risk perceptions. Together, these literatures provide the foundation for analyzing whether seasonal affective disorder may influence the relative performance of ESG versus non-ESG stocks.

4.1 Mood and environmental determinants of investor behavior

Behavioral finance challenges the traditional assumption that investors are fully rational agents whose decisions are based solely on objective information. A growing body of psychological and neuroeconomic research demonstrates that emotional states systematically influence cognitive processing, belief formation, and risk-taking behavior. Neuroeconomic evidence shows that brain regions associated with emotional processing are directly involved in financial decision-making. Research in behavioral finance suggests that emotional states systematically influence financial decision-making.

The relationship between affect and financial decision-making is typically characterized by systematic shifts in risk preferences. Periods of positive mood are often linked to increased optimism and a greater willingness to bear risk, while negative mood states tend to heighten sensitivity to potential losses and encourage more cautious behavior (Kuhnen and Knutson, 2011). Importantly, these changes in behavior can occur even in the absence of any variation in underlying probabilities or information sets, indicating that mood itself can act as an independent driver of decision-making. When such mood-driven responses are shared across a large number of market participants, their effects may aggregate at the market level. In these cases, individual behavioral deviations need not cancel out, and standard arbitrage mechanisms may be insufficient to fully eliminate the resulting pricing pressures (Barberis et al., 1998; Baker and Wurgler, 2006). This aggregation channel provides a key theoretical foundation for studying how psychological factors can translate into observable patterns in financial markets.

A broad strand of behavioral finance research focuses on the idea that financial markets respond not only to economic information, but also to emotionally charged events that are economically irrelevant. A well-known example is provided by Edmans et al. (2007), who examine international football outcomes across 39 countries and document systematic negative abnormal returns following losses by national teams. The effect is particularly strong after tournament elimination, while victories generate a much weaker response. After accounting for expected match outcomes and macroeconomic controls, the authors attribute these patterns primarily to shifts in investor mood rather than to fundamental information. The asymmetry in reactions is also consistent with loss aversion, as predicted by prospect theory.

Evidence that sentiment effects operate at the market level is further supported by Kumar and Lee (2006), who shift the focus from aggregate sentiment indices to micro-level trading behavior. Using detailed transaction data from U.S. equity markets, they show that stocks with high retail investor participation exhibit stronger co-movement, even after controlling for fundamentals, industry structure, and standard risk factors. This suggests that correlated trading among individual investors can translate into correlated price movements across otherwise unrelated assets. The authors further argue that retail investors are particularly susceptible to mood fluctuations and behavioral biases, meaning that their collective activity can shape broader market dynamics. This sentiment-driven co-movement is especially pronounced among geographically close firms, implying that shared local environments and common emotional influences may reinforce these effects.

The literature also highlights that investor sentiment may vary in predictable cycles linked to biological or environmental rhythms. Yuan et al. (2006) investigate lunar cycle effects in international equity markets and document lower returns during full moon periods compared to new moon phases. These patterns persist after controlling for macroeconomic conditions and common risk factors, suggesting that cyclical changes in mood may influence aggregate financial outcomes. The variation in results across countries further indicates that institutional and market-specific characteristics may mediate the strength of such effects.

A more direct behavioral channel is explored by Kamstra et al. (2000), who study stock market reactions around daylight saving time transitions. They find that returns decline significantly following the spring transition, when sleep loss is more pronounced, while no comparable effect is observed in the autumn shift. The authors interpret this asymmetry as evidence that reduced sleep may impair cognitive functioning and increase risk aversion among investors. Since the timing of clock changes is unrelated to economic fundamentals, the findings are interpreted as support for biologically driven mood and alertness effects on financial markets.

Weather-related studies provide another perspective on how external conditions may shape investor sentiment. Saunders (1993) documents a relationship between cloud cover and stock returns on the New York Stock Exchange, showing that returns tend to be lower on cloudy days compared to sunny ones. The study proposes that such environmental conditions influence mood, which in turn affects financial decision-making. Building on this idea, Hirshleifer and Shumway (2003) extend the analysis to an international setting by examining sunshine levels across 26 stock markets between 1982 and 1998. Instead of focusing on a single country, they use morning sunshine in major financial centers as a proxy for mood variation and test its relationship with daily returns. Their work is grounded in psychological evidence suggesting that sunshine improves mood and promotes more optimistic judgments, thereby reinforcing the link between environmental conditions and investor sentiment.

The results of Hirshleifer and Shumway (2003) show that stock returns tend to be lower on cloudier days and higher when sunshine exposure is greater, even after controlling for alternative explanatory variables. By linking local weather conditions to systematic return variation, the study challenges the strong form of the efficient market hypothesis and supports the behavioral finance view that investor sentiment can influence market outcomes independently of economic fundamentals.

Kamstra et al. (2003) are most closely associated with introducing seasonal affective disorder into financial economics. Their study proposes that seasonal changes in psychological well-being influence investor risk tolerance and, through this channel, generate predictable variation in stock market returns. The authors document lower returns during autumn and higher returns during spring, particularly in countries where SAD prevalence is expected to be greater. By linking seasonal mood variation to asset pricing, the study introduced a new behavioral perspective that had previously received limited attention in both traditional finance and early behavioral economics.

Kamstra et al. (2003) introduce a framework that shifts the measurement of seasonal affective disorder away from simple calendar-based seasonality toward a direct link with daylight exposure. Instead of treating SAD as a fixed seasonal period, their approach emphasizes the role of the actual duration of daylight as the relevant psychological input. In this setting, shorter days are interpreted as increasing the likelihood of depressive symptoms, which in turn may reduce risk tolerance and strengthen preferences for safer financial assets. By grounding the analysis in variation in daylight length across countries and over time, the framework provides a more structured way of capturing potential mood-related effects in financial data. This methodological contribution has been particularly influential in later empirical studies, where it has been adopted as a standard reference point for examining seasonal patterns in returns and investor sentiment.

Nevertheless, the SAD hypothesis has faced substantial criticism. Kelly and Meschke (2010) provide a comprehensive reassessment of the Kamstra et al. (2003) findings. Extending the analysis to 36 countries and employing alternative methodological specifications, they fail to find consistent evidence that cross-country variation in stock returns can be explained by SAD prevalence. Moreover, they argue that clinical psychology evidence does not clearly support the magnitude of seasonal mood variation implied by the financial results.

Kelly and Meschke (2010) critically reassess the SAD-based asset pricing framework introduced by Kamstra et al. (2003). They argue that the observed seasonal return patterns may arise mechanically from overlapping seasonal variables rather than from psychological effects and suggest that conventional year-end seasonality provides a more plausible explanation. Drawing on medical and psychological literature, the authors also question the theoretical foundations of the SAD hypothesis and conclude that the evidence linking seasonal mood variation to aggregate market returns remains limited. While acknowledging that sentiment may play a role in shaping financial market behavior, the authors stress that simple co-movement between mood-related proxies and asset returns does not, by itself, provide evidence of causality. Such correlations can arise from a range of confounding factors, and therefore cannot be directly interpreted as proof of a behavioral channel. This limitation highlights the importance of employing more rigorous identification strategies, as well as maintaining methodological consistency, when studying sentiment effects within behavioral finance.

A natural point of departure in the weather–sentiment literature is the reassessment of whether individual trading behavior actually responds to short-term environmental conditions. Using detailed account-level data from investors located in five major U.S. cities between 1991 and 1995, Goetzmann and Zhu (2005) test whether trading decisions vary systematically with weather conditions. Contrary to earlier studies suggesting strong mood effects, they find that buy and sell behavior at the individual level is largely unaffected by transitions between sunny and cloudy days. At the same time, they observe that market-level variables do exhibit variation: bid–ask spreads widen on cloudy days at the New York Stock Exchange, implying that any weather-related effects may operate through market-making and liquidity provision rather than through retail trading decisions.

A similar question is addressed in a Nordic setting by Kaustia and Rantapuska (2016), who study Finnish investor behavior using an extensive dataset covering both individual and institutional trades across 444 municipalities from 1995 to 2002. Their analysis links local weather conditions to trading activity in order to assess whether environmental factors influence investment decisions. The results show that certain adverse weather conditions, particularly rainfall, are associated with reduced trading intensity, whereas sunshine has only a weak and statistically insignificant effect on purchase behavior. When compared with these environmental variables, calendar effects—especially increased trading activity around year-end—emerge as more robust predictors of investor behavior. This suggests that structural and institutional factors may provide a stronger explanation for trading patterns than mood-based mechanisms alone, and it also indicates that the relevance of weather effects may vary depending on market context.

While several studies therefore cast doubt on the robustness of weather-driven trading effects, other evidence points to more heterogeneous and context-dependent relationships. Bhattarai and Joshi (2007), for instance, analyze the Nepal Stock Exchange over the period 1995–2005 and report a positive association between cloud cover and stock market performance, whereas temperature and SAD-related proxies show no significant effects. These results differ not only from earlier evidence of negative cloud–return relationships (Saunders, 1993; Hirshleifer and Shumway, 2003) but also from studies documenting seasonal affective disorder effects in more developed markets (Kamstra et al., 2003). The divergence in findings reinforces the idea that mood-related anomalies are not universal and may depend on institutional structure, market efficiency, and local investor characteristics.

Taken together, this body of research points to a broader and more nuanced interpretation of sentiment in financial markets. Investor behavior appears to be influenced by a combination of economic fundamentals, environmental conditions, and psychological states, yet the empirical support for these channels is far from uniform. Across different studies, sentiment effects are documented in relation to sports outcomes, weather patterns, sleep cycles, lunar phases, and seasonal daylight variation, all of which suggest that mood can influence risk-taking and market outcomes under certain conditions. However, later research frequently questions the robustness, generalizability, and causal interpretation of these effects, emphasizing that their visibility depends heavily on sample period, market design, and empirical methodology.

Despite this extensive literature, relatively little attention has been given to Nordic equity markets, where seasonal variation in daylight is particularly pronounced. This setting provides a natural laboratory for examining whether prolonged reductions in daylight translate into systematic changes in investor risk-taking and asset prices. At the same time, the mixed evidence from previous studies implies that any such effects should be tested carefully rather than assumed to be universal. Building on this background, the present study investigates whether stock returns in Nordic markets exhibit seasonal patterns consistent with increased risk aversion during SAD periods, which forms the basis for hypothesis H1.

4.2 ESG investing and perceptions of risk

A useful way to link mood-based finance with ESG investing is to move away from aggregate return effects and instead focus on how investors perceive risk under different emotional states. In this view, the key mechanism is not only whether markets rise or fall, but how uncertainty is interpreted across different types of assets. ESG characteristics may matter in this process if they systematically alter how risky or ambiguous an investment appears when investor sentiment changes.

Experimental evidence supports the idea that emotional states can directly shape risk-taking behavior. Yuen and Lee (2003) study this relationship using controlled laboratory experiments with students at the University of Hong Kong, where participants are induced into different mood states before making financial choices under risk. Their results show a clear asymmetry: negative mood leads to more cautious behavior and reduced willingness to take risks, while positive mood does not produce a comparably strong increase in risk-taking. This suggests that negative affect plays a more influential role in shaping financial caution than positive emotions do in encouraging risk-seeking.

A similar mechanism is documented in neuroeconomic research, where emotional processes are shown to be embedded in the cognitive systems underlying financial decision-making. Kuhnen and Knutson (2011) demonstrate that neural activity associated with affective responses is closely linked to how individuals evaluate financial risk and reward. Positive emotional states tend to increase confidence and willingness to take risk, whereas negative emotions shift behavior toward caution. Importantly, emotions also influence information processing itself, as individuals tend to reinforce prior beliefs and selectively attend to information that supports existing decisions. In experimental settings, participants exposed to emotionally charged stimuli adjust portfolio choices accordingly, with negative cues reducing risk-taking and reinforcing conservative decisions.

These insights can be extended to recurring mood fluctuations such as those associated with seasonal affective disorder. If transient emotional states are capable of altering risk preferences in controlled environments, it is plausible that longer-lasting seasonal changes in mood may influence how investors evaluate financial assets in real markets. In this sense, investment behavior may reflect a combination of analytical evaluation and emotionally driven shifts in risk tolerance, rather than purely objective assessment of fundamentals.

Within this broader framework, ESG investing introduces an additional dimension related to perceived safety and uncertainty. Empirical studies suggest that firms with strong ESG profiles often exhibit more stable cash flows, lower idiosyncratic risk, and greater resilience during downturns (Nofsinger and Varma, 2014; Derwall and Koedijk, 2009). These characteristics are frequently linked to improved disclosure practices and reduced information asymmetry, which may lower uncertainty about firm fundamentals (Dhaliwal et al., 2011; Ng and Rezaee, 2015). At the same time, ESG preferences are not purely financial. Riedl and Smeets (2017) show that social identity, moral satisfaction, and prosocial preferences also play a role in shaping demand for sustainable investments, while Hartzmark and Sussman (2019) document that ESG labels influence fund flows in ways consistent with heuristic decision-making.

These financial and behavioral channels may interact with changing emotional states. During periods of heightened pessimism, such as those associated with seasonal affective disorder, investors may place greater weight on perceived stability and downside protection. ESG assets, often associated with transparency and long-term orientation, may therefore become relatively more attractive not only because of their risk characteristics but also because they provide psychological reassurance in uncertain conditions.

A related dimension concerns ambiguity rather than risk in the narrow statistical sense. Epstein and Schneider (2008) show that investors dislike ambiguity, meaning uncertainty about probability distributions themselves, and require additional compensation for holding assets with unclear informational structure. Emotional states can intensify this aversion, making investors more sensitive to assets that appear complex or difficult to evaluate. ESG disclosure practices may reduce this type of uncertainty by providing standardized reporting and more comprehensive information, thereby lowering perceived ambiguity.

This distinction is particularly relevant when interpreting ESG assets through a behavioral lens. Rather than only reflecting ethical preferences, ESG investments may also be interpreted as less ambiguous and more predictable in informational terms. When combined with seasonal increases in pessimism and risk sensitivity, this can reinforce demand for ESG assets during periods of negative mood, even if underlying financial risk does not change.

From a risk perspective, ESG characteristics may also be linked more strongly to downside protection than to average volatility. Bolton and Kacperczyk (2021) show that markets price carbon-intensive firms as more exposed to long-term adverse risks, suggesting that ESG factors capture vulnerability to extreme outcomes rather than short-term fluctuations. In periods of heightened anxiety or pessimism, such tail risks may become more salient, increasing the relative attractiveness of firms perceived as more sustainable or better governed. This literature suggests a coherent mechanism in which emotional states influence perceived risk, ambiguity, and downside sensitivity, and these perceptions may interact with ESG characteristics. Rather than affecting only average returns, mood fluctuations are therefore more likely to operate through how investors interpret uncertainty across different types of assets.

Pedersen et al. (2021) provide a utility-based explanation for why ESG investments may influence investor risk perceptions. In their theoretical framework, investors derive utility not only from financial returns but also from holding assets that align with personal values and preferences. As a result, ESG investment can increase total investor utility even without offering superior risk-adjusted returns. This additional non-financial utility may cause sustainable assets to be perceived as relatively safer or more desirable because ethical and psychological benefits partly offset financial uncertainty. During periods of heightened risk aversion or negative mood, such as those associated with seasonal affective disorder, these non-financial benefits may further strengthen the attractiveness of ESG investments.

Taken together, the literature suggests multiple complementary channels through which ESG investing interacts with investor sentiment and risk perception. ESG assets may reduce perceived ambiguity through enhanced disclosure, mitigate exposure to downside risk by signaling long-term resilience, and provide psychological utility through alignment with personal values. If seasonal mood variation increases risk aversion and sensitivity to uncertainty, as suggested by the literature reviewed in section 4.1, these characteristics may become relatively more salient during darker months. Consequently, seasonal shifts in investor mood may not only affect aggregate market returns but also generate cross-sectional differences between ESG-classified and conventional stocks. This theoretical mechanism motivates hypothesis H2, which tests whether ESG portfolios display differential sensitivity to seasonal affective disorder relative to non-ESG firms.

5 Data and methodology

The data and methodology used in this thesis are presented in this chapter. The dataset, which combines financial market data, sustainability classifications, and environmental indicators to capture the possible effects of seasonal affective disorder on stock performance in the Nordic countries between 2014 and 2024, is first presented along with its sources. The data is presented in section 5.1. Section 5.2 describes the analytical approach, including how returns and SAD-related variables are calculated and how regression models are used.

5.1 Data

This chapter presents the data sources and empirical methodology employed to examine whether seasonal affective disorder influences stock returns and whether ESG-classified firms display differential sensitivity to seasonal mood variation in Nordic equity markets. To examine potential behavioral effects related to seasonal variation in daylight exposure, the dataset combines information from financial markets, sustainability classifications, and meteorological indicators.

The dataset used in this thesis is constructed from multiple sources and combines firm-level financial information, sustainability indicators, and meteorological observations. At its core, it covers publicly listed companies from Finland, Sweden, Norway, and Denmark over the period 2014–2024. These markets form the backbone of the Nordic equity region due to their size, liquidity, and relatively high level of integration. Iceland is excluded because its market is considerably smaller and less liquid, which would reduce comparability and potentially introduce additional noise into the empirical analysis. Focusing on the four main economies therefore ensures a more coherent and statistically reliable sample structure.

A key feature of the empirical design is the Nordic setting itself, which is particularly relevant for studying seasonality-related behavior. The region is characterized by extreme variation in daylight between summer and winter, creating substantial exogenous shifts in environmental conditions over the year. These fluctuations provide a natural context for examining whether investor behavior and risk-taking respond to seasonal changes in mood. Importantly, the Nordic countries are also institutionally similar, which allows environmental variation to be studied without large structural differences in market functioning.

From a financial perspective, the analysis is built on weekly firm-level returns, calculated as simple percentage changes in stock prices. This choice is primarily motivated by interpretability, as the resulting coefficients can be directly understood in percentage terms. At a weekly frequency, the distinction between log returns and simple returns is minimal, meaning that this specification does not materially affect the results. To capture broader market movements, country-level returns are included as controls for systematic risk. In addition, a rolling twelve-week volatility measure is constructed to reflect short-term fluctuations in uncertainty at the firm level.

Sustainability information is integrated through ESG ratings obtained from LSEG Workspace. The analysis relies on the Thomson Reuters ESG score (TRESGS), which is based on publicly available firm disclosures and evaluates environmental, social, and governance performance. The same platform is used to obtain stock return data from DataStream, ensuring consistency across financial and ESG variables. Firms are then grouped according to their ESG performance, with lower-rated companies classified as non-ESG firms. This separation enables a comparison between sustainability-oriented and traditional firms in terms of their sensitivity to seasonal effects.

Environmental conditions are incorporated through meteorological data collected from national institutes: FMI in Finland, SMHI in Sweden, MET Norway, and DMI in Denmark. The variables include sunshine duration, cloud cover, and temperature, all measured at capital-region weather stations. Sunshine duration, expressed in hours, is used as the primary proxy for daylight exposure, while cloud cover and temperature provide additional contextual controls. Because reporting formats differ between countries, all variables are standardized prior to analysis. One limitation arises from Denmark, where continuous cloud cover data are not available; to address this, observations from Malmö are used as a geographically close proxy, given its similar climatic conditions and proximity.

Seasonal affective disorder is incorporated indirectly through daylight-based proxies rather than direct psychological measures. Two alternative specifications are used to capture seasonal effects. The first is a binary indicator defining a SAD period from September to March. The second is a continuous measure based on deviations in weekly daylight hours relative to each country’s long-run average. This second approach isolates within-country seasonal variation while accounting for permanent differences in latitude across the Nordic region.

5.2 Methodology

This study employs an empirical design that draws on the seasonal daylight framework introduced by Kamstra et al. (2003), in which variations in daylight exposure are linked to investor sentiment and stock market performance. Instead of focusing on aggregate market indices, the approach is adapted here to a firm-level setting, allowing for heterogeneity across companies. The model is further extended by introducing ESG classifications, which makes it possible to examine whether sustainability characteristics are associated with different sensitivities to seasonal mood fluctuations. The construction of variables and the regression setup are presented in the following sections, and all models are estimated using robust standard errors to account for potential heteroskedasticity.

In contrast to a single-measure approach, seasonal affective disorder is proxied using two different specifications based on daylight exposure. The purpose of using multiple measures is to improve robustness and reduce dependence on a specific proxy definition. One specification relies on a binary classification of the year, where the period from September to March is treated as the SAD season and used to distinguish darker months from brighter ones. This captures broad seasonal shifts in environmental conditions in a simplified form.

Alongside this, a second and more granular measure is constructed using continuous daylight data. Weekly daylight duration is collected from national meteorological sources for each country and then transformed into a deviation from its long-term average. This transformation produces a standardized indicator that reflects within-country seasonal variation in daylight while controlling for persistent differences in geographical location. For each country, total weekly daylight duration is obtained from national meteorological institutions and transformed into a deviation-from-mean measure:

$$D_{c,t} = D\text{aylightHours}_{c,t} - \overline{\text{DaylightHours}}_{c} \tag{8}$$

The daylight deviation measure focuses on changes in daylight intensity within each country rather than on permanent geographic differences in latitude. Lower values of $D_{c,t}$, therefore, correspond to movement toward darker seasonal periods, when SAD-related symptoms are expected to become more pronounced. To account for additional environmental influences that may affect investor mood, the analysis also includes cloud cover and temperature as control variables.

The empirical analysis is conducted using a panel ordinary least squares (OLS) framework based on the approach of Kamstra et al. (2003). In contrast to the original study, however, the methodology is adapted to firm-level data and expanded to include sustainability classifications. The dataset is organized so that each observation corresponds to the weekly return of either an ESG or non-ESG portfolio within a specific country. The base-line regression model is specified as follows:

$$R_{i,t} = \alpha + \beta_1 SAD_t + \beta_2 (SAD_t \; x \; ESG_i) + \delta_1 \text{MarketReturn}_{c,t} + \epsilon_{i,t} \tag{9}$$

The dependent variable $R_{i,t}$, measures the weekly return of portfolio *i* in period t. Seasonal effects are captured using the indicator SAD_t, which takes the value one during the SAD season and zero otherwise. To analyze whether sustainability characteristics influence seasonal return behavior, the regression includes the interaction term $SAD_t\ x\ ESG_i$, which captures whether ESG portfolios respond differently during the SAD period relative to non-ESG portfolios. The variable $\text{MarketReturn}_{c,t}$, is included to control for systematic market exposure at the country level, consistent with standard asset pricing theory.

To reduce the possibility that estimated seasonal effects simply reflects short-term environmental conditions, the baseline specification is extended with additional weather-related controls. These include standardized measures of sunshine duration, temperature, and cloud cover.

$$R_{i,t} = \alpha + \beta_1 SAD_t + \beta_2 (SAD_t\ x\ ESG_i) + \delta_1 \text{MarketReturn}_{c,t} + \delta_2 Sunshine_{c,t} + \delta_3 Temperature_{c,t} + \delta_4 CloudCover_{c,t} + \epsilon_{i,t} \quad (10)$$

A key challenge in isolating seasonal mood effects is separating them from other factors that vary over time, particularly short-term weather conditions. For this reason, the empirical specification includes variables that capture meteorological influences alongside the main seasonal measures. This is motivated by earlier findings showing that weather conditions may have an impact on both investor sentiment and financial market behavior (Saunders, 1993; Hirshleifer and Shumway, 2003), which makes it important to account for these effects when studying seasonal patterns. To further ensure that the results are not driven by general fluctuations in market conditions, an additional robustness specification is estimated. In this version of the model, rolling twelve-week volatility is introduced as a control variable. This allows the analysis to distinguish between effects that are specifically related to seasonal mood variation and those that may instead reflect changes in overall market uncertainty.

$$R_{i,t} = \alpha + \beta_1 SAD_t + \beta_2 (SAD_t \; x \; ESG_i) + \delta_1 \text{MarketReturn}_{c,t} + \delta_2 Sunshine_{c,t} + \delta_3 Temperature_{c,t} + \delta_4 CloudCover_{c,t} + \delta_5 VOL\_12W_{i,t} + \epsilon_{i,t} \quad (11)$$

Panel least squares estimation is applied in all regressions, and inference is based on white period-clustered robust standard errors to address potential heteroskedasticity and cross-sectional dependence within weekly observations. Because the number of cross-sectional portfolio units is limited, the results are interpreted with caution. Accordingly, greater emphasis is placed on the direction and economic magnitude of the estimated coefficients, as well as on the consistency of findings across alternative model specifications. Seasonal subsample regressions are also estimated separately for SAD and non-SAD periods to evaluate whether ESG-related return differences are concentrated in darker months. Overall, the methodological framework is designed to assess whether seasonal mood variation influences stock returns and whether sustainability characteristics moderate such effects. The next chapter presents the empirical results and evaluates the hypotheses within this econometric framework.

6 Empirical analysis and results

The study's empirical research is presented in this chapter, which looks at how seasonal affective disorder affects stock returns in the Nordic markets and whether ESG and non-ESG companies are affected differently. During the dark season, when mood-related seasonal influences are anticipated to change investors' risk choices, the goal is to assess if sustainability-oriented businesses exhibit more steady performance and reduced volatility. Regression models are used to test the statistical significance of the observed differences between ESG and non-ESG portfolios after descriptive statistics are used to summarize the key features of the data and give an overview of return behavior during the SAD months from September to March.

6.1 Descriptive statistics

Table 6.1 presents descriptive statistics for the weekly returns of ESG and non-ESG stocks in the Nordic markets over the period from September 2014 to March 2024, corresponding to months associated with seasonal affective disorder. Companies from Finland, Sweden, Norway, and Denmark are included in the data; their sustainability classifications are used to separate their portfolios into ESG and non-ESG categories. To ensure that the research concentrates on the time when mood-related seasonal affects are most noticeable in investor behavior, only observations made during the SAD season (September-March) were considered when calculating returns, the same season that Kamstra et al. (2003) used in their study.

The table presents descriptive statistics for ESG and non-ESG portfolios across the Nordic countries during the SAD season. Reported measures include the mean, median, and standard deviation, together with the difference in average returns between ESG and non-ESG portfolios and the corresponding F-statistic. While the mean and median summarize average return performance, the standard deviation reflects return volatility and associated risk exposure. The mean difference and F-statistic further provide an initial indication of whether return differences between ESG and non-ESG portfolios are economically meaningful during darker seasonal periods.

	ESG			Non-ESG				
Country	Mean	Median	SD	Mean	Median	SD	Mean Diff	F-stat
Finland	-0,00024	0,00218	0,02405	-0,00071	0,00062	0,02453	0,02453	1,04
Sweden	0,0028	0,00461	0,02826	0,00238	0,0000	0,03919	0,00042	1,92
Norway	0,00188	0,00271	0,03692	0,00347	0,00321	0,04138	-0,00159	1,26
Denmark	0,00288	0,0036	0,02729	0,00068	0,00047	0,02896	0,0022	1,13

Table 1 Descriptive statistics for stock returns during the SAD season

During the SAD period, average weekly returns are generally small across all countries and groups. In Finland, both ESG and non-ESG portfolios exhibit slightly negative mean returns, suggesting marginally weaker performance during darker months. In Sweden and Denmark, mean returns remain positive but modest, with ESG portfolios generating 0,00070 and 0,00091 on average, respectively. Norway shows similarly subdued performance, with ESG returns slightly negative and non-ESG returns marginally positive. Overall, the magnitude of mean differences between ESG and non-ESG portfolios during the SAD period is economically limited, typically below 0,001 weekly.

More notable differences emerge in volatility. Across all four countries, standard deviations are higher during the SAD period compared to the non-SAD period (see Table 2 below). For example, in Norway, ESG volatility increases to 0,03692 during the SAD months compared to 0,02017 during non-SAD months. A comparison of volatility across periods suggests that fluctuations in risk are more pronounced during the darker part of the year. This is particularly visible in the Finnish sample, where the standard deviation of returns for non-ESG portfolios is higher in the SAD period than in the rest of the year, increasing from 0,01604 to 0,02453. When viewed more generally, the descriptive results point in the same direction across the dataset: return variability tends to rise during months with limited daylight. Taken together, these initial patterns are consistent with the idea underlying H1, namely that reduced daylight conditions coincide with elevated market uncertainty and risk levels.

Return behavior across portfolios suggests that risk is not evenly distributed over time, with distributional features pointing toward more adverse outcomes during the darker part of the year. In several cases, returns exhibit pronounced left-skewness, implying that extreme negative observations occur more frequently than positive ones of similar magnitude. This is especially evident in the ESG portfolios of Norway and Sweden, where skewness reaches -2.78 and -2.54, respectively. At the same time, elevated kurtosis values are observed in the ESG portfolios of Norway and Sweden as well as in the Finnish non-ESG group, indicating distributions with heavier tails than would be expected under normality.

Taken together, these characteristics suggest that return distributions become more prone to extreme negative outcomes during periods associated with reduced daylight. Such patterns are consistent with the idea that seasonal mood effects may amplify downside risk in financial markets. To place these findings in context, Table 2 presents descriptive statistics for the non-SAD period (April–August). Comparing the two seasonal subsamples provides a preliminary indication of whether return behavior and risk characteristics differ systematically between darker and brighter months.

	ESG			Non-ESG				
Country	Mean	Median	SD	Mean	Median	SD	Mean Diff	F-stat
Finland	0,00099	0,00175	0,01904	0,00137	0,00285	0,016	-0,00038	1,41
Sweden	0,00181	0,00329	0,02018	0,00408	0,00504	0,0233	-0,00227	1,34
Norway	0,0015	0,0023	0,02017	0,00004	0,00052	0,0193	0,00146	1,10
Denmark	0,0016	0,00282	0,01885	0,0023	0,00362	0,0201	-0,0007	1,14

Table 2 Descriptive statistics for stock returns during the non-SAD season

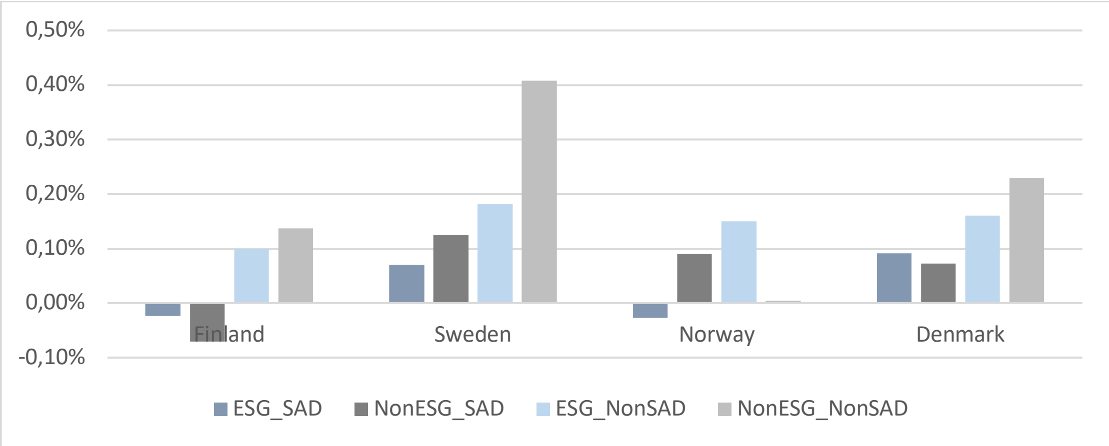

Figure 2 Average weekly portfolio returns by country, ESG classification, and season

The descriptive evidence presented in Table 2 and Figure 2 suggests that average weekly returns are generally positive during the non-SAD period across most countries and portfolio categories. Among the Nordic markets, Sweden stands out with the strongest performance, particularly within the non-ESG segment, while Norway and Denmark exhibit more moderate return levels. Finland shows relatively similar magnitudes across portfolio types, with mean weekly returns of 0.00099 for ESG firms and 0.000137 for non-ESG firms.

When compared with the SAD period, returns in the brighter months appear somewhat higher in several cases, although the magnitude of these differences remains limited. The variation is therefore more consistent with small seasonal fluctuations than with a clearly identifiable return premium. This pattern is also reflected in Figure 2, which illustrates a slight upward shift in average returns during the non-SAD period across multiple countries, rather than a pronounced structural difference between seasonal regimes.

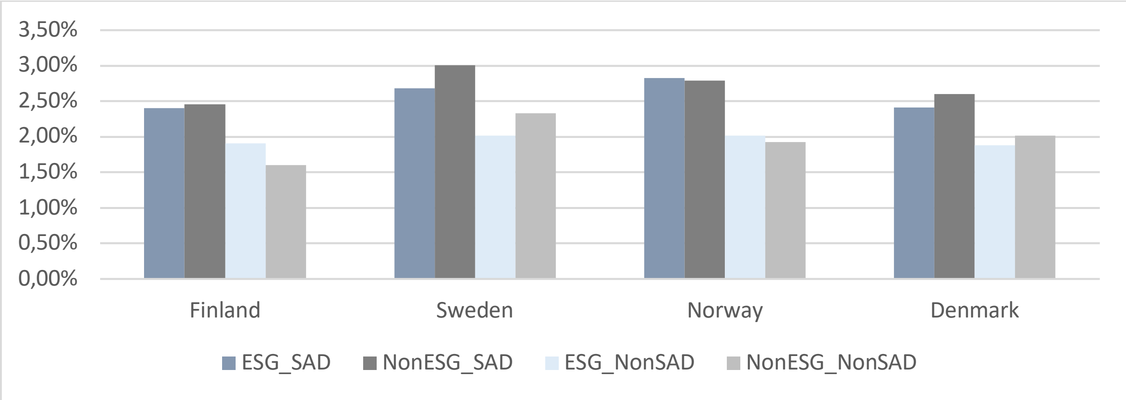

Figure 3 Weekly return volatility (standard deviation) by country, ESG classification, and season

A clear seasonal pattern is also visible in return volatility. Across all countries, standard deviations are lower during the non-SAD period, indicating more stable market conditions during brighter months. This pattern is particularly evident in Sweden, where ESG portfolio volatility declines from 0,02682 during the SAD season to 0,02018 in the non-SAD period. Similar decreases in volatility can also be observed in Finland and Norway. Figure 3 further illustrates this relationship, as volatility levels are consistently lower during the brighter season across nearly all country and portfolio categories. Overall, the descriptive evidence suggests that darker months are associated with greater return variability and heightened uncertainty, which is consistent with the theoretical mechanisms underlying H1.

Overall, the descriptive evidence suggest that seasonal variation is reflected more strongly in return volatility than in average returns. Mean returns remain relatively modest across both ESG and non-ESG portfolios during the SAD period, whereas differences in standard deviation are noticeably larger. This indicates that darker months are associated primarily with increased uncertainty and greater dispersion in returns rather than with substantial changes in average performance. In particular, Finland and Norway exhibit greater variation in returns, especially among ESG portfolios, where volatility levels are higher during the SAD period compared to the non-SAD period. Such findings are broadly consistent with earlier literature emphasizing seasonal variation in risk conditions rather than persistent shifts in expected returns (Kamstra et al., 2003).

The descriptive results do not indicate a systematic performance advantage for ESG portfolios. Rather than being reflected in average returns, the main differences between ESG and non-ESG groups appear to be related to their risk profiles. In a number of countries, ESG portfolios show slightly lower volatility and more stable return behavior compared to non-ESG portfolios. This could be consistent with the interpretation that sustainability-oriented firms are perceived as more resilient in uncertain environments. However, these differences remain limited in magnitude and are not consistently observed across all markets. As a result, they do not provide strong evidence of distinct performance patterns based on ESG classification when viewed in isolation. This underlines the need for the subsequent regression analysis, which enables a more formal assessment of seasonal effects while accounting for market-wide movements and time-varying risk conditions.

Country	SAD SD	Non-SAD SD	Difference	F-stat
Finland	0,02405	0,01904	0,00501	1,60
Sweden	0,02826	0,02018	0,00808	1,96
Norway	0,03692	0,02017	0,01675	3,35
Denmark	0,02729	0,01885	0,00844	2,1

Table 3 Difference-in-means tests comparing average stock returns

Table 3 provides a statistical comparison between the SAD and non-SAD periods to test whether differences in return behavior are significant. The results show a consistent increase in volatility during the SAD season across all countries, reflected in higher standard deviations and significant F-statistics. The effect is most pronounced in Norway and Sweden, where variance ratios indicate clearly higher return variability in darker months. In contrast, differences in average returns remain relatively limited. The findings therefore suggest that seasonal effects are reflected more strongly in changing risk conditions than in large shifts in mean returns. While the observed increases in volatility provide support for H1 by indicating heightened uncertainty during the SAD period, the results do not imply extreme shifts in market risk conditions. Overall, the evidence points toward moderate but systematic increases in return variability during periods associated with reduced daylight exposure.

When comparing ESG and non-ESG portfolios within each season, the results are less consistent. Although ESG firms occasionally exhibit slightly higher mean returns during the SAD period, these differences are not uniformly statistically significant across countries. Consequently, the difference-in-means analysis provides limited support for H2. Seasonal mood fluctuations appear to affect overall market returns more clearly than they do influence cross-sectional sustainability-based return differentials.

Distributional properties also change between seasons. Skewness values during the non-SAD period are generally closer to zero, and kurtosis declines substantially relative to the SAD period. For instance, Norway ESG kurtosis falls from 20,02 during the SAD season to 0,91 during the non-SAD period. This market reduction in tail thickness indicates that extreme negative returns are less frequent during brighter months.

A direct comparison of Tables 1 and 2, therefore suggests that darker months are associated with lower average returns in several cases, higher volatility across nearly all markets, and substantially greater downside tail risk. These descriptive patterns are broadly consistent with H1, which posits that seasonal affective disorder may increase aggregate risk aversion and amplify return variability. The descriptive evidence provides only limited support for H2. While ESG portfolios in some cases appear slightly less volatile during the SAD period, this pattern is not accompanied by consistently higher average returns relative to non-ESG portfolios. As a result, the findings do not indicate a clear or systematic shift toward sustainable investments during darker months.

	PORT_RET	SAD	SAD_X_ESG	MKT_RET	VOL_12W
PORT_RET	1				
SAD	-0,03	1			
SAD_X_ESG	-0,02	0,546	1		
MKT_RET	0,949	-0,03	-0,016	1	
VOL_12W	0,018	0,003	-0,016	0,021	1

Table 4 Correlation matrix

The correlation matrix for the primary variables utilized in the regression analysis is shown in Table 4. With a correlation coefficient of 0,949, portfolio returns and market returns have a high positive correlation, as predicted. The mechanical comovement between the portfolio and the larger market index is reflected in this strong correlation, demonstrating that a significant portion of the fluctuation in portfolio returns may be explained by general market dynamics. The SAD variable, on the other hand, only shows a very weak negative correlation with portfolio returns, indicating that any possible seasonal mood effect needs to be assessed using a multivariate regression framework rather than being driven by simple linear dependence. Likewise, there is very little connection between the interaction term and portfolio performance.

In terms of the correlations between the independent variables, SAD and the interaction term have a moderate (0,546) correlation, which is mechanically predicted as SAD is used to build the interaction variable. Crucially, correlations between the remaining explanatory variables continue to be small, well below frequently mentioned thresholds for multicollinearity concerns. The fact that volatility exhibits almost zero correlations with the other variables suggests that it represents a separate aspect of market dynamics. The dependability of the empirical results is supported by the correlation structure, which indicates that multicollinearity is unlikely to appreciably skew the regression values.

Overall, the descriptive statistics, seasonal comparisons, difference-in-means tests, and correlation analysis collectively indicate the presence of moderate seasonal patterns in Nordic stock returns. The analysis suggests that darker months are associated with moderately lower average returns and higher volatility across several markets, offering preliminary support for H1. In contrast, the evidence related to H2 remains weak, as the results do not show a consistent or statistically convincing tendency for investors to shift toward ESG stocks during the SAD period. The following section examines the hypotheses using multivariate regression models.

6.2 Regression results

This section presents the empirical findings of the study, with a focus on how seasonal affective disorder relates to return patterns in Nordic equity markets and whether ESG portfolios exhibit distinct behavior compared to non-ESG portfolios. Building on the methodological framework outlined earlier, the emphasis here shifts from model construction to the interpretation of estimated effects, their robustness across specifications, and their economic relevance in light of existing literature.

Rather than relying on a single estimation strategy, the empirical analysis is structured in two complementary dimensions. First, a series of panel regressions is estimated for the full sample, where the specification is gradually enriched by adding additional control variables. This stepwise approach allows for an assessment of coefficient stability and is commonly applied in empirical asset pricing research to evaluate whether results are sensitive to model design. Second, the analysis is extended by dividing the sample into SAD and non-SAD periods, enabling separate estimations for each subsample. This decomposition provides a more direct test of whether any seasonal effects are concentrated in periods of reduced daylight, as suggested in earlier theoretical and empirical contributions (Kamstra et al., 2003).

The Nordic context is central to this analysis due to its pronounced seasonal variation in daylight, which provides a natural setting for examining potential mood-related mechanisms in financial markets. Prior research in psychology and behavioral finance suggests that reduced daylight exposure may influence mood, cognitive processing, and risk preferences, thereby affecting investment behavior (Kamstra et al., 2003). At the same time, it is an empirical question whether such effects are sufficiently strong to persist once market efficiency and broader financial forces are taken into account. In this sense, the results contribute to the broader literature on sentiment-based anomalies and their relevance in developed markets (Fama, 1998; Baker and Wurgler, 2006).

Table 5 reports the main panel regression results, starting from a baseline specification and progressively incorporating additional explanatory variables. This incremental structure is designed to test whether the coefficients associated with seasonal affective disorder and ESG classification remain stable as the model becomes more comprehensive. The inclusion of market returns, weather-related controls, and a proxy for time-varying volatility further allows the analysis to distinguish potential seasonal mood effects from standard sources of systematic financial risk.

Variable	Model (1)	Model (2)	Model (3)
Constant	-0,000005	-0,000320	-0,000251
	0,9747	0,2967	0,4839
SAD	0,000077	0,000111	0,000126
	0,8209	0,6738	0,6352
SAD x ESG	-0,000268	-0,000287	-0,000319
	0,2949	0,5477	0,5028
MKT_RET	0,980818***	0,980801***	0,981408***
	0,0000	0,0000	0,0000
SUNSHINE_HOURS		0,000013	0,000013
		0,537	0,5175
TEMPERATURE		0,000007	0,000008

		0,5125	0,4729
CLOUD_COVER		0,000006 0,1414	0,000006 0,1410
VOL_12W			-0,004254
			0,5276
R-Square	0,8992	0,8988	0,9001
Observations	4584	4564	4508

P-values in parentheses. *** p<0,01, ** p<0,05, * p<0,10

Table 5 Baseline panel regression results

The regression results in Table 5 remain highly consistent across all model specifications. In every regression, the SAD coefficient is statistically insignificant and economically very small. Although the estimated coefficient is positive throughout the models, implying slightly higher returns during SAD months, the magnitude of the effect is negligible in practical terms. For example, in model (3), the coefficient corresponds to a weekly return difference of roughly 0,013 percentage points, which is minimal relative to the average weekly return volatility of approximately 2-3 percent. This finding indicates that hypothesis H1 is not supported, as seasonal affective disorder does not appear to have a statistically or economically significant effect on stock returns.

From an economic perspective, this finding indicates that even if a seasonal pattern exists, it is too weak to be considered meaningful in practical terms. This aligns with the view that many behavioral anomalies documented in earlier literature tend to diminish or disappear over time as markets become more efficient (Fama, 1998). In contrast to the strong SAD effects reported by Kamstra et al. (2003), the present results suggest that such effects may not persist in contemporary Nordic equity markets.

The interaction term between SAD and ESG classification is consistently negative across all models, implying that ESG portfolios may exhibit slightly lower returns relative to non-ESG portfolios during SAD periods. However, the effect is not statistically significant in any specification and remains small in magnitude. This indicates that ESG classification does not meaningfully moderate seasonal return patterns.

The interaction between ESG classification and seasonal affective disorder does not emerge as statistically or economically meaningful in any of the specifications. This result is particularly relevant in light of behavioral finance interpretations, where ESG investment is often associated with non-financial considerations such as ethical preferences and social responsibility (Riedl and Smeets, 2017). If these preferences were strongly state-dependent, one would expect ESG assets to react differently to changes in seasonal mood. However, the empirical evidence does not support such a differentiated response, as ESG and non-ESG portfolios exhibit broadly similar behavior across both seasonal regimes.

A much more stable pattern is observed for the market return variable, which remains consistently significant and close to unity in all models. Rather than changing across specifications, its role is persistent, indicating that portfolio returns are primarily driven by aggregate market movements. This is in line with standard asset pricing theory, where systematic market risk explains most variation in returns (Fama and French, 1993). The fact that this relationship remains unaffected by additional controls reinforces the idea that market exposure dominates other explanatory factors in the dataset.

When the model is expanded to include weather-related variables, the overall structure of the results remains largely unchanged. These variables are intended to capture short-term environmental conditions, yet none of them reach statistical significance. At the same time, the coefficients associated with seasonal affective disorder remain virtually unaffected. This pattern suggests that weekly return variation is not systematically linked to temporary weather fluctuations. Although earlier literature has documented weather-related effects in financial markets (Saunders, 1993; Hirshleifer and Shumway, 2003), the present findings indicate that such mechanisms are not strongly present in this Nordic sample at the weekly frequency.

A similar lack of sensitivity is observed when rolling volatility is introduced as an additional control variable in the final specification. This variable is included to account for time-varying market risk, yet it does not attain statistical significance, nor does it alter the estimated effects of seasonal affective disorder in any meaningful way. The stability of the main coefficients across all model extensions therefore suggests that the results are not driven by short-term fluctuations in risk conditions or alternative environmental controls. This stability suggests that the lack of a significant SAD effect cannot be explained by omitted variation in marker risk over time. Instead, the findings imply that seasonal mood variation has limited explanatory power for stock return dynamics in Nordic equity markets. Taken together, the baseline regressions provide no statistically or economically meaningful evidence supporting the hypothesis that seasonal affective disorder systematically influences stock returns.

Variable	SAD period	Non-SAD period	Full sample
Constant	0,000192	0,000364	0,000292
	0,3924	0,112	0,1033
SAD			-0,000057
			0,6633
SAD x ESG	-0,000268		
	0,5704		
ESG		-0,000472	-0,000354
		0,3228	0,2971
MKT_RET	0,983904***	0,973136***	0,980896***
	0,0000	0,0000	0,0000

R-Square	0,9130	0,8646	0,8992
Observations	2656	1928	4584

P-values in parentheses. *** p<0,01, ** p<0,05, * p<0,10

Table 6 Seasonal subsample regression results

The subsample results reported in Table 6 provide additional insight into the seasonal dynamics of returns. By estimating separate regressions for SAD and non-SAD periods, it is possible to directly assess whether ESG-related differences are concentrated during darker months.

The subsample regressions provide little evidence that ESG portfolios respond differently during periods associated with heightened seasonal affective disorder. Although the interaction term between SAD and ESG is negative during darker months, it remains statistically insignificant, indicating no systematic difference between ESG and non-ESG portfolio returns. This suggests that any mood-related effects linked to ESG investing are economically small or absent, providing limited support for hypothesis H2. When the sample is restricted to the non-SAD period, the results remain largely unchanged, as the ESG coefficient continues to lack statistical significance. This absence of effect is not confined to a specific seasonal window but appears consistently across both subsamples. Taken together, the stability of the estimates suggests that ESG classification does not play a systematic role in explaining return variation in Nordic equity markets over the period studied.

Across the subsample regressions, no clear structural break emerges between the SAD and non-SAD periods. Although point estimates suggest slightly higher average returns during the brighter months, these differences do not attain statistical significance when the sample is split. In this sense, the results do not provide strong support for persistent seasonal return effects in the Nordic data. This outcome stands in contrast to earlier findings on seasonal anomalies but is more consistent with later literature emphasizing that sentiment-based patterns are often weak, unstable, or difficult to exploit in developed financial markets (Baker and Wurgler, 2006). Regardless of the seasonal division, the market return factor continues to dominate the regressions, remaining highly significant and absorbing most explanatory power across all specifications. The relatively high R^2 values, ranging from approximately 0,86 to 0,91, imply that systematic market factors explain most return variation, leaving limited room for additional explanatory variables such as seasonal indicators to contribute meaningfully.

Overall, the results reported in Tables 5 and 6 provide no statistically or economically meaningful evidence that seasonal affective disorder influences stock returns in Nordic equity markets. Consequently, hypothesis H1 is not supported. The analysis also fails to show that ESG classification meaningfully alter this relationship, offering no support for hypothesis H2. These findings contribute to the behavioral finance literature by suggesting that seasonal mood effects may be weaker or less persistent in modern developed markets than earlier studies have implied. In relatively efficient markets such as those in the Nordic region, potential sentiment-driven mispricing may be corrected quickly, limiting its effect on observable return patterns.

The lack of statistically significant effects should not be interpreted as evidence that investor mood plays no role in financial decision-making. Instead, it is plausible that any mood-related influences are too limited in magnitude, too short in duration, or too unevenly distributed across investors to be captured using aggregated portfolio-level data. In this sense, the absence of a clear effect may reflect limitations in measurement and aggregation rather than the absence of underlying behavioral mechanisms. This opens up several directions for future research, including the use of alternative sentiment proxies, higher-frequency return data, or more granular investor-level datasets, which could provide a more direct test of the channels considered in this study.

6.3 Discussion

Across the empirical specifications, seasonal affective disorder does not emerge as a robust determinant of stock returns in Nordic equity markets over the 2014–2024 period. The estimated coefficients associated with SAD are generally small, lack statistical significance, and show limited stability across model variations. While the direction of the estimates is often consistent with theoretical expectations, the magnitude of the effects remains weak and does not provide strong empirical support for a persistent seasonal anomaly. Only a single specification produces marginal significance at the 10 percent level, yet even in that case the implied effect size remains limited. Relative to earlier findings such as those documented by Kamstra et al. (2003), the evidence here indicates a considerably weaker relationship between daylight-related mood variation and returns.

This limited statistical relevance is further reinforced when the results are considered in economic terms. The estimated SAD-related return differences are very small when compared to normal fluctuations in weekly returns. While return volatility during the SAD period typically lies in the range of 3 to 6 percent, the implied seasonal effects are measured in only a few basis points, generally between 0.01 and 0.06 percentage points. As a result, even if interpreted as genuine pricing effects, their practical importance for investment decisions would be minimal. This pattern is consistent with broader findings in behavioral finance, where sentiment-driven anomalies often lose economic significance once standard adjustments for risk, market efficiency, and trading frictions are taken into account (Baker and Wurgler, 2006). Overall, the evidence suggests that seasonal mood variation, at most, accounts for a very small residual portion of return variation in these markets.

The regression models instead emphasize the dominant role of systematic market risk. Across all specifications, the market return coefficient remains highly significant and close to one, while the models explain roughly 90 percent of total return variation. This indicates that stock returns in Nordic markets are driven primarily by broad macroeconomic and market-wide forces rather than by seasonal psychological fluctuations. From an asset pricing perspective, these findings are highly consistent with standard factor-based explanations of returns (Fama and French, 1993). In highly integrated financial systems, any potential sentiment-driven mispricing may therefore be corrected quickly through arbitrage and institutional trading activity.

The evidence related to ESG investing follows a similarly cautious pattern. One motivation of this thesis was the possibility that ESG-oriented firms could exhibit greater resilience during periods associated with heightened pessimism and risk aversion. Descriptive statistics provide some preliminary support for this idea. However, these differences disappear in the regressions, where ESG-related coefficients remain statistically insignificant. The results therefore do not support the argument that investors systematically reallocate toward ESG assets during darker months. Instead, the observed ESG differences appear more closely related to broader portfolio risk characteristics than to mood-related behavioral effects. This interpretation differs from earlier studies linking ESG characteristics to lower firm risk and enhanced resilience (El Ghoul et al., 2011).

The findings of this thesis position the SAD anomaly in a more critical empirical light, as the estimated effects do not form a stable or consistently significant pattern across different model specifications or subsamples. While earlier research, particularly Kamstra et al. (2003), reports a clear relationship between reduced daylight exposure, higher risk aversion, and lower stock returns, the evidence from Nordic equity markets in this study does not replicate such a systematic effect. Some estimated coefficients occasionally align with the expected theoretical direction, but this alignment is not robust once the specification is altered or the sample is divided into subsamples. Consequently, the results do not support the existence of a persistent seasonal pricing effect in the examined markets, and instead suggest that the empirical relevance of the SAD anomaly may depend heavily on methodological choices, sample period, and market context rather than reflecting a stable behavioral regularity.

The findings also carry implications for the efficient market hypothesis. Strict market efficiency would imply that predictable seasonal daylight variation should not influence asset prices. The recurring, though insignificant, negative SAD coefficients indicate that behavioral mechanisms may still exist in principle, consistent with theories of investor sentiment and limited arbitrage (Barberis et al., 1998). Nevertheless, the weakness of these effects suggests that they are largely absorbed in modern financial markets characterized by institutional participation, algorithmic trading, and globally integrated capital flows. This interpretation is also consistent with evidence that sentiment effects tend to be stronger in markets with greater retail investor participation and fewer arbitrage opportunities (Baker and Wurgler, 2006).

Several contextual and methodological explanations may account for the absence of stronger SAD effects. High institutional ownership in Nordic markets may reduce the aggregate influence of retail investor sentiment. In addition, investors in Nordic countries may be more accustomed to substantial seasonal variation in daylight, potentially weakening its psychological impact. The use of weekly return data may also contribute to the results, since aggregation can smooth short-lived mood-related effects that might otherwise appear in higher-frequency data.

At the same time, the descriptive statistics indicate that seasonal variation is reflected more clearly in volatility and distributional characteristics than in mean returns. This observation is important because it suggests that mood-related mechanisms may affect financial risk conditions more strongly than expected return premia. This interpretation aligns with prior literature suggesting that sentiment-related mechanisms are more strongly reflected in measures of risk than in average return levels. In particular, earlier research indicates that psychological factors tend to influence volatility, downside risk, and overall market uncertainty rather than generating persistent return predictability (Edmans et al., 2007). From this perspective, seasonal mood variation may be transmitted into financial markets primarily through changes in risk conditions, rather than through systematic anomalies in expected returns.

Against this background, the empirical results of this thesis indicate that seasonal affective disorder does not have a meaningful impact on stock return performance in Nordic equity markets over the sample period. The observed return dynamics are largely explained by broader market-wide factors, while ESG classification does not appear to alter exposure to seasonal mood variation in any systematic way. Although behavioral finance highlights the potential role of psychological influences in shaping investment decisions, the findings suggest that their effect on realized returns is limited in magnitude or difficult to identify in highly developed and efficient markets.

These results also point toward several avenues for future research. Rather than focusing exclusively on average returns, further work could explore whether seasonal mood variation is more clearly reflected in higher-frequency data or in investor-level trading behavior. Alternative sentiment indicators may also provide a more direct link between psychological states and market outcomes. In addition, cross-country analyses involving markets with different institutional characteristics or investor compositions could help clarify whether seasonal effects are more likely to emerge through changes in volatility, trading intensity, or investor participation patterns rather than through persistent return anomalies.

7 Conclusion

This thesis examined whether seasonal affective disorder is associated with systematic variation in stock returns and ESG-related investment behavior in Nordic equity markets over the period 2014–2024. The central objective was to assess whether seasonal changes in daylight exposure translate into observable differences in financial performance, and whether such effects differ between ESG and non-ESG firms.

The analysis is grounded in two complementary strands of literature. Behavioral finance emphasizes that investor decisions may deviate from fully rational benchmarks due to psychological factors such as mood and sentiment (Barberis and Thaler, 2003). In parallel, sustainable finance research suggests that ESG characteristics may influence perceived risk and stability, thereby shaping investor preferences (Ng and Rezaee, 2015; Pedersen et al., 2021). The combination of these perspectives motivates an examination of whether seasonal variation in sentiment is reflected differently across ESG classifications.

The Nordic region provides a particularly relevant empirical setting due to pronounced seasonal variation in daylight. Firm-level data from Finland, Sweden, Norway, and Denmark allow for the analysis of heterogeneous responses across companies while maintaining a relatively comparable institutional environment. Seasonal affective disorder is operationalized using both a binary seasonal indicator and a continuous daylight-based measure, capturing alternative dimensions of seasonal variation.

Preliminary descriptive evidence indicates that financial market behavior exhibits some seasonal variation. Volatility tends to be higher during periods associated with reduced daylight, while average returns are somewhat lower compared to brighter months. In addition, return distributions display more negative skewness and higher kurtosis during the SAD period, suggesting increased downside risk and a greater frequency of extreme negative outcomes. These patterns are broadly consistent with prior findings linking reduced daylight exposure to heightened risk aversion and pessimistic sentiment (Kamstra et al., 2003; Dolvin et al., 2009).

However, the regression analysis does not provide robust evidence of a systematic seasonal effect on returns. The estimated coefficients associated with seasonal affective disorder are generally small and statistically insignificant across specifications. Moreover, interaction terms between SAD and ESG classification do not indicate differential sensitivity of ESG portfolios to seasonal variation. Any differences observed in descriptive statistics are not robust once market-wide controls and risk factors are included. Across all model specifications, systematic market exposure emerges as the dominant determinant of returns. Market return variables are consistently highly significant and account for the majority of variation in portfolio performance, in line with standard asset pricing theory (Fama and French, 1993). Relative to these factors, seasonal variables contribute limited explanatory power, suggesting that any behavioral component is economically modest in magnitude.

The results also offer insights into ESG-related return dynamics. While ESG portfolios exhibit some variation in risk characteristics at the descriptive level, there is no evidence that sustainability orientation moderates exposure to seasonal mood effects in a systematic manner. This implies that differences between ESG and non-ESG assets are more likely driven by structural firm characteristics rather than time-varying sentiment. Consequently, the findings do not support the hypothesis that ESG investments become relatively more attractive during periods of increased seasonal risk aversion.

Overall, the evidence suggests that seasonal affective disorder does not represent a statistically or economically meaningful determinant of stock returns in Nordic equity markets during the sample period. Although seasonal variation is observable in raw return characteristics, these patterns are not robust in a multivariate framework once standard risk controls are included. This highlights the importance of distinguishing between descriptive seasonal regularities and economically significant pricing effects.

From a methodological perspective, the study contributes by applying a firm-level panel framework combined with ESG classification and interaction effects, rather than relying on aggregate market indices. In addition, the Nordic context strengthens identification due to substantial variation in daylight exposure across seasons.

Several limitations should be acknowledged. Seasonal affective disorder is measured indirectly using daylight-based proxies, which may also capture other seasonal influences unrelated to investor sentiment. ESG ratings are sourced from a single provider, which may introduce measurement variation relative to alternative classification systems. The sample period further includes major macroeconomic shocks, such as the COVID-19 pandemic, which may interact with seasonal patterns in complex ways.

Future research could extend the analysis in several directions. Higher-frequency data may allow for the detection of short-term behavioral responses that are not observable at the weekly level. Investor- or fund-level data could provide a more direct assessment of whether capital flows into ESG assets vary seasonally. Expanding the geographical scope beyond the Nordic region would also help evaluate whether the findings are specific to high-latitude environments. Finally, incorporating direct sentiment measures could improve identification of the psychological channel.

In conclusion, while the results are consistent with the idea that mood-related factors may influence financial behavior at the margin, there is limited evidence that seasonal affective disorder has a systematic or economically meaningful impact on stock returns or ESG-related performance differences in Nordic equity markets once conventional risk factors are properly accounted for. Overall, the findings suggest that any observable mood-related effects are likely to be subsumed by broader risk exposures and market-wide dynamics, rather than representing a distinct or persistent pricing anomaly in the data.

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