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The Impact of Seasonal Affective Disorder on Stock Markets

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UNIVERSITY OF VAASA**School of Accounting and Finance****Author:** Mira Mannil**Title of the Thesis:** The Impact of Seasonal Affective Disorder on Stock Markets**Degree:** Bachelor of Science in Economics and Business Administration**Programme:** Finance**Supervisor:** Veda Fatmy**Year:** 2026 **Number of Pages:** 43

ABSTRACT:

This thesis aims to examine the impact of Seasonal Affective Disorder (SAD) on stock markets. In particular, the study examines whether stock returns are significantly lower during periods of reduced daylight hours and whether the SAD effect appears asymmetrically between the autumn and winter seasons. Such deviations from market efficiency may have significant economic consequences in financial markets if they systematically influence investor behavior. The SAD phenomenon has been shown to have a significant association with seasonal variation in stock markets. A decrease in daylight hours affects investors' mood and increase risk aversion, which is reflected in stock returns. The SAD effect is stronger in the Northern Hemisphere, where seasonal changes in daylight hours are more pronounced. Furthermore, some studies suggest that the SAD effect is asymmetric around the winter solstice: risk-taking decreases during the autumn, whereas the winter season progresses, it begins to recover. On the other hand, the literature also presents critical perspectives according to which the observed seasonality may be explained by other calendar anomalies or by time-varying risk premia.

KEYWORDS: Seasonal Affective Disorder, SAD, Stock Markets, Efficient Markets, Market Efficiency, Anomalies, Behavioral Finance, Investor Behavior, Seasonality, Asymmetry

Vaasan yliopisto**Laskentatoimen ja rahoituksen yksikkö****Tekijä:** Mira Mannil**Tutkielman nimi:** The Impact of Seasonal Affective Disorder on Stock Markets**Tutkinto:** Kauppatieteiden kandidaatti**Koulutusohjelma:** Rahoitus**Ohjaaja:** Veda Fatmy**Vuosi:** 2026 **Sivumäärä:** 43

TIIVISTELMÄ:

Tämän tutkielman tarkoituksena on tarkastella kausiluonteinen masennushäiriön (seasonal affective disorder, SAD) vaikutusta osakemarkkinoihin. Erityisesti tutkimuksessa selvitetään, ovatko osaketuotot merkitsevästi alhaisempia vähäisen päivänvalon tuntien kausina sekä ilmenekö SAD-vaikutus epäsymmetrisenä syys- ja talvikauden välillä. Tällaisilla markkinatehokkuuden poikkeamilla voi olla huomattavia taloudellisia seurauksia rahoitusmarkkinoilla, mikäli ne vaikuttavat systemaattisesti sijoittajien käyttäytymiseen. SAD-ilmiöllä on havaittu olevan merkittävä yhteys osakemarkkinoiden kausivaihteluun. Päivänvalon tuntien väheneminen vaikuttaa sijoittajien mielialaan ja lisätä riskinkarttamista, mikä heijastuu osaketuottoihin. SAD-vaikutus on voimakkaampi pohjoisella pallonpuoliskolla, jossa päivänvalon tuntien kausittaiset muutokset ovat selkeämpiä. Lisäksi osa tutkimuksista viittaa siihen, että SAD-vaikutus on epäsymmetrinen talvipäivänseisauksen suhteen: syksyllä riskinottohalukkuus heikkenee, kun taas talvikauden edetessä se alkaa palautua. Toisaalta kirjallisuudessa on myös kriittisiä näkökulmia, joiden mukaan havaittu kausivaihtelu saattaa selittyä muilla kalenterianomaliailla tai ajassa vaihtelevalla riskipreemiolla.

AVAINSANAT: Kausiluonteinen masennushäiriö, SAD, osakemarkkinat, tehokkaat markkinat, markkinatehokkuus, anomaliat, käyttäytymistaloustiede, sijoittajakäyttäytyminen, kausivaihtelu, epäsymmetria

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1 Introduction

Traditional finance theory does not recognize the influence of mood-related traits such as happiness or sadness on people's everyday behavior. Individuals are assumed to make decisions free from emotions. The objective of economic agents is utility maximization, which corresponds to happiness in other words. Therefore, in traditional economics and finance, happiness is regarded as an insignificant factor rather than an emotional state. (Kramer, 2014.) Additionally, the well-known Efficient Market Hypothesis (EMH) (Fama, 1970) assumes that markets behave rationally and utilize available information in an efficient and rational manner: an economically rational person, *homo economicus*, thinks like Albert Einstein, stores as much memory as IBM's Big Blue, and exercises the willpower of Mahatma Gandhi (McKelvey & Yalamova, 2011; Thaler & Sunstein, 2009, p. 7).

In reality, human psychology plays a role in individuals' financial decisions. Research findings provide compelling evidence that human mood has an impact on individual investors' financial decisions. External factors, in turn, influence people's mood, thereby indirectly affecting financial and statistical outcomes in the financial markets. One such external factor impacting the financial markets is environmental factors. (Kramer, 2014.) Thaler and Sunstein (2009, p. 7) state that real people are not *homo economicus* (Econs), but rather *homo sapiens* (Humans). They introduce the term "nudge", which is defined as any factor that significantly alters the behavior of Humans, even though Econs would ignore it.

This thesis examines in detail the phenomenon of seasonal affective disorder (SAD) and its effects on stock markets. The phenomenon of SAD refers to a depressed mood during the winter months when there is less daylight hours. The seasonal decrease in daylight hours towards the darkest time of the year reduces people's optimism: the willingness to take risks decreases, and stock market returns decline. Conversely, during periods of increasing daylight hours, people's mood improves and their outlook on the future brightens, leading to increased risk-taking willingness on stock market. (Lin, 2015.)

1.1 Purpose of the study

During the winter in the Northern Hemisphere, prolonged periods of darkness lasting several months cause psychological issues and changes in biorhythms, necessitating adjustments in human activities and behavior. North of the Arctic Circle, there is even a phenomenon known as polar night, during which the sun does not rise above the horizon from late December to early January. (Brunn et al. 2004.)

The effect of seasonal affective disorder on stock market returns has been studied by examining the relationship between stock prices and the length of the day (Garrett et al., 2005; Kramer, 2014). Studies have shown results regarding risk appetite. The SAD effect triggered by shortening days in the fall and winter causes investors to avoid risk and reduce active trading, for example, after earnings announcements. (Lin, 2015.) According to Kamstra et al. (2003), studies have also indicated that SAD-related depression may develop asymmetrically around the winter solstice. Thus, it is interesting to study external factors that affect individuals' mood changes, particularly when their effects may be asymmetric around the winter solstice, as they can have considerable economic consequences in financial markets.

Based on the existing literature, the purpose of this study is to examine the impact of seasonal affective disorder on stock markets. To study this, the hypotheses are as follows:

H1: Stock market returns are significantly lower during periods of reduced daylight hours.

H2: The impact of seasonal affective disorder on stock market returns is asymmetrical between fall and winter.

The research findings are relevant to professional investors aiming to challenge prevailing market theories, such as the Efficient Market Hypothesis, and achieve excess returns by exploiting seasonal anomalies caused by the SAD effect. For example, if investors' immediate reaction to earnings announcements is significantly weaker during the SAD

season, investors can leverage this information when assessing the weight of analyst recommendations across different seasons and adjust their investment strategies accordingly, as well as capitalize on potential buying opportunities in undervalued stocks. (Lin, 2015.)

1.2 Structure of the study

This study consists of five chapters. The first chapter introduces the topic and motivation of the study, and presents the hypotheses. The second chapter examines the theoretical foundations and key assumptions of traditional finance theory. The chapter begins with Rational Choice Theory and Expected Utility Theory, followed by an examination of the Efficient Market Hypothesis, Random Walk Theory, and the relationship between risk and return, including the most important asset pricing models. Examining these traditional finance theories is essential because the SAD phenomenon challenges their underlying assumptions.

The third chapter examines behavioral finance, which provides an alternative theoretical framework to traditional finance assumptions of full rationality and market efficiency. The chapter introduces the key pillars of behavioral finance: limits to arbitrage and investor psychology, which are used to analyze the impact of irrational investor behavior on market prices and to examine behavioral biases influencing investors' decision-making. In addition, the chapter reviews calendar market anomalies that are particularly relevant to the SAD phenomenon.

In the fourth chapter, the hypotheses of this study are examined in light of prior finance literature. The chapter first introduces Seasonal Affective Disorder (SAD) as a phenomenon and its theoretical connection to investors' mood, risk aversion, and decision-making. Subsection 4.1 reviews empirical research evidence on the effect of the SAD phenomenon on stock market returns. Subsection 4.2 examines whether the SAD effect is symmetric or asymmetric between the autumn and winter periods, specifically whether

stock returns are determined solely by the number of daylight hours or whether the direction of change in daylight hours around the winter solstice also affects returns. The fifth chapter presents the main conclusions of this study and provides suggestions for future research.

2 Traditional Finance

This chapter introduces the theoretical foundation of Seasonal Affective Disorder in traditional finance. Traditional finance theory is based on the assumption of rational market participants and efficiently functioning markets, in which prices reflect all available information and risk and return move hand in hand. This chapter forms the theoretical foundation for the later chapters, in which these assumptions are evaluated in relation to investors' actual behavior.

2.1 Rational Choice Theory and Expected Utility

Traditional finance theory is built on the assumption of rational economic behavior. Investors are rational actors who seek to maximize returns in the stock market. (Woo et al., 2020.) According to Zey (1997), in rational choice theory (RCT), the central focus is the individual decision-maker, who acts purposefully and chooses their course of action by weighing the benefits and costs of different alternatives in relation to their own objectives and goals.

Expected utility theory (EUT) also seeks to explain rational decision-making behavior. According to it, a rational actor makes decisions by comparing alternatives on the basis of their expected utilities and selects the one that maximizes expected utility (Lopez-Wild, 2025). According to Mongin (1998), expected utility values are obtained as weighted sums: the utility of each possible outcome is multiplied by its probability of occurrence, and these products are then summed together.

According to Lopez-Wild (2025), rational choice behavior can be described by means of a utility function, which enables the comparison of alternatives based on their expected utilities. Bodie et al. (2023, Ch. 12.1) present the traditional utility function (see Figure 1), in which the investor experiences greater utility, that is, satisfaction, as wealth increases. However, the curve becomes flatter as wealth increases, meaning that the

marginal utility gained from additional wealth decreases as wealth grows. This illustrates the risk aversion of a rational investor: a loss of a given size reduces utility more than an equivalent gain increases it.

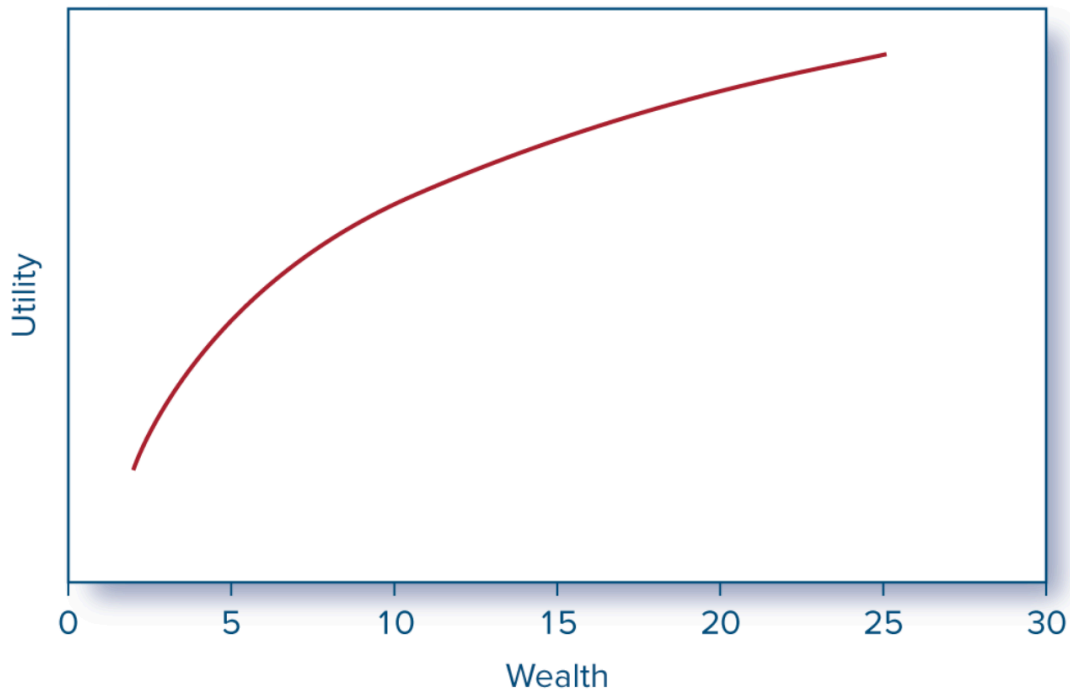


Figure 1. Conventional Utility Function (Bodie et al., 2023, Ch. 12.1)

2.2 Efficient markets

One of the most influential economic theories in traditional finance, the efficient market hypothesis, assumes that prices fully reflect all available information at any given time (Fama, 1970). If efficient capital markets impartially reflect all currently available information, the expected return is also based on this price, which is why arbitrage opportunities are not continuously available to be identified and exploited. The realized return is considered to be aligned with the observed risks, and investors are assumed to act rationally and to value securities on the basis of maximum expected utility. (Naseer & Tariq, 2015.)

According to Fama (1970), in an ideal situation the allocation of resources functions such that firms make their investment decisions and investors make their choices between securities on the basis of prices, since prices fully reflect the available information. Information is thus reflected in asset prices without delay, meaning that positive or negative news affects prices immediately (Malkiel, 2013). In this context, Fama (1970) developed three forms of market efficiency based on the type of information utilized, and these forms partly determine the possibilities of earning abnormal returns, that is, EMH anomalies (see Figure 2).

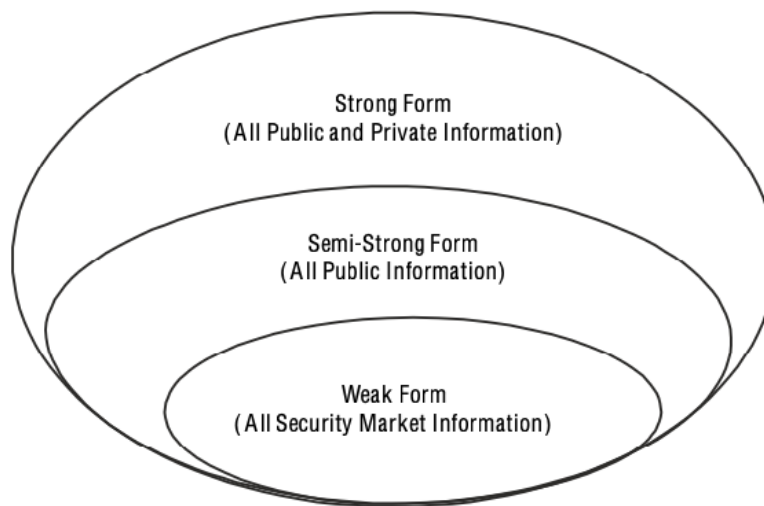


Figure 2. Aggregated Forms of Market Efficiency (Naseer & Tariq, 2015).

The weak form of efficiency suggests that current stock prices incorporate all historical market information, such as past trading volumes and prices, and therefore the consistent achievement of excess returns by predicting historical data should not be possible, because all available information is already reflected in current stock prices. The semi-strong form of efficiency includes all publicly available information. Thus, the consistent earning of excess returns should not be possible, since prices adjust efficiently, for example, after annual earnings announcements, stock splits, mergers, and changes in shares. In the strong form of efficiency, stock prices are assumed to fully reflect all information—both public and non-public insider information. In this case, the continuous accumulation of excess returns should also be impossible, because markets are so efficient

that all information is immediately incorporated into stock prices: even illegal insider information could not be exploited. (Fama, 1970; Malkiel, 2013.)

All forms of the efficient market hypothesis suggest that market prices cannot be predicted. The EMH is therefore considered to be largely based on the so-called random walk theory, a statistical description of unpredictable price changes, which Fama also developed and incorporated as part of the efficient market hypothesis (Malkiel, 2013; Naseer & Tariq, 2015). Random walk theory is examined in more detail in the following subsection 2.2.

2.3 Random walk

The earliest studies on market efficiency are based on random walk theory, which claims that the stock market moves in a random and completely unpredictable manner. A random walk refers to a statistical phenomenon in which a variable does not exhibit a recognizable pattern and thus appears to move unpredictably. (Naseer & Tariq, 2015; Oluwafemi et al., 2024.) In this context, the term randomness refers specifically to an efficient, well-functioning, and non-irrational market in which rationally determined prices always reflect all current information (EMH), so that only new and unpredictable information causes prices to change in a “random walk” manner (Malkiel, 2013; Bodie et al., 2023, Ch. 11).

The concept of the random walk originally emerged in the early twentieth century from Karl Pearson, who, in correspondence published in *Nature*, described the steps of a drunken man as random and unpredictable. The French mathematician Louis Bachelier applied the random walk analogy and, based on his empirical research, laid the foundation for random walk theory in financial markets: he concluded that stock price movements resemble the steps of a drunken man, that is, they move randomly. Random walk theory was subsequently developed by, among others, Paul Samuelson (1965) in his article “Proof That Properly Anticipated Prices Fluctuate Randomly”, Eugene Fama (1965)

by examining serial correlation coefficients that did not generate abnormal profits, and M. F. M. Osborne (1977) by studying stock price movements, which he found to resemble the Brownian motion of random physical particles. (Oluwafemi et al., 2024; Malkiel, 2013.)

Random walk theory consists of an economic and a statistical hypothesis. The economic hypothesis assumes that an investor cannot systematically earn superior returns, because securities markets are efficient markets. The statistical hypothesis, in turn, assumes that changes in security prices are completely independent random variables. (Cheng & Deets, 1971.)

In other words, random walk theory assumes that stock prices are independent of their historical development: the probability of a stock price increasing is exactly equal to the probability of it decreasing at any given moment. According to random walk theory, it is also not possible to outperform the market without taking risk. (Naseer & Tariq, 2015; Oluwafemi et al., 2024.) In this context, the following subsection 2.3 examines the traditional finance theory of the risk–return relationship in more detail.

2.4 Risk and return

In efficient securities markets, where prices reflect all existing information, risk and return are described as moving hand in hand: higher-risk assets are priced to offer higher expected returns compared to lower-risk assets. If the expected return of an asset were higher without additional risk, its price would increase as investors rushed to buy it, making the asset less attractive to investors; the expected return would decline from excess return to a fair return relative to the asset’s risk. (Bodie et al., 2023, Ch. 1.5.)

Conversely, if expected returns were not tied to risk, high-risk assets would be sold in large volumes if they did not offer returns commensurate with their risk. This would cause their prices to fall until they became sufficiently low for investors to repurchase

them as the expected return increased. Thus, investors should rarely expect to find overvalued or undervalued securities in the market. (Bodie et al., 2023, Ch. 1.5.)

The total risk of an investment consists of systematic and unsystematic risk (see Figure 3). Unsystematic risk arises from factors that affect the stock returns of a particular firm, such as the resignation of the CEO, deteriorating earnings prospects, or the loss of a major customer. Unsystematic risk can be reduced through diversification. (Knüpfer & Puttonen, 2018, Ch. 6.3.1.) This is based on Markowitz's portfolio theory from 1952, which explains how a risk-averse investor can construct a portfolio that maximizes return at a given level of risk. (Knüpfer & Puttonen, 2018, p. 263; Nikkinen et al., 2002, p. 89; Petzel, 2022, Ch. 3).

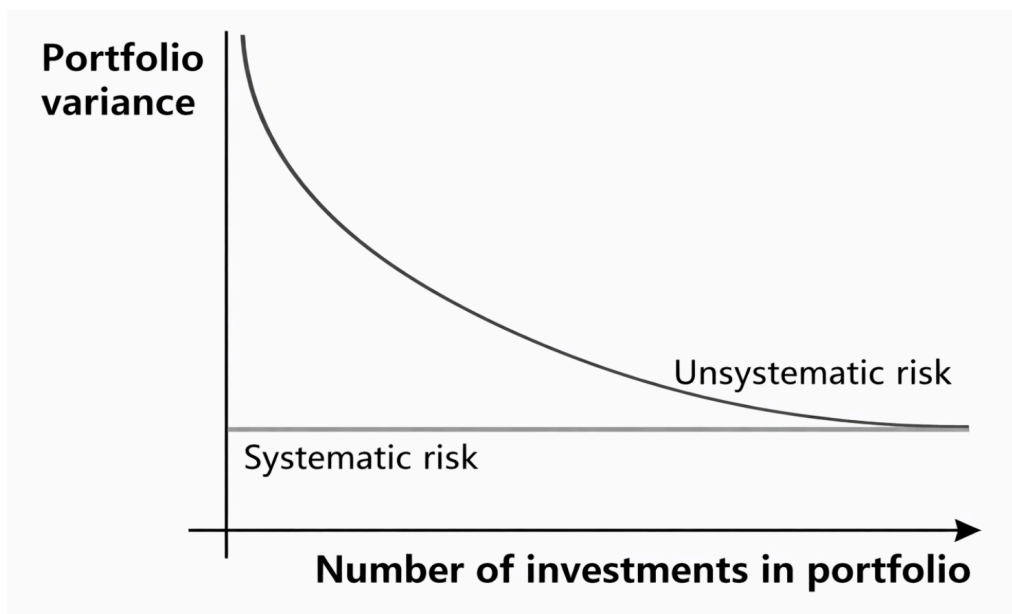


Figure 3. Total risk of an investment: systematic and unsystematic risk (adapted from Knüpfer & Puttonen, 2018, Ch. 6.3.1).

Systematic risk, in turn, consists of macroeconomic changes that affect the entire market, meaning all stocks simultaneously, such as inflation, interest rates, and exchange rates. Due to its market-wide nature, systematic risk cannot be eliminated even through diversification. Systematic risk becomes central when investors seek to maximize returns within given risk limits or targets: it is the risk for which investors require compensation

in the form of returns. The systematic risk of a stock is expressed by the beta coefficient, which measures the sensitivity of a particular stock to changes in the market portfolio (see Equation 1 below):

$$1. \beta_i = \frac{\sigma_{im}}{\sigma_m^2}$$

, where σ_{im} is the covariance between the return of investment i and the return of the market portfolio, and σ_m^2 is the variance of the return of the market portfolio. (Knüpfer & Puttonen, 2018, Ch. 6.3.1-2.)

In the following subsections 2.3.1, 2.3.2, and 2.3.3, the relationship between risk and expected return is further examined through asset pricing models.

2.4.1 Capital Asset Pricing Model

The capital asset pricing model (CAPM) is a widely used breakthrough theory in finance that describes the relationship between expected return and systematic risk, also referred to as beta. The model was developed in the mid-1960s by the economists William Sharpe, John Lintner, and Jack Treynor. CAPM links a stock's expected return directly to its risk:

$$2. E(r_i) = r_f + \beta_i(E(r_m) - r_f)$$

, where $E(r_i)$ is the expected return of an individual investment i , r_f is the return on a risk-free asset, β_i is the beta of the individual investment, and $(E(r_m) - r_f)$ is the market risk premium, defined as the expected return on the market portfolio minus the risk-free rate. (Brealey et. al., 2023, Ch. 8-8.2. & Knüpfer & Puttonen, 2018, Ch. 6.3.3.) Thus, CAPM indicates how high the return on an investment should be given a certain level of risk (Nikkinen et al., 2002, p. 68).

CAPM assumes that all investors behave rationally in accordance with the EMH and invest over a homogeneous single-period horizon, forming an optimal portfolio based on expected return and standard deviation in line with portfolio theory, using the same initial information and analyses. CAPM further assumes perfect competition in the market, with no taxes and no transaction costs arising from trading, meaning that stocks can be bought and sold without cost. The model allows unlimited short selling, so investors may sell unlimited quantities of stocks they do not own. In addition, assets in the CAPM framework are infinitely divisible, enabling investors to purchase fractions of shares in arbitrarily small amounts, for example, for the value of a single currency unit. (Nikkinen et al., 2002, Ch. 3.3., p. 89)

2.4.2 Arbitrage Pricing Theory

Whereas CAPM includes only one factor, the market portfolio (beta), the arbitrage pricing theory (APT), developed by Stephen Ross in the mid-1970s, may include multiple factors without specifying how many they are or what they represent. Arbitrage refers to earning a risk-free profit through trading in which the same security can be simultaneously bought at a lower price and sold at a higher price. (Nikkinen et al., 2002, pp. 76, 89).

According to Bodie et al. (2023, Ch. 10.2), Ross developed APT based on three assumptions: security returns can be described using a factor model; there are sufficiently many securities in the market so that firm-specific random idiosyncratic risk can be eliminated through diversification; and arbitrage opportunities do not persist in efficient markets. This is because any investor would be willing to exploit risk-free arbitrage profits immediately upon discovering them, although arbitrage should not be possible in perfectly efficient markets (Nikkinen et al., 2002, p. 76).

Nikkinen et al. (2002, pp. 77–78) present stock returns according to the mathematical formula of APT as follows:

$$3. E(r_i) = a + b_1(r_{Factor\ 1}) + b_2(r_{Factor\ 2}) + b_3(r_{Factor\ 3}) + \dots + e$$

, where $E(r_i)$ is the expected return of stock i , a is a constant term (such as the risk-free rate), $b_1, b_2, b_3 \dots$ are the sensitivity coefficients of stock i to different factors, $r_{Factor\ 1}, r_{Factor\ 2}, r_{Factor\ 3}, \dots$ represent systematic factors, and e represents firm-specific noise. However, when modeled using APT, the outcome is ultimately the same as in CAPM, since in both models the investor is compensated only for bearing systematic risk, while firm-specific risk can be eliminated through diversification.

2.4.3 Three-factor Model

Due to the weak performance of CAPM in modeling realized returns, Eugene Fama and Kenneth French published their study on the three-factor asset pricing model in 1993 (Eraslan, 2013). According to Nikkinen et al. (2002, p. 79) and Bodie et al. (2023, Ch. 10.5), the three-factor model explains stock returns in the same way as the APT model, but by using three specifically identified factors:

$$4. E(r_i) = r_f + b_m(E(r_m) - R_f) + b_{SMB}SMB + b_{HML}HML$$

, where $E(r_i)$ is the expected return of stock i , r_f is the risk-free rate, $b_m(E(r_m) - R_f)$ is the market factor, showing how sensitive the stock is to overall market movements, $b_{SMB}SMB$ is the size factor (Small Minus Big), which captures the difference in returns between small-cap and large-cap firms and $b_{HML}HML$ is the value factor (High Minus Low), which represents the difference in returns between value stocks (with high book-to-market ratios) and growth stocks (with low book-to-market ratios).

3 Behavioral Finance

The asset pricing models presented above explain stock returns from the perspective of rational investors and efficient markets. According to Sinclair (2020, Ch. 2), this line of thinking dominated finance theory from the 1960s until the late 1980s, after which an alternative view began to emerge, arguing that the assumption of investors' perfect rationality does not correspond to reality.

According to Ricciardi and Simon (2000), behavioral finance began to appear in academic publications in the 1990s. However, its roots extend back to the late nineteenth and early twentieth centuries, when, for example, Selden (1912) published *Psychology of the Stock Market*, which can be regarded as one of the earliest works to apply a psychological perspective directly to the stock market.

Behavioral finance refers to the study of economics from the perspectives of psychology and sociology. It shifted the focus from the rational model of efficient markets to the psychological and behavioral aspects of market participants, which began to be applied alongside traditional economic and finance theories. Behavioral theories were used to explain irrational behavior as well as market inefficiencies (Naseer & Tariq, 2015).

According to Barberis and Thaler (2002, p. 2), some financial phenomena are better explained by models that assume not all market participants behave fully rationally. According to Sinclair (2020, Ch. 2), the most compelling arguments against the EMH come from the field of behavioral economics. In perfectly efficient markets, there should be a complete flow of information, making profitable trading based on any particular information impossible.

However, investors seek to identify inefficiencies in financial markets, which are essentially exceptions that enable profitable trading. Individuals have been shown to behave inconsistently in many ways, which may create opportunities for more rational market participants. Thus, the EMH can be regarded as an important theoretical principle, but

not as a complete description of how real markets function, where traders attempt to profit from EMH anomalies. (Sinclair, 2020, Ch. 2.) Naseer and Tariq (2015) also state that the EMH has been criticized particularly for the speed at which it assumes markets react to new information: information is not reflected in security prices as quickly as the theory suggests.

According to Malkiel (2013), the EMH does not imply that asset prices are always correct. Prices may be wrong, but it is impossible to know with certainty whether they are too high or too low. Empirical evidence strongly supports the version of the EMH which asserts that arbitrage opportunities for riskless gains do not exist in efficiently functioning markets and, if they do emerge, they do not persist. Therefore, the EMH can be regarded as an established theory that exists alongside behavioral finance rather than as a complete description of real-world market behavior.

The following subsections 3.1 and 3.2 examine in more detail the two fundamental pillars of behavioral economics: (1) limits to arbitrage and (2) psychology (Kihn, 2011, p. 63). According to Barberis and Thaler (2002, pp. 2–3), the research literature on limits to arbitrage shows that the actions of irrational investors in financial markets may have significant and long-lasting effects on prices. Psychology, in turn, explains various biases and tendencies that influence investors' behavior and decision-making. Subsection 3.3 then examines market anomalies that behavioral finance seeks to explain (Woo et al., 2020).

3.1 Limits to Arbitrage

Barberis and Thaler (2002, pp. 59–60) note that only a few decades ago it was widely believed in financial markets that the efficient market hypothesis held true, as arbitrage was assumed to eliminate all pricing errors. However, they emphasize that this view was overly simplistic: in reality, limits to arbitrage may allow significant mispricing to persist in the markets.

Shleifer and Vishny (1997) state that arbitrage is an essential part of the functioning of securities markets, through which prices tend to adjust more closely to the fundamental values of assets and market efficiency is maintained. However, they also argue that the simple theoretical definition of arbitrage, which assumes no risk and no capital requirements, does not correspond to reality: almost all arbitrage requires capital and is typically risky. A more realistic understanding of arbitrage can therefore provide a better explanation for several phenomena observed in securities markets that traditional theoretical models are not fully able to explain.

According to Kihn (2011, pp. 63–65), situations in which arbitrage would not exist in any market or in which arbitrage would occur perfectly in every market represent theoretical extremes that do not correspond to reality. In real market environments, arbitrage is subject to limitations, and pure arbitrage or a completely risk-free security does not, in practice, exist.

According to Kihn (2011, p. 65), in addition to investors' irrational behavior, arbitrage is constrained by various transaction costs, such as brokerage fees and taxes, which may render arbitrage unprofitable. Limited capital can also restrict investors' ability to exploit arbitrage opportunities, and noise and other behavioral limits to arbitrage may increase the risk associated with arbitrage and make its implementation more uncertain.

In addition to the previously mentioned limits to arbitrage, Kihn (2011, p. 65) identifies three key factors that constrain the realization of pure arbitrage: (1) fundamental risk, (2) noise trader risk, and (3) implementation costs. These are examined in more detail in the following subsections 3.1.1, 3.1.2, and 3.1.3.

3.1.1 Fundamental risk

Bodie et al. (2023, Ch. 12.1) define fundamental risk as a situation in which, even if a security is mispriced in the market, an arbitrage opportunity does not necessarily arise,

because the mispricing may worsen before the price eventually converges toward its true value. Similarly, Shleifer and Summers (1990) argue that an arbitrageur's assessment of mispricing may prove incorrect if the true value of a stock changes unexpectedly, thereby generating losses for the arbitrageur. In addition, Kihn (2011, p. 65) refers, in the context of fundamental risk, to Summers (1986), who maintains that in practice it is impossible for an arbitrageur or researcher to know with certainty what the true value of a security is.

Barberis and Thaler (2002, p. 5) illustrate fundamental risk with an example in which an arbitrageur purchases shares of a company that are perceived to be undervalued, but their price declines further following unfavorable news. Before prices correct, this results in losses for the arbitrageur. Although the arbitrageur may hedge the position by short selling shares of a similar company, perfect hedging is not possible: not all fundamental risk can be eliminated.

3.1.2 Noise trader risk

According to Ulibarri et al. (2009), noise trading refers to a situation in which investors buy and sell securities without regard to their fundamental value. For example, investors may continue purchasing overvalued securities during an economic expansion because they believe that prices will keep rising, or they may continue selling undervalued securities because they expect prices to decline further.

Accordingly, Ulibarri et al. (2009) argue that noise trader risk arises when the behavior of irrational investors, noise traders, intensifies mispricing instead of allowing prices to adjust toward their fundamental values. In such cases, rational arbitrageurs must bear the risk that prices may move even further away from their true value before eventually correcting.

Barberis and Thaler (2002, pp. 5–6) further explain that noise trader risk occurs when an arbitrageur tries to exploit a mispricing, but the market temporarily moves in the opposite direction before the mispricing corrects. This may generate short-term losses for the arbitrageur's position and increase the uncertainty associated with arbitrage.

3.1.3 Implementation costs

According to Kihn (2011, p. 65), implementation costs refer to all practical costs and constraints that may render arbitrage unprofitable. These include, for example, transaction costs, taxes, price impact, short-sale constraints, legal constraints, as well as horizon and information costs. Shleifer and Vishny (1997) likewise state that various trading costs, such as transaction costs, are significant factors that limit the practical implementation of arbitrage.

Bodie et al. (2023, Ch. 12.1) emphasize that exploiting overpriced securities in particular may be difficult due to implementation costs. Short selling is one example of this, as it involves significant costs and risks. An investor must often borrow shares in order to sell them, creating the risk that the borrowed shares may be recalled at short notice, thereby making the investment horizon uncertain. In addition, the costs associated with borrowing shares may vary substantially depending on market conditions, and in some cases, shares may not be available for borrowing at all, making short selling impossible. These factors complicate the activities of arbitrageurs and may prevent the efficient correction of mispricing in the market.

Another example provided by Bodie et al. (2023, Ch. 12.1) concerns institutional investors, such as pension fund and mutual fund managers. Their activities are constrained by strict rules regarding short selling, which means that they cannot always exploit mispricing in the market. This slows the adjustment of prices toward their fundamental values.

3.2 Psychology

The second pillar of behavioral economics, psychology, complements the first pillar concerning limits to arbitrage (Kihn, 2011, p. 93). Barberis and Thaler (2002, pp. 11–12) argue that, for financial market models, it is essential to understand how investors actually form expectations, beliefs, and preferences.

Kahneman and Tversky (1979) developed prospect theory as a critique of expected utility theory, which has been widely regarded as a normative model of rational decision-making. They argued that expected utility theory inadequately describes investors' actual risk-taking and decision-making behavior, which systematically deviates from its predictions.

In addition, Bodie et al. (2023, Ch. 12.1) present a range of behavioral biases identified in behavioral economics that explain investors' tendency to make less rational decisions. Accordingly, subsection 3.3.1 examines the key principles of prospect theory as well as various behavioral biases that significantly influence how investors perceive the relationship between risk and return and make investment decisions.

Bodie et al. (2023, Ch. 12.1) further note that investors may misjudge the probabilities of events due to biases in information processing. In this context, subsection 3.3.2 discusses seven psychological biases presented by Kihn (2011, pp. 63, 93–95) that may affect investors' decision-making and the pricing of securities in financial markets. These biases represent systematic deviations from the rational behavior assumed in normative finance theory.

3.2.1 Prospect Theory and Behavioral Biases

Prospect theory, developed by Kahneman and Tversky (1979), challenged the traditional expected utility theory, in which the utilities of outcomes are weighted by their

probabilities. They identified behavioral tendencies that arise when individuals make decisions between risky alternatives.

The first tendency is known as the certainty effect. According to this effect, individuals place greater weight on certain outcomes than on uncertain ones—those that are merely probable. As a result, people tend to avoid risk when it comes to certain gains, but are more willing to take risks in situations involving certain losses. (Kahneman and Tversky, 1979.)

The second tendency identified by Kahneman and Tversky (1979) is the isolation effect. It suggests that individuals simplify their decision-making by focusing on differences between alternatives while disregarding elements that are common to all options. This can lead to inconsistent choices, as similarities and differences between outcomes can be framed and structured in multiple ways.

Based on these tendencies, Kahneman and Tversky (1979) formulated the structure of prospect theory to explain how individuals make decisions under uncertainty. In their alternative theory of choice, the value associated with a decision is based on changes in wealth, namely gains and losses, rather than on final levels of wealth. In addition, the probabilities used in the traditional utility function are replaced in prospect theory by decision weights.

Kahneman and Tversky (1979) illustrate prospect theory with a value function that is typically concave in the domain of gains and convex in the domain of losses, and steeper for losses than for gains (see Figure 4). According to them, decision weights are generally smaller than the corresponding probabilities, except in the case of small probabilities, which individuals tend to overweight. This may help explain why people often overestimate the likelihood of risks covered by insurance or the probability of winning in gambling.

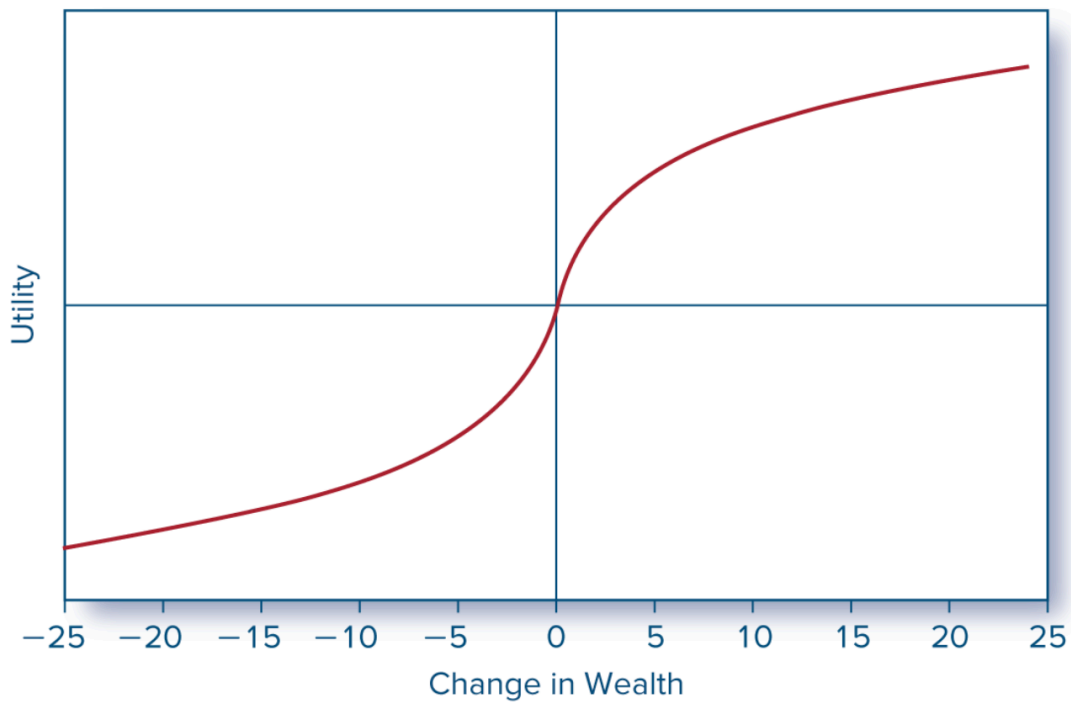


Figure 4. Value Function under Prospect Theory (Bodie et al., 2023, Ch. 12.1).

Bodie et al. (2023, Ch. 12.1) identify several behavioral biases in behavioral finance that may cause investors to deviate from rational decision-making. One of these is framing bias. In this bias, decisions are influenced by how a choice situation is presented or framed. For example, an investor may respond differently to acquiring a risky security depending on whether the situation is described in terms of potential gains or potential losses. If the purchase is presented from the perspective of possible gains, the investor may avoid risk and refrain from buying the security. However, when the same situation is framed in terms of potential losses, the investor may take on more risk in order to avoid the loss and decide to purchase the security.

Another behavioral bias discussed by Bodie et al. (2023, Ch. 12.1) is mental accounting bias, which can be viewed as a specific form of framing. In this case, individuals do not evaluate their financial decisions rationally from the perspective of their overall portfolio; instead, each decision is treated as separate. For instance, an investor may take

substantial risks in one account while acting very cautiously in another account that is designated for their child's future.

The third behavioral bias identified by Bodie et al. (2023, Ch. 12.1) is regret avoidance bias. In this bias, investors experience stronger regret over unsuccessful investment decisions involving what may be considered an unconventional security, such as a start-up company's stock, than over investments in more traditional securities, such as blue-chip stocks. As a result, investors may avoid such unconventional investments and instead favor well-known companies.

The fourth behavioral bias highlighted by Bodie et al. (2023, Ch. 12.1) relates to affect and feelings. In this case, the positive or negative emotions and associations that investors attach to an investment, such as perceived responsibility, a trendy brand, or poor working conditions, influence what they purchase and at what price. A high level of positive affect may lead to an increase in the price of a security while simultaneously lowering its average expected return. Affect also partly explains home bias, in which investors place greater weight on domestic investments that feel familiar and safe, even if this results in suboptimal diversification.

3.2.2 Psychological biases

Among the systematic psychological biases listed by Kihn (2011, pp. 94–95) that affect investors' decision-making, the first is overconfidence. According to Thaler and Sunstein (2009, p. 35), this refers to individuals' tendency to believe that they are above average, leading them to overestimate their own skills, abilities, and chances of success. Barber and Odean (2001) argue that such overconfidence causes investors to trade excessively in financial markets, as they believe their information to be more accurate than it actually is and consequently assess expected returns to be higher than they truly are.

The second systematic psychological bias identified by Kihn (2011, pp. 94–95) is optimism and wishful thinking. By this, he refers to the tendency of individuals to overestimate the probability of favorable events and underestimate the probability of unfavorable events. This distortion may lead to misjudgments in financial markets and result in deviations in security prices from their fundamental values.

The third psychological bias described by Kihn (2011, pp. 94–95) is representativeness. According to Kihn, individuals make probability judgments based on how closely an event resembles something familiar or a previously observed pattern, rather than relying on actual statistical information. Chung and Lee (2024) suggest that in financial markets this may appear, for example, when investors assume that a company that has performed well in the past will continue to perform well in the future.

The fourth psychological bias listed by Kihn (2011, pp. 94–95) is conservatism. In this bias, investors adhere to their prior beliefs and underweight new information when assessing probabilities. Wu et al. (2009) argue that this is reflected in investors' slow reaction to new information, such as corporate earnings announcements. According to Bodie et al. (2023, Ch. 12.1), conservatism contributes to the momentum effect observed in stock market returns. Traditionally, momentum refers to the tendency of stock prices to continue their previous trend in the short term, meaning that stocks that have performed well continue to rise, while those that have performed poorly continue to decline (Novy-Marx, 2012).

The fifth psychological bias identified by Kihn (2011, pp. 94–95) is belief perseverance and confirmation bias. This refers to individuals' tendency to adhere to their existing beliefs by misinterpreting or disregarding information that challenges their views and by perceiving opposing evidence as supportive of their own position. According to Barberis and Thaler (2002, p. 14), this bias may appear in financial markets when investors continue to believe in the EMH despite the availability of strong evidence that calls these beliefs into question.

The sixth psychological bias discussed by Kihn (2011, pp. 94–96) is anchoring. This bias refers to the tendency of individuals to rely excessively on an initial value or piece of information in their decision-making, even when more updated information is available. In financial markets, this may lead investors to use a previous price level as a reference point, even if market conditions have changed.

The seventh psychological bias is availability bias (Kihn, 2011, p. 94). According to Pompien (2012, Ch. 13) and Schwartz (2010), individuals assess probabilities based on how easily an event comes to mind or how familiar it feels, relying on experience, memory, or imagination. Schwartz illustrates this bias in financial markets with the example of an investor who strongly favors domestic stocks and neglects foreign return opportunities because the readily available and familiar information is based on a limited sample of reality.

3.3 Market Anomalies

The core idea of behavioral finance is that real individuals often make decisions in ways that deviate from strict rationality. Such persistent phenomena that depart from traditional finance theory and the EMH are referred to as anomalies (Nikkinen et al., 2002, p. 86; Bodie et al., 2023, Ch. 12.1). Woo et al. (2020) argue that this is precisely what makes behavioral finance significant, as it is able to explain market anomalies that the EMH cannot fully model.

Among the wide range of anomalies observed in financial markets, calendar anomalies refer to those market anomalies in which stock returns are found to deviate systematically according to specific calendar-related periods, such as times of the day, days of the week, months, or seasons of the year (Rossi, 2015). The following subsections 3.3.1–3.3.3 examine selected calendar anomalies.

3.3.1 January effect

Rossi (2015) presents the January effect as the best-known calendar anomaly. In January, stock market returns are on average exceptionally high compared to other months of the year. The January effect has been documented in several countries and across different time periods. Rossi refers to Wachtel (1942) as the first researcher to provide evidence of unusually strong January returns in the U.S. stock market, as well as to the findings of Rozeff and Kinney (1976), who examined U.S. stock market data from 1904 to 1974 and reported that January returns on the New York Stock Exchange were clearly higher than in other months.

In addition, Rossi (2015) mentions, among others, Mylonakis and Tserkezos (2008), who find evidence of the January effect in the Athens Stock Exchange during the period 1985–2001. Dahlquist and Sellin (1994) studied seasonal variation in the Swedish stock market and likewise observed a strong January effect in average monthly returns.

According to Thaler (1987), the January effect has been explained, among other factors, by the tax-loss selling hypothesis. Under this hypothesis, investors sell loss-making stocks at the end of the tax year in order to realize capital losses, which intensifies the price decline of poorly performing stocks. When the new tax year begins, stock prices rebound as the selling pressure subsides, which may explain the unusually high returns in January. However, Thaler notes that taxation alone cannot fully account for the January effect, referring, for example, to Japan, where the January effect has been observed despite the absence of capital gains taxation and the ability to deduct losses.

3.3.2 Day-of-the-week effect

Another calendar anomaly discussed by Rossi (2015) is the day-of-the-week effect, first identified by Osborne (1962) in the U.S. stock market. According to Rossi, the day-of-the-week anomaly was later examined by, among others, French (1980) and Jaffe et al. (1989), who demonstrated systematic variation in U.S. stock market returns across

different weekdays. Average returns were clearly negative on Mondays, whereas on Fridays they were on average positive and higher than on other weekdays.

Copeland et al. (2014, p. 403) note that no satisfactory explanation has been found for this weekend effect, although attempts have been made to explain it, for example, by the market-closure effect and by the possibility that firms delay the release of negative news until after the market closes on Friday. They further argue that the weekend effect cannot be profitably exploited as an investment strategy, since transaction costs of approximately 0,25 % would already eliminate any excess returns.

Empirical findings by Martikainen and Puttonen (1996) indicate the presence of an apparent day-of-the-week effect in the Finnish financial markets. They did not observe a specific Monday effect in Finnish stock returns, but returns on Tuesdays and Wednesdays were found to be below average in the Finnish stock market. They also note that these Tuesday and Wednesday effects disappeared once the study controlled for the impact of derivatives returns.

3.3.3 Halloween effect

Bouman and Jacobsen (2002) examined whether stock returns decline significantly during the period from May to October compared to the rest of the year. According to their findings, in 36 out of 37 countries in the sample, stock returns during May–October differ significantly from returns in other months: on average, returns do not differ from zero and often even turn negative. New Zealand was the only country in which the Halloween effect was not observed. The results provide particularly strong evidence for the effect in European stock markets. The Nordic countries included in the study were Denmark, Finland, Norway, and Sweden. The phenomenon is referred to as the Halloween effect or indicator, and in line with the traditional market saying “Sell in May and go away.”

Zhang and Jacobsen (2021) also examined the Halloween effect in a study covering stock market returns from 114 countries, as well as total returns and risk premia for 65 markets over a combined 37 167 monthly observations. The results, based on global stock indices, show that in 87 of the 114 countries, average stock returns are lower during May–October than during the November–April period. They identified the Halloween effect in all 37 countries included in the original study by Bouman and Jacobsen (2002), with particularly strong evidence in Europe, North America, and Asia. In addition, their findings indicate that the Halloween market anomaly has strengthened over the past 50 years.

According to Bouman and Jacobsen (2002), the Halloween effect persists in the markets even though, according to the EMH, arbitrage should eliminate such predictable seasonal return differences. When examining potential explanations for the Halloween effect, they find that the timing of summer holiday periods is clearly associated with variations in trading activity. In contrast, they do not find evidence that the January effect, risk-based explanations, changes in interest rates or trading volume, data mining, or industry-specific factors explain the Halloween effect.

Zhang and Jacobsen (2021) similarly argue that the most likely explanation relates to seasonal vacation patterns. They also reject the view that the phenomenon is driven by changes in risk aversion, stating that there is no reason to assume that individuals have become more prone to seasonal affective disorder over time.

4 Seasonal Affective Disorder (SAD)

The previous chapter demonstrated that financial markets exhibit several calendar anomalies in which stock returns deviate systematically according to specific calendar-related periods. Since traditional finance theory and the efficient market hypothesis are unable to explain these deviations, behavioral finance offers alternative explanatory frameworks that take into account both limits to arbitrage, which allow the actions of irrational investors to influence market prices even in the long run, and the psychological biases and behavioral tendencies that affect investors' decision-making.

One key factor influencing investors' decision-making is mood, which has been shown to vary according to seasons and environmental conditions (Kramer, 2014). Kihn (2011, pp. 105–107) argues that the limits to arbitrage and the psychological dimension recognized in behavioral finance provide an essential framework for examining the relationship between mood and investor behavior. He highlights seasonal affective disorder, often referred to as “winter depression,” as an example of a phenomenon in which mood depression caused by reduced daylight hours is associated with increased risk aversion in investors' decision-making, thereby influencing security returns in financial markets. Rosenthal et al. (1985) likewise present SAD as an example of how environmental factors, particularly the amount of light, affect individuals' mood and psychological responses.

Accordingly, this chapter first examines seasonal affective disorder as a phenomenon. Subsection 4.1 then focuses on reviewing prior literature on the impact of SAD on stock market returns. Subsection 4.2 examines whether the impact of SAD on returns is symmetrical or asymmetrical between autumn and winter. If the SAD effect is symmetrical, stock market returns are determined solely by the length of the night. An asymmetrical SAD effect, by contrast, implies that stock market returns differ between autumn and winter even when the length of the night is the same, suggesting that the direction of change in daylight hours also influences investor behavior (Kamstra et al., 2003).

According to Kamstra et al. (2003), seasonal affective disorder (SAD) is a clinically recognized mood disorder associated with seasonal variation, particularly linked to the dark autumn and winter months, and classified as a severe seasonal form of depression. The reduction in daylight hours disrupts the brain's production of melatonin, resulting in circadian rhythm disturbances. Individuals affected by SAD typically experience prolonged periods of chronic fatigue, general lack of energy, and decreased alertness. In addition, SAD is often associated with reduced social activity, diminished libido and pleasure, and changes in sleep patterns. A common symptom of SAD is also a change in appetite, particularly an increased craving for sweets and carbohydrate-rich foods, which may lead to weight gain during the autumn and winter season.

Rosenthal et al. (1985) examined a group of patients whose mood and behavior responded strongly to seasonal changes. The sample included individuals who experienced seasonal autumn–winter depression for at least two consecutive winters, but whose depressive symptoms eased with the transition to spring or summer. Their findings correspond to the severe symptoms of depression described by Kamstra et al. (2003).

Rosenthal et al. (1985) suggest that the seasonal behavioral changes associated with SAD resemble patterns observed in the animal kingdom. Among animals, day length functions as a key biological signal that regulates reproduction, behavior, and hormonal activity. Unlike in animals, their findings indicate that SAD particularly affects individuals living at higher latitudes: patients' symptoms typically became milder, or did not occur at all, the closer they lived to the equator.

Kamstra et al. (2003) likewise report that the effects of SAD are significant in most countries, with the exception of those located near the equator, where the length of the dark period remains relatively constant throughout the year (see Figure 5). In the Southern Hemisphere, the impact of SAD appears approximately six months later than in the Northern Hemisphere.

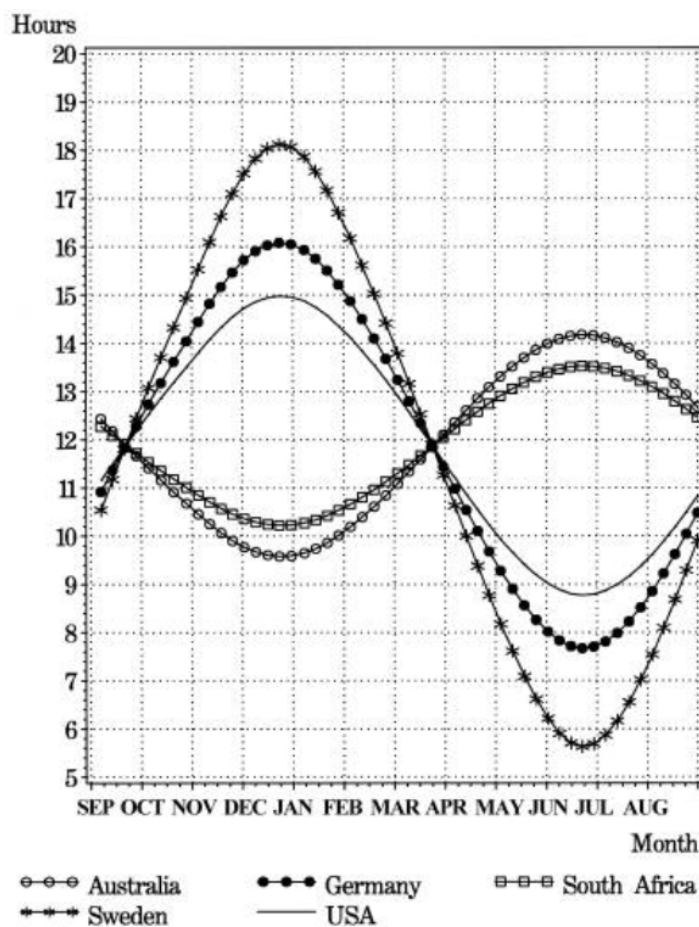


Figure 5. Seasonal variation in hours of night at different latitudes (Kamstra et al., 2003).

Garrett et al. (2005) and Kramer (2014) specify that the SAD phenomenon is primarily related to daylight through day length, defined as the period between sunrise and sunset, which varies according to season and latitude. In contrast, sunshine is a separate weather-related factor that is not directly tied to day length but fluctuates randomly depending on cloud cover.

According to Rosenthal et al. (1985), bright light therapy can significantly reduce SAD symptoms, as exposure to bright light decreases melatonin secretion and rapidly improves mood. Avery et al. (2001) also acknowledge the effectiveness of bright light therapy but note that nearly 70 percent of individuals suffering from SAD find it difficult to sit in front of bright light, and almost 20 percent discontinue the treatment. Rosenthal

et al. (1985) further state that light therapy does not produce permanent effects, as symptoms tend to recur once the treatment ends. Nevertheless, Campbell et al. (2017) report that bright light therapy remains the primary treatment for SAD symptoms.

Since no long-term treatment that permanently ensures symptom-free conditions is available, it is justified to examine the relationship between SAD, decision-making, and risk-taking behavior. According to Kihn (2011, p. 6), psychological research has shown that depressive symptoms are directly associated with decision-making through increased risk aversion. Similarly, Kramer (2014) reports that, compared to non-depressed individuals, those experiencing depression score significantly higher on measures of risk aversion.

In addition, Eisenberg et al. (1998) examined university students' decision-making in two studies involving choices between a risky and a certain option. Their findings indicate that individuals in an anxious emotional state and those experiencing depressive symptoms are more likely to avoid risk, meaning that they tend to refrain from choosing alternatives with uncertain outcomes. This risk aversion is linked to a cognitive tendency to perceive negative outcomes as more likely and their consequences as more severe. However, the study also found that anxiety and depression were associated with risk aversion only in decisions concerning oneself. In situations where decisions concerned others rather than oneself, pessimistic thoughts about riskier outcomes weakened or disappeared altogether. No differences were observed between genders.

4.1 SAD and stock market returns

According to Kamstra et al. (2003), the depression associated with SAD, which is significantly linked to reduced risk-taking willingness, is also reflected economically in the seasonal variation of stock returns. They examined the impact of the SAD phenomenon on stock returns during the autumn and winter seasons and formulated a hypothesis according to which the length of the night, defined as the period between sunset and

sunrise, affects investors' risk tolerance and thereby stock returns. The study utilized daily stock index return data from four U.S. stock indices as well as from eight other countries, allowing for a broad representation of major economies across different latitudes in both the Northern and Southern Hemispheres (see Figure 6).

Country	Index	City	Latitude
United States	S&P 500	New York	41°N
United States	NYSE	New York	41°N
United States	NASDAQ	New York	41°N
United States	AMEX	New York	41°N
Sweden	Veckans Affärer	Stockholm	59°N
Britain	FTSE 100	London	51°N
Germany	DAX 30	Frankfurt	50°N
Canada	TSE 300	Toronto	43°N
New Zealand	Capital 40	Auckland	37°S
Japan	NIKKEI 225	Tokyo	36°N
Australia	All Ordinaries	Sydney	34°S
South Africa	Datastream Global Index	Johannesburg	26°S

Figure 6. Selected countries, stock indices, cities and latitudes (Kamstra et al., 2003).

Next, the annual and monthly averages of the daily percentage returns of the stock indices included in Kamstra et al. (2003) are examined using the graphs presented in Figures 7, 8, and 9 below. To ensure comparability of seasonal patterns across countries, the horizontal axis of each country's graph is arranged so that the observation period begins at the autumnal equinox. For countries located in the Northern Hemisphere, the horizontal axis therefore begins in September, whereas for countries in the Southern Hemisphere, the months on the horizontal axis begin in March.

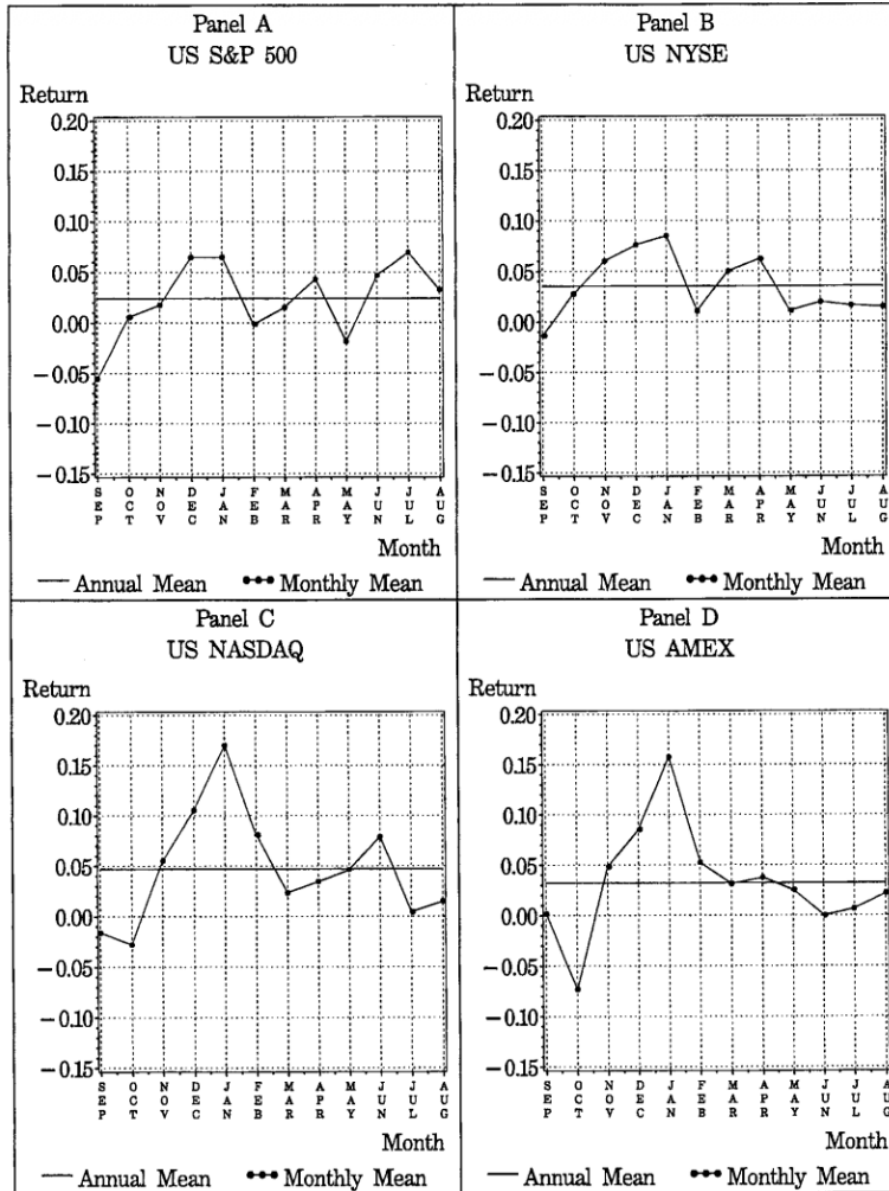


Figure 7. Annual and monthly mean returns of the U.S. indices (Kamstra et al., 2003).

As all U.S. index graphs in Figure 7 above illustrate, returns are at their lowest in early autumn and then gradually increase, reaching their peak in the first month of the year. Thereafter, returns tend to decline and stabilize during the spring and summer seasons. A similar seasonal return pattern to that observed in the U.S. indices can also be identified in the countries presented in Figure 8 below, as well as in Japan among the countries shown in Figure 9, all of which, like the United States, are located in the Northern Hemisphere (Kamstra et al., 2003).

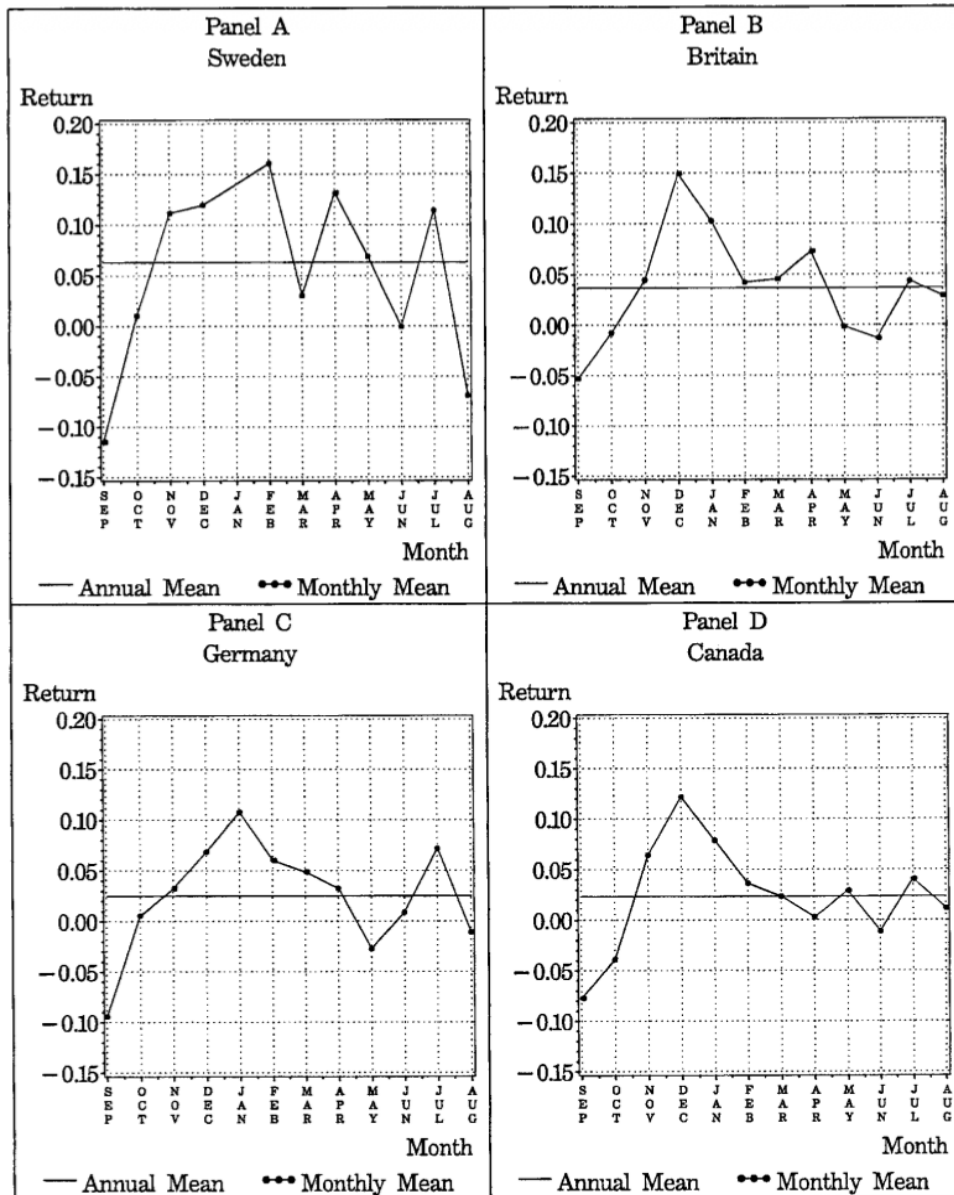


Figure 8. Annual and monthly mean returns of Sweden, Britain, Germany and Canada (Kamstra et al., 2003).

In contrast, among the countries presented in Figure 9, New Zealand, Australia, and South Africa are located in the Southern Hemisphere, closer to the equator, where seasonal variations in daylight hours are less pronounced. Consequently, their stock return graphs do not display as significant a seasonal pattern as those observed in countries located in the Northern Hemisphere (Kamstra et al., 2003).

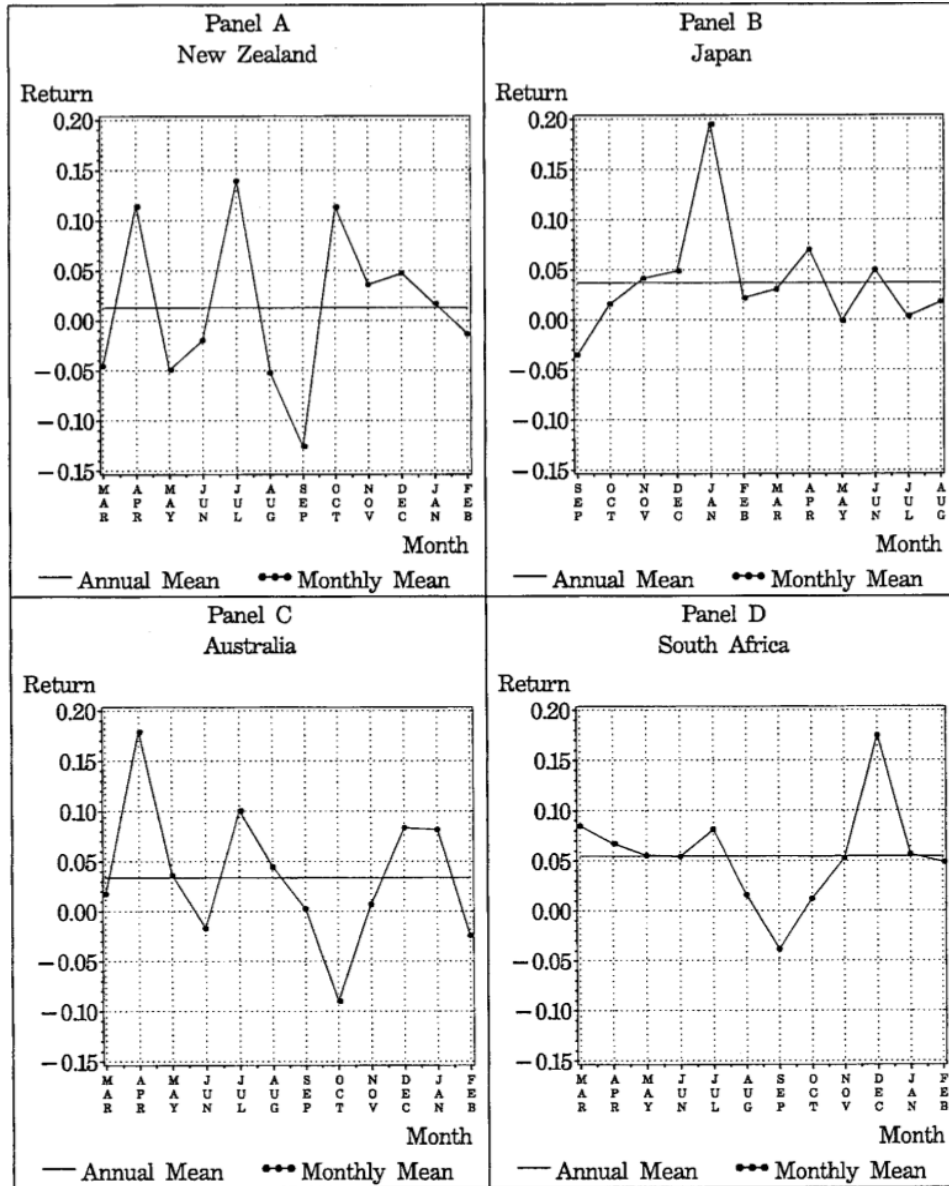


Figure 9. Annual and monthly mean returns of New Zealand, Japan, Australia and South Africa (Kamstra et al., 2003).

Kamstra et al. (2003) conducted their study using a regression model constructed separately for each stock index included in the study. In the regression model, daily stock returns r_t are explained by several variables:

$$5. \quad r_t = \mu + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \mu_{Monday} D_t^{Monday} + \mu_{Tax} D_t^{Tax} + \mu_{SAD} SAD_t + \mu_{Fall} D_t^{Fall} + \mu_{Cloud} Cloud_t + \mu_{Precipitation} Precipitation_t + \mu_{Temperature} Temperature_t + e_t.$$

In their regression model, Kamstra et al. (2003) include the variables r_{t-1} and r_{t-2} to account for one- and two-day lagged returns, ensuring that potential autocorrelation in stock returns does not bias the results. The regression model also includes three dummy variables, D_t^{Monday} , D_t^{Tax} , and D_t^{Fall} , which control for the Monday effect discussed in subsection 3.3.2, as well as for the effects of tax-loss selling and the autumn period. In the model, dummy variables take the value of one when the respective phenomenon occurs and zero otherwise, allowing for the identification of systematic deviations in stock returns during these periods. The autumn dummy is examined in more detail in subsection 4.2.

In addition, Kamstra et al. (2003) control for environmental factors by including the effects of cloud cover, precipitation, and temperature through the variables $\mu_{Cloud}Cloud_t$, $\mu_{Precipitation}Precipitation_t$, and $\mu_{Temperature}Temperature_t$. The SAD measure, $\mu_{SAD}SAD_t$, is constructed using the following formula, where H_t represents the number of hours between sunset and sunrise at a given location:

$$6. \quad SAD_t = \begin{cases} H_t - 12 & \text{during fall and winter trading days} \\ 0 & \text{in other periods} \end{cases}$$

Kamstra et al. (2003) find that the SAD phenomenon affects individuals' mood and, through this channel, also influences investors' risk tolerance. The effects of SAD are reflected significantly in seasonal changes in stock returns even after controlling for other market seasonality patterns and environmental factors. The results are strongest in the Northern Hemisphere.

Following these findings, Kamstra et al. (2003) examined whether investors could earn excess returns by incorporating the SAD effect into their trading strategy. They illustrated and compared the returns an investor would have obtained over a 20-year period using a neutral investment strategy, in which the portfolio maintained a 50/50 allocation

between Swedish and Australian stock indices, with those generated by a pro-SAD investment strategy.

Under the pro-SAD strategy, the portfolio was reallocated seasonally so that investments were held in Sweden during the Northern Hemisphere's autumn–winter period and in Australia during the Southern Hemisphere's autumn–winter period. They concluded that by following the neutral strategy, the investor's average annual return would have been approximately 13 %, whereas the pro-SAD strategy would have generated excess returns without a significant change in the risk profile, yielding an average annual return of approximately 21 %. (Kamstra et al., 2003.)

In later studies, numerous other researchers have also examined the impact of the SAD phenomenon on stock markets. Garrett et al. (2005) examined the effect of SAD on daily and monthly stock market returns in the United States, Japan, the United Kingdom, Sweden, New Zealand, and Australia by applying the CAPM presented in subsection 2.4.1 in a conditional form. Their findings indicate that the effect of SAD on stock returns is significant in all markets included in the study.

Furthermore, Garrett et al. (2005) argue that the impact of SAD on stock returns can be explained within a conditional CAPM framework, in which the risk premium, the price of risk, is allowed to vary over time according to seasonal changes in day length. This time variation reflects increased risk aversion associated with investors' seasonal depression.

Jacobsen and Marquering (2008) examined the findings of Kamstra et al. (2003) and Garrett et al. (2005) concerning the impact of the SAD phenomenon on investors' mood and stock market returns. They confirm that stock returns show clear seasonal patterns, but their results don't provide sufficient evidence that SAD specifically explains the seasonal behavior of stock returns. They even argue that the market anomaly discussed in subsection 3.3.3, the Halloween indicator, explains the same seasonal pattern in stock

returns as the SAD effect examined by Kamstra et al. (2003) and Garrett et al. (2005), but more convincingly.

Kelly and Meschke (2010) re-examined the SAD hypothesis proposed by Kamstra et al. (2003) as well as the study by Jacobsen and Marquering (2008). Their findings support the conclusions of Jacobsen and Marquering (2008), as they reject the SAD hypothesis due to insufficient empirical evidence to establish a causal link between risk aversion associated with SAD symptoms and seasonal fluctuations in stock returns. They further argue that the psychological literature doesn't support the SAD hypothesis.

Keef and Khaled (2011) critically re-evaluated the study by Kamstra et al. (2003) on the effect of SAD on investor behavior in light of the earlier critiques by Jacobsen and Marquering (2008) and Kelly and Meschke (2010). According to them, the results of Kamstra et al. (2003) contain four weaknesses. First, they question the regression model used in the study, arguing that it is inconsistent for testing the SAD hypothesis. This leads to a second weakness: the empirical results don't support the proposed SAD hypothesis. The third and fourth weaknesses, which relate to the asymmetry of the SAD effect, are examined in subsection 4.2.

Dolvin and Fernhaber (2014) examined the impact of the SAD phenomenon on the initial public offerings (IPOs) of young firms. Since an IPO provides a company with the opportunity to expand, they aimed to investigate whether the pessimistic and risk-averse investment behavior associated with SAD during the autumn and winter seasons has a stronger effect on younger, higher-risk firms going public. Their findings indicate that younger firms experience a stronger level of IPO underpricing during SAD periods. As a result, they suggest that it may be more advantageous to time an IPO during the spring or summer months, or at least to reduce the SAD effect by selecting a more reputable underwriter or keeping a larger ownership stake in the IPO.

Dolvin and Fernhaber (2014) also note that the SAD period differs from the timing of the Halloween effect by only one month, which raises the possibility that the two phenomena capture similar patterns of behavior. However, they argue that the SAD phenomenon has a clear theoretical and psychological explanation, whereas the Halloween effect is primarily regarded as an observed market anomaly without an equally strong theoretical foundation.

Lin (2015) examined the impact of the SAD phenomenon on stock markets during earnings announcements. The objective of the study was to determine whether investors' price reactions to earnings announcements and the post-announcement price dynamics differ during SAD periods compared to other times of the year. The findings indicate that the SAD phenomenon significantly affects stock market pricing. During SAD periods, investors' reactions to positive earnings announcements are more cautious and slower than during other periods, when day length and risk-taking willingness are higher. Investors prefer to avoid uncertainty rather than exploit positive investment opportunities, which is reflected in a more moderate and delayed price response to immediate positive earnings news. In contrast, no corresponding seasonal difference was observed in reactions to negative earnings announcements. This suggests that investors aim to avoid losses when confronted with bad news, particularly during SAD periods.

As a more recent contribution to the literature on the SAD phenomenon, Škrinjarić et al. (2021) examined the impact of SAD on investors' mood and risk-taking behavior on the Croatian stock market at the Zagreb Stock Exchange (ZSE). The study used daily stock market return data from the CROBEX index covering the period 2010–2021. In their regression model, control variables similar to those used by Kamstra et al. (2003) were included, such as the Monday and tax effects, along with an additional COVID-19 dummy variable capturing the pandemic period. Their findings are consistent with the original results of Kamstra et al. (2003) that the SAD phenomenon significantly affects investors trading on the Croatian stock market. SAD symptoms increase investors' risk aversion, which is reflected in the selling of riskier securities during the autumn period.

4.2 Asymmetry of the SAD effect between fall and winter

Kamstra et al. (2003) also examined the asymmetry of the SAD effect between autumn and winter, specifically whether the symptoms caused by SAD are asymmetric around the winter solstice. According to their hypothesis, the risk aversion associated with SAD symptoms begins in the autumn in the Northern Hemisphere and is reflected in investors shifting toward lower-risk assets. This shift leads to systematically lower stock returns prior to the winter solstice. After the winter solstice, SAD symptoms begin to ease as day length increases, which is reflected in a movement toward riskier assets and significantly higher stock returns.

In their study, Kamstra et al. (2003) defined the winter solstice as December 21, when the longest night of the year occurs in the Northern Hemisphere. As noted earlier, the effect of SAD in the Southern Hemisphere appears approximately six months later than in the Northern Hemisphere. Consequently, the peak in night length for the Southern Hemisphere was defined as June 21. To test for autumn–winter asymmetry, an autumn dummy variable was added to the regression model. This dummy takes the value of one on trading days during the autumn period in each country and zero otherwise:

$$7. D_t^{Fall} = \begin{cases} 1 & \text{during fall trading days} \\ 0 & \text{in other periods} \end{cases}$$

The findings of Kamstra et al. (2003) provide significant support for the hypothesis of asymmetry in the SAD effect between autumn and winter. In the majority of the stock markets included in the study, the coefficients of both the SAD variable and the autumn dummy variable are statistically significant. Figure 10 below shows the average percentage stock return related to the SAD variable and the autumn dummy for each stock index included in the study. These values are calculated using the estimated regression coefficients from the regression model by multiplying the daily values of the SAD variable and the autumn dummy by their respective parameter estimates and then converting the results into annual returns. The rightmost column of the figure 10 additionally reports

the average annual percentage return for each stock index. Statistical significance of the results is indicated at the 1, 5, and 10 % levels.

Country	Annual return due to SAD	Annual return due to fall dummy	Unconditional annual return
United States: S&P 500	9.2***	-3.6**	6.3***
United States: NYSE	6.1*	-2.5*	9.2***
United States: NASDAQ	17.5***	-8.1***	12.5***
United States: AMEX	8.4***	-5.1***	8.4***
Sweden	13.5**	-6.9**	17.1***
Britain	10.3**	-2.3	9.6***
Germany	8.2*	-4.3**	6.5**
Canada	13.2***	-4.3**	6.1***
New Zealand	10.5**	-6.6**	3.3
Japan	6.9*	-3.7**	9.7***
Australia	5.7	0.5	8.8***
South Africa	17.5*	-2.1	14.6***

* Significant at the 10-percent level, one-sided.

** Significant at the 5-percent level, one-sided.

*** Significant at the 1-percent level, one-sided.

Figure 10. Asymmetric effects of SAD on annual stock returns (adapted from Kamstra et al., 2003).

Overall, the findings of Kamstra et al. (2003) indicate that the annual percentage returns associated with the SAD variable are positive for every stock index included in the study and statistically significant in all cases except Australia. In several of the examined indices, the return related to the SAD effect is also higher the average annual total return. The average annual return associated with the autumn dummy is also noteworthy. It is negative for all stock indices except Australia, supporting the view that the effects of SAD on stock markets are asymmetric. Therefore, lower returns in the autumn are followed by

higher returns during the winter period, reflecting a temporal shift in returns across seasons.

Garrett et al. (2005) also re-examined the findings of Kamstra et al. (2003) regarding the asymmetry of stock returns between the autumn and winter seasons. Their results are consistent with Kamstra et al. (2003) in showing that the autumn dummy variable receives a negative and statistically significant coefficient in most of the examined countries, while the SAD variable receives a positive coefficient. This indicates that stock returns behave asymmetrically around the winter solstice.

However, Garrett et al. (2005) show that the overall effect of the SAD variable and the autumn dummy on stock returns largely disappears once market risk and the price of risk are allowed to vary over time. The time variation in the market risk premium captures the seasonal pattern attributed to the SAD and autumn variables. For this reason, they don't conclude that the SAD phenomenon enables an investment strategy capable of generating abnormal excess returns.

Keef and Khaled (2011) question the asymmetry of the SAD effect in their study. As a third weakness of Kamstra et al. (2003), they challenge the theoretical prediction of positive stock returns during the winter period. According to them, the SAD effect should be negative in both autumn and winter, as improving mood toward the spring would increase risk-taking and raise security prices. As a fourth weakness, they argue that the empirical findings of Kamstra et al. (2003) don't support the original SAD hypothesis, nor do they support their own revised SAD hypothesis. In their view, the estimated results indicate that night length is positively related to stock prices in both autumn and winter, which implies that no asymmetry arises.

Lin (2015) empirically examined the asymmetry of the SAD effect between the autumn and winter periods during earnings announcements. The results indicate that the effects of SAD are asymmetric in connection with positive earnings announcements. The

pessimism associated with SAD is stronger during the autumn, when daylight hours decrease, compared to the winter period, when investors' risk tolerance begins to recover.

Škrinjarić et al. (2021) also find evidence of asymmetry around the winter solstice when examining the impact of the SAD phenomenon on investors trading on the Croatian stock market at the Zagreb Stock Exchange (ZSE). According to their findings, risk-taking willingness among investors in the ZSE varies seasonally. This variation is reflected in portfolio composition: as daylight hours shorten, higher-risk securities are sold during the autumn, whereas riskier securities are repurchased as daylight hours increase.

5 Conclusions

This thesis examines the impact of seasonal affective disorder on stock markets. In particular, it examines whether stock market returns are significantly lower during periods of reduced daylight hours and whether the impact of seasonal affective disorder on stock market returns is asymmetrical between autumn and winter seasons.

The thesis also includes a theoretical framework that reviews the cornerstones of traditional finance, such as the assumption of rational market participants, efficient markets, and the CAPM. Furthermore, the theoretical section introduces behavioral finance as an alternative perspective to traditional finance, emphasizing psychological and behavioral aspects of market participants as well as limits to arbitrage.

Based on the existing literature, the SAD phenomenon has been shown to have a significant association with seasonal variation in stock markets. SAD affects investors' mood, particularly in the form of mood-related depressive symptoms, which in turn influence their risk tolerance. Risk aversion increases in investors' decision-making, which is reflected in stock returns. The SAD effect is stronger in the Northern Hemisphere, where seasonal changes in daylight hours are more pronounced. On the other hand, the literature also presents critical perspectives on the impact of SAD on stock returns, particularly emphasizing the close timing of the SAD effect and the Halloween effect.

There is also evidence in the literature that the SAD effect between autumn and winter is asymmetric around the winter solstice. Investors in the Northern Hemisphere who experience SAD symptoms tend to shift toward lower-risk assets in the autumn as daylight hours decrease, and after the winter solstice, they move back to riskier assets as symptoms begin to ease. This shift is reflected in significantly higher stock returns following the solstice. However, some studies question these findings and certain results suggest that the seasonal effect of SAD on stock returns disappears once market risk and the price of risk are allowed to vary over time.

When evaluating the findings, it's important to acknowledge the limitations of this thesis. Part of the existing research focuses on individual country indices only, which limits the ability to generalize the results. For future research, this thesis therefore suggests that the impact of the SAD phenomenon, particularly its asymmetry, should be examined across a broader range of countries and latitudes.

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