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The Effect of Seasonal Depression on Stock Market Returns*

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The study analyses the statistical relationship between the degree of seasonal depression and stock index returns. For this analysis, we examine the daily returns of two US and five European stock indices using OLS regression. The analysis found a statistically significant relationship between seasonal depression and the change in returns. However, due to the limited use of the reduced form, this only confirms the link between seasonal depression and returns, and further observations would be required to confirm a causal relationship.

Journal of Economic Literature (JEL) codes: C10, G14, G20, G40

Keywords: investor sentiment, seasonal depression, stock indices, stock market returns

1. Introduction

Our study focuses on a subset of behavioural finance, namely, seasonality and investor sentiment, and the impact of the latter on stock markets. Relying on applied psychology, behavioural finance takes a new and previously overlooked perspective from classical finance, and is able to draw conclusions from certain cognitive biases that can explain specific financial and economic anomalies and phenomena better than classical financial models.

Price analyses of different financial markets may serve both explanatory and predictive purposes. The seasonal depression examined in this study is presumed to reduce the risk-taking propensity of investors. *Kamstra et al.* (*2003*) attempt to show this effect by analysing the returns on stock indices. On the one hand, this also has explanatory power, as the authors seek to provide information on part of the variation in stock market returns. In addition, if the effect of seasonal depression does have a statistically detectable impact on stock market returns, taking into

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consideration the degree of seasonal depression may become part of a successful trading strategy for specific stock exchanges.

The relevance of the topic stems from several factors. While providing an academic narrative accepted by the finance literature, behavioural finance still has many unexplored areas. Part of this is a series of studies on investor sentiment and mood, as well as on different seasonal effects. In their paper, *Kamstra et al.* (*2003*) identified several studies that derived seasonal depression in the same way, from the length of nights; it is therefore worth examining in detail the methodology and theoretical considerations applied by the authors.

The link between climate change and public sentiment as well as stock markets underlines the relevance of our research. Warming weather increases the risk of mental health problems and depression (*Palinkas – Wong 2020*). *Peillex et al.* (*2021*), for example, found that heat waves reduced trading volume on the Paris stock exchange significantly by 4–10 per cent, and *Lanfear et al.* (*2019*) pointed out a link between extreme weather events and market anomalies.

The purpose of this study is twofold: it is intended (1) to examine methodological considerations, and (2) to be a partial reproduction with some methodological changes. In the reproduction, the original regression model is adjusted in accordance with various causal aspects, and among the selected stock indices, a special focus is placed on the Central European market through the returns of the Czech and Polish stock exchanges. Regardless of the causal deficiencies of the original study, it is reasonable to assume that the results of this paper will take values that are approaching those of that study and will be statistically significant.

The analysis of the risk-reducing effect of the Seasonal Affective Disorder (SAD) – i.e. seasonal depression – and the reproduction of *Kamstra et al.* (*2003*) on some level remains an exciting area of research. More recently, *Škrinjarić* (*2018*) examined eleven countries in Central and South East Europe, and found that Croatia, Hungary, Romania, Serbia, Slovakia and Ukraine exhibited significant SAD effects. *Škrinjarić et al.* (*2021*) focused specifically on the Croatian stock market, while *Škrinjarić* (*2022*) constructed a profitable trading strategy based on seasonal depression.

In three out of the seven stock markets examined here (NASDAQ, FTSE 10, DAX), we obtained significant results pointing to the impact of SAD on the stock markets.

In *Section 2* we present the literature on behavioural finance. *Section 3* then details the method of *Kamstra et al.* (*2003*) and the conditions for using the instrumental variable. *Section 4* includes the stock indices selected for analysis and the causal map that underpins the analysis presented in the study, which clarifies the control and explanatory variables required for the OLS regression applied in the analysis.

Finally, the results obtained are compared with those of the original study. We conclude our study with a summary.

2. Literature review

As a result of the approach and toolkit of behavioural finance, the literature has developed a new, methodologically sound perspective on the impact of emotions in various decision-making situations, demonstrating, for example, how empirical analysis is able to show a relationship between sentiment and stock market volatility or risk-taking propensity. Research in the field of behavioural finance suggests that emotions and mood, as well as certain human cognitive characteristics, can be considered as informative variables in financial analysis (see, for example, *Tversky – Kahnemann 1974; Johnson – Tversky 1983; De Bondt – Thaler 1985; Thaler 1999; Barberis – Thaler 2003; Barberis 2013*).

The relevance of the topic is demonstrated by the fact that the number of investor sentiment surveys more than doubled between 2016 and 2020 compared to the previous five-year period. The research of *Kamstra et al.* (*2003*) belongs to the early part of the literature linking seasonality and emotions to financial market movements. Subsequently, *Dowling – Lucey* (*2008*) and *Joëts* (*2012*), for example, also relied on their study, as suggested in the literature review by *Goodell et al.* (*2023*). Hungarian literature is also linked to the research on behavioural finance, for example, via articles by *Golovics* (*2015*) or *Neszveda* (*2018*), where the field of behavioural finance is outlined in the light of Thaler's work, introducing key concepts of behavioural finance.

2.1. The role of sentiment and emotions in investor decision-making

In the following, we briefly review the theoretical framework of behavioural finance, including studies on seasonal effects on financial market returns and the literature on individual investor emotions and sentiment. Investor and consumer sentiment and the influence of such on their decisions is a crucial issue. This notwithstanding, some research directions have yet to receive sufficient attention, despite the fact that the results of the articles written on the subject are not always consistent with each other. This suggests that the exact methodology for the analysis of this issue has yet to be developed (*Goodell et al. 2023*).

2.1.1. Behavioural finance

Modern financial models are based on economic models whose dominant paradigm is neoclassical economics. The main assumptions of neoclassical economics are that individuals and firms are self-interested and try to optimise limited resources to the best of their ability. People have rational preferences between possible outcomes or states of nature. Preferences are described by utility functions (see, for example, *Fama 1970*; *Markowitz 1952*; *Miller – Modigliani 1961*). Obviously, even scholars who rely on modern financial theories based on neoclassical economic models do not consider human behaviour and decision-making to be perfectly rational (*Thaler 1999*); however, these financial models have proved inadequate, overall, to explain certain market phenomena correctly. The behavioural finance narrative has criticised modern financial theories since the 1970s (*Tversky – Kahnemann 1974*).

Behavioural finance combines psychological and financial insights. Based on *De Bondt – Thaler* (*1985*) and *Barberis – Thaler* (*2003*), we can detect systematic biases and better understand financial market movements by assuming a specific form of irrationality using experimental results from cognitive psychology. As pointed out by *Barberis – Thaler* (*2003*), our understanding of bounded rationality is largely due to the work of cognitive psychologists such as the already cited *Tversky – Kahneman* (*1974*). Thanks to their initial work and the work of other researchers, the field of behavioural finance has produced concrete empirical results. Building on this, it is possible to catalogue the systematic set of biases and beliefs on the basis of which people form expectations and make decisions.

There have also been publications in Hungarian on behavioural finance and capital market anomalies. *Molnár* (*2006*) provides a comprehensive summary of the criticisms of the efficient markets theory. Among seasonalities, the author mentions the January and weekend effects, and among the value-based anomalies, the P/E and small company effects, as well as the Value Line Investment Survey puzzle, where investments included in the investment advisor's newsletter realise unusually high, abnormal returns.

In their empirical research on the most liquid, large cap stocks on the Budapest Stock Exchange, *Nagy – Ulbert* (*2007*) analysed irrational decision inconsistencies in addition to the aforementioned seasonal and value-based anomalies. Examining the dataset between 1996 and 2007, they found that the reversal phenomenon identified by *De Bondt – Thaler* (*1985*) also held true for the BSE, i.e. stocks that performed well (poorly) in the past became the poorly (well) performing stocks in the period that followed. In a similar study, *Naffa* (*2009*) pointed out that investors were willing to forgo part of their expected return in exchange for investments that are more resilient to market turmoil.

The reversal phenomenon on the BSE was studied by *Lakatos* (*2016*), as well. The author identified the reversal phenomenon in a larger database from 1996 to 2015; however, he found that the phenomenon disappeared towards the end of the period. *Fömötör et al.* (*2017*) summarised the factors limiting consumer rationality in loan contracts. *Kutasi et al.* (*2018*) investigated factors determining the behavioural biases of retail investors in Hungarian government bonds.

2.1.2. The role of sentiment and emotions in investor decision-making

A subset of the phenomenon of bounded rationality used in behavioural finance is the observation of the role of emotions in the decision-making of investors. Drawing on the literature, we find that emotions influence both the perception of future prospects; see *Johnson – Tversky* (*1983*) and *Arkes et al.* (*1988*), and the assessment of risks, as pointed out by *Loewenstein et al.* (*2001*) and *Slovic et al.* (*2004*).

Several studies have demonstrated the impact of positive and negative emotions on investors' decision-making: positive (negative) emotions motivate (demotivate) investors' risk-taking (see, for example, *Kuhnen – Knutson 2011*). Following the outbreak of the Covid-19 pandemic, several researchers observed a significant relationship between the emotional effects of Covid-19 and financial market movements. *Subramaniam – Chakraborty* (*2021*) analysed the correlation between fear of the pandemic and exchange rates. According to *Chundakkadan – Nedumparambil* (*2022*), this emotional effect is directly related to the volatility observed in financial markets.

Hirshleifer – Shumway (*2003*) found a high correlation between sunshine and the returns on stock indices, which is inconsistent with the notion of rational investors. *Cao – Wei* (*2005*) detected an inverse relationship between temperature and returns, with yields being lower on very hot days. According to research by *Shanaev et al.* (*2022*), there is a consistent and irrational optimism in investor behaviour around Groundhog Day in the USA.

Building on the work of *Kamstra et al.* (*2003*), studies by *Dowling – Lucey* (*2008*) and *Joëts* (*2012*) identified a significant relationship between seasonal depression and stock market price movements.

Jacobsen – Marquering (*2008*) partially refuted the findings of *Kamstra et al.* (*2003*) and *Cao – Wei* (*2005*). Although they reviewed a longer period and worked with monthly rather than daily data, they were able to reproduce the findings of both studies, but pointed out that it was difficult to single out possible explanations. According to their results, there is no evidence that SAD, higher temperatures or the old market adage 'Sell in May and go away' are the reasons for lower returns in summer. It was pointed out that the proximity of a country to the equator does not affect the phenomenon, and a simple winter/summer dummy has better explanatory power than SAD or temperature.

In their response, *Kamstra et al.* (*2009*) were only partially able to reproduce the results of *Jacobsen – Marquering* (*2008*). In the authors' view, they used inappropriate data and it was a mistake to include countries where the length of days and nights does not vary, or where it is not the intensity of seasonal depression in an investor's life that matters, but the number of new people who reallocate their portfolio because of the onset of depression. However, *Jacobsen – Marquering* (*2009*) argued in their response that *Kamstra et al.*'s *(2009*) justification for omitting certain countries was arbitrary and that if the full picture were examined, it would not be clear whether SAD or other seasonality was causing the rise in returns.

Kelly – Meschke (*2010*) contested the study of *Kamstra et al.* (*2003*) mainly from the perspective of psychological impact. The length of the nights used in the original article varies, and it does not show a strong correlation with the actual seasonal depression experienced, i.e. the months when the nights are longest were not the months when people felt the worst. The variable applied by *Kamstra et al.* (*2003*) was, in this case, split into two separate periods, autumn and winter SAD. After re-running the analysis they found that only the winter effect holds and accordingly, the authors believe that the original SAD variable measures the 'turn of the year' effect instead. Responding to the criticism, *Kamstra et al.* (*2012*) stressed that the original model also included a dummy variable for the end of the tax year. They re-ran their models on more sophisticated panel and time-series models, with seasonal depression measured on actual clinical data. Their results further confirmed the original article.

Although the original article has been broadly criticised, recent research appears to support their original findings. *Ruan et al.* (*2018*) found that SAD was the Granger cause of the higher returns on the Chinese stock market. *Škrinjarić* (*2022*) constructed a successful trading strategy on the Zagreb Stock Exchange based on this phenomenon.

Goodell et al. (*2023*) emphasise in their literature review that although the impact of emotions on financial markets is an extensively researched topic, there is a gap in the literature in some respects: it is not clear which emotions will be important for decision-making, nor in what context they occur. In addition, investors may react consciously to certain financial market phenomena: for example, according to some research, the calendar effect (a fall in stock prices in December followed by a rise in January, or lower returns at the beginning of the trading week) is priced in on the market, and emotions have less influence on the decision-making processes of sophisticated investors (*Duxbury et al. 2020*).

2.2. Seasonal depression and risk-taking propensity

The relationship between different weather factors and investor decision-making has been the subject of psychological research for decades (*Goodell et al. 2023*). In a study by *Kamstra et al.* (*2003*), the length of nights is used as an explanatory variable to measure seasonal depression and, through that, the variation in financial market returns. In the following, we present the above study and its findings, including the validity of the methodology.

Research in experimental psychology has shown a direct link between depression and higher-than-average risk aversion (*Zuckerman 1984*, *2007*). Seasonal depression is classified as a specific type of clinical depression by *Leonhardt et al.* (*1994*), i.e. the decline detected by *Zuckerman* (*1984, 2007*) in risk-taking propensity is presumed to apply to people with seasonal depression as well. Depression is a mental illness associated with disturbed levels of serotonin in the brain, and studies have shown depressive changes in certain brain areas when the body is exposed to less sunlight (*Cohen et al. 1992*). According to a study by *Kamstra et al.* (*2003*), seasonal depression may affect about one tenth of the population.

The results of the experiments conducted by *Zuckerman* (*1984*) using the Sensation Seeking Scale developed by the author can be applied to financial decision-making based on *Kamstra et al.* (*2003*). Experiments using the Sensation Seeking Scale find that people with depressive or anxiety disorders have a significantly lower-than-average risk-taking propensity, and the severity of the disorders is directly proportional to the degree of risk aversion (*Kamstra et al. 2003*).

2.2.1. A possible measure of the effect of seasonal depression

Drawing on research on behavioural finance, in their study, *Kamstra et al.* (*2003*) attempted to explore seasonal depression as a prolonged altered emotional state and its impact on the financial market. In their research, they estimated the value of the SAD_t variable based on the length of nights, as subsequently was done by *Joëts* (*2012*) and *Dowling – Lucey* (2008). Both studies found that the model constructed using SAD_t performed the best relative to the use of all sentiment variables.

Kamstra et al. (*2003*) used the length of nights and daily returns as a starting point for the stock indices reviewed by them. In order to properly measure the impact of seasonal depression, the summer months were taken into consideration for stock markets in the Southern Hemisphere. In their study, the authors selected stock market indices from twelve countries for further analysis. The selection took into account the different geographical locations, both in terms of latitude and Northern and Southern Hemispheres. According to the authors, the selected indices are diversified geographically and include stocks with high market capitalisation.

Kamstra et al. (*2003*) applied a first-order autoregressive (AR(1)) model and included several different non-time series variables. For the purposes of the analysis, the most important variable among those was SAD_t, calculated by the authors to capture the level of seasonal depression.

The SAD_t variable was calculated as the length of night normalised by 12 hours. Only two values are needed to determine the length of night: the latitude of the location (σ) and the day of the year ($julian_t$). Spherical trigonometry formulae can then be used to first determine the sun's declination angle (λ_t), using formula (1).

$$\lambda_t = 0.4102 \cdot \sin\left[\frac{2\pi}{365} \cdot (julian_t - 80.25)\right] \tag{1}$$

$$H_t = 24 - 7.72 \cdot \arccos\left[-\tan\left(\frac{2\pi\sigma}{365}\right) \cdot \tan(\lambda_t)\right] \tag{2}$$

Using λ_t, the time between sunset and sunrise at a given latitude for a given trading day, i.e. the length of the night, can be obtained from H_t. In addition to formula (2) for the Northern Hemisphere, an H_t value was also calculated for the Southern Hemisphere, where the second half of the formula is not subtracted from 24. The next step after the calculation of the given H_t is normalisation by 12, which produces the SAD_t variable calculated by *Kamstra et al.* (*2003*)*:*

$$SAD_t = \begin{cases} H_t - 12: for\ trading\ days\ in\ winter\ and\ autumn \\ 0: otherwise \end{cases} \tag{3}$$

In addition to SAD_t, the authors relied on additional binary variables: D_t^A, which controls for asymmetry between autumn and winter, the binary variables D_t^M, which pertains to the effect of Mondays, and D_t^T, which pertains to sales for the purpose of tax cuts; moreover, they controlled for weather-related variables on specific trading days: precipitation (I_t^P), cloud cover(I_t^C) and temperature (I_t^T).

Accordingly, the regression model presented in the study by *Kamstra et al.* (*2003*) applies the following variables: the SAD_t variable, which is estimated from the length of nights, the lagged variable of stock index returns, i.e. $\rho_1 r_{t-1}$, as well as the three D_t binary variables and the weather-related I_t variable. The variables take their values according to the geographic location of the twelve stock exchanges reviewed by the authors.

$$r_t = SAD_t + \rho_1 r_{t-1} + D_t^M + D_t^A + D_t^T + I_t^P + I_t^C + I_t^T + \epsilon_t \tag{4}$$

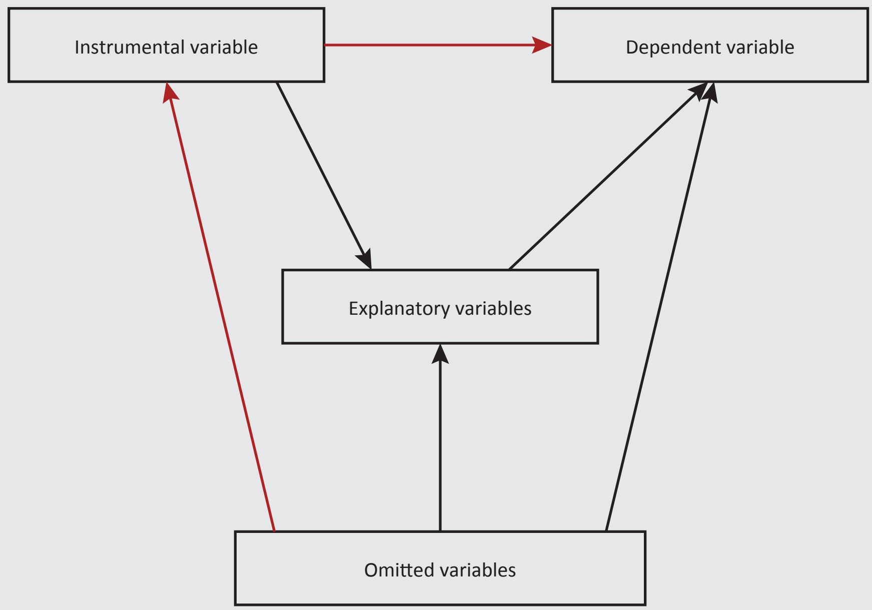
Next, the authors ran regression (4) for each of the twelve index countries selected in their paper. Their results show that the coefficients of the SAD_t variable and the lagged variable are significant for most indices, and for several indices the coefficients of the binary variables are significant, while the weather-related coefficients are typically not. To calculate the seasonal depression returns of the respective indices, *Kamstra et al.* (*2003*) assigned a SAD value to each trading day. The value of SAD_t is obtained by multiplying the coefficient of the SAD_t variable from the regression (4) with the SAD_t variable itself calculated from the length of nights, and averaging it over the year, i.e. assigning a value to each index to reflect the return from seasonal depression. This average annualised return is positive in all countries, ranging from 5.7 to 17.5 per cent, and significant for all indices except for the Australian stock market. Furthermore, it can be stated that countries closer to the equator tend to have a lower average value, with less significant returns attributed to seasonal depression than countries further away from the equator.

From the above, *Kamstra et al.* (*2003*) conclude that the pattern associated with seasonal depression is reflected in the returns on the stock indices under review as expected by the authors. In other words, due to the effect of seasonal depression, risk-averse investors are more likely to avoid risky assets in autumn on average and more likely to invest in riskier assets in winter on average, resulting in lower-than-average stock index returns in autumn and higher-than-average returns after the longest night of the year. It can also be observed that there is a correlation between the significance and magnitude of the effect of seasonal depression and the latitude of the stock exchange. Countries at higher latitudes (where the seasonal variation in the length of nights and days is more extreme) have higher returns and the SAD value is explanatory at a higher significance level on average (*Kamstra et al. 2003*).

2.2.2. The instrumental variable and its conditions of use

Although not discussed specifically in *Kamstra et al.* (*2003*), the methodology they apply corresponds to the use of the instrumental variable's reduced form. The instrumental variable is used for the construction of models in cases where the exogeneity condition for the OLS regression is violated due to an unobserved confounding variable that is not causally related, i.e. there is no independence between the error term and the explanatory variable (*Pearl – Mackenzie 2018*). An instrumental variable is a variable for which the conditions shown in *Figure 1* pertain: (1) the instrumental variable has an effect on the explanatory variable (there is a high correlation between the two, possibly a causal relationship based on specialised knowledge); (2) the instrumental variable has an effect on the dependent variable only indirectly through the explanatory variable; and (3) there is no unobserved confounding variable between the instrumental variable and the dependent variable (*Pearl – Mackenzie 2018*). Accordingly, in *Figure 1*, the existence of the relationships marked in black and the exclusion of the existence of the relationships marked in red describe, in a simple manner, the fulfilment of the instrumental variable's conditions of use.

Figure 1
Causal map with instrumental variable



Source: Based on Pearl – Mackenzie (2018)

If an instrumental variable satisfying the conditions shown in *Figure 1* is available in an analysis, a causal relationship between two variables can be estimated using the two-stage least squares method. In order to do this, we first need to estimate the biased explanatory variable of our hypothesis using the instrumental variable in an OLS regression where the explanatory variable is explained by the inclusion of the instrumental variable, as we assume that the instrumental variable gives a more accurate value for the original explanatory variable. The resulting estimated coefficients are then substituted into the original model in place of the original explanatory variable to run the second OLS regression, which no longer violates the exogeneity assumption and captures a causal relationship (*Pearl – Mackenzie 2018*).

However, in their paper *Kamstra et al.* (*2003*) do not use a two-stage least squares method to estimate the effect of seasonal depression on returns; instead, they apply a reduced form as they estimate the returns on stock indices directly from the instrumental variable (SAD_t). The reduced form of the model that includes the instrumental variable can be used primarily as a model diagnostic tool to test the relevance of the use of the instrumental variable (*Pesaran – Taylor 1999*).

3. Measuring the effect of seasonal depression

3.1. Data applied in the analysis

As the research of *Kamstra et al.* (*2003*) is an important part of the literature and investigates an easy-to-describe cognitive bias, it is worth examining in more detail. Moreover, as *Goodell et al.* (*2023*) pointed out, articles focusing on Europe account for roughly 12 per cent of all studies on investor sentiment and finance; therefore, later in our paper we will examine the way in which the explanatory power of seasonal depression can be applied to the European financial market in particular.

Our analysis is focused on the stock market indices of seven countries. These include the stock indices applied by *Kamstra et al.* (*2003*) and two indices from the Central European markets, namely, the Polish WIG and the Czech PX stock indices. For the latter two countries, *Škrinjarić* (*2018*) found no significant relationship between SAD and returns.

For the selection, we considered the volume of trading on the specific stock exchange and its location; consequently, a total of two US and five European stock indices are included in the analysis. All indices are weighted by capital value. The US indices are included in the analysis in order to verify the effect described by *Kamstra et al.* (*2003*) in a reproduction attempt, and the rest of the indices are used to examine the effect of seasonal depression in Europe, in particular in Central Europe.

Table 1 summarises the cities and corresponding latitudes for the selected indices. Latitudes were taken from the simplemaps database,[1] and values are rounded up as in the case of *Kamstra et al.* (*2003*). Daily returns for each index were obtained using the quantmod package constructed by *Ryan – Ulrich* (*2022*) for the RStudio software.

Table 1
Indices selected for the analysis

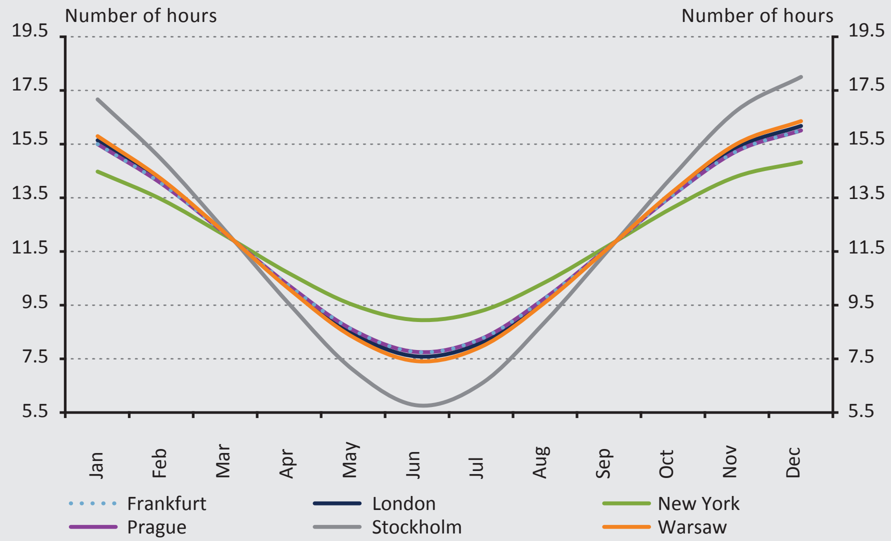
Country	Index	City	Latitude	Review period
United States	S&P 500	New York	41°N	01.12.1983–14.04.2023
United States	NASDAQ	New York	41°N	31.01.1985–14.04.2023
United Kingdom	FTSE 100	London	51°N	03.01.1989–14.04.2023
Germany	DAX	Frankfurt	50°N	04.01.1988–14.04.2023
Sweden	OMX	Stockholm	59°N	20.11.2008–14.04.2023
Poland	WIG	Warsaw	52°N	30.04.2013–01.10.2021
Czech Republic	PX	Prague	50°N	30.04.2013–01.10.2021

Source: Based on simplemaps

[1] https://simplemaps.com/data/world-cities. Downloaded: 28 February 2023.

In consideration of the latitude and the trading days, the length of the nights associated with specific trading days was determined using the spherical trigonometry formulae [(1) and (2)] described above. *Figure 2* displays the variation in the length of night by city, broken down by month, as determined by spherical trigonometry. The values displayed are smoothed, but for the purposes of subsequent calculations, the discrete values associated with specific trading days are applied. As demonstrated by the Figure, there is no significant difference for stock exchanges that are geographically close to each other (Prague, Frankfurt, Warsaw).

Figure 2
Length of nights for each stock exchange



Note: Calculated using the spherical trigonometry formula

Table 2 shows simple descriptive statistics for the stock market indices selected for analysis. The number of observations for the Swedish OMX, Polish WIG and Czech PX indices is significantly lower than the number of observations for the rest of the indices, but does not differ significantly from the index with the lowest number of observations used by *Kamstra et al.* (*2003*).

Table 2
Descriptive statistics with returns expressed in percentages

Indices	Sample size	Mean	Standard deviation	Min	Max	Skewness	Kurtosis
S&P500	9,923	0.04	1.15	–20.47	11.58	–0.76	22.88
NASDAQ	9,628	0.05	1.41	–12.32	14.17	–0.12	11.08
FTSE 100	8,659	0.02	1.10	–10.87	9.84	–0.14	10.32
DAX	8,919	0.04	1.40	–13.14	11.40	–0.11	9.44
OMX	3,612	0.05	1.29	–10.57	10.37	–0.04	8.63
WIG	2,024	0.03	1.09	–12.65	5.80	–1.05	15.67
PX	2,027	0.02	0.94	–7.84	7.65	–0.76	12.80

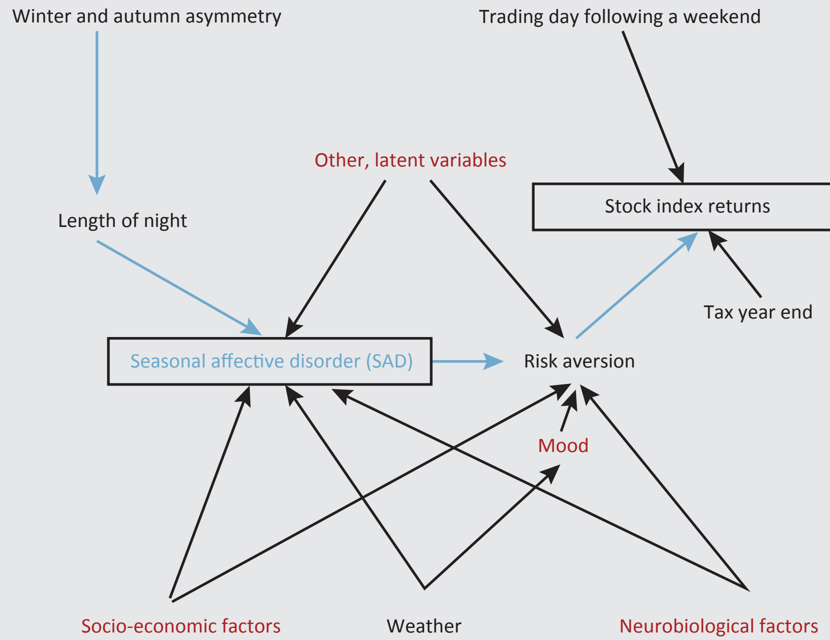
Source: Based on data from the Quantmod package (Ryan – Ulrich 2022)

We did not use completely overlapping trading periods partly because of the specificities of the quantmod package constructed by *Ryan – Ulrich* (*2022*), and partly because the data are much more recent than those observed in *Kamstra et al.* (*2003*). However, as expected, the descriptive statistics take similar values for each index; for example, returns are negatively skewed for all indices.

3.2. Methodology applied for the analysis

In order to construct the model required for estimating the effect of seasonal depression on the returns of the selected indices, we relied on the causal map shown in *Figure 3*, which can be used to plot different causal and non-causal paths, and also provides a clear summary of the variables associated with the phenomenon to be analysed as described by *Pearl – Mackenzie* (*2018*). In *Figure 3*, the causal path (i.e. the relationship whose effect we wish to estimate with the model) is indicated by blue arrows, and unobservable variables are presented in red. Some of the variables in the causal path are primarily based on the variables used in *Kamstra et al.* (*2003*); however, when placed on the causal map, it appears that their study controls for some variables redundantly.

Figure 3
Causal map associated with the model used for the analysis



Note: Unobservable variables in red, instrumental variables and causal path in blue.
Source: Based on Kamstra et al. (2003) and Pearl – Mackenzie (2018)

For example, one such variable is the asymmetry around the winter solstice, for which the D_t^A binary variable was included in the regression model. In fact, this variable has no indirect effect on stock index returns in itself; instead, it acts through the length of the night; consequently, controlling for it will yield a biased result. For seasonal depression and risk-taking propensity, we can see variables that affect both but cannot be observed. These are the variables that we should control for if they were observable; however, either the data are insufficient or the variables cannot be adequately quantified, such as neurobiological characteristics which, based on the literature, have a clear effect on the onset and magnitude of seasonal depression and also on the level of individual risk-taking propensity (*Zuckerman 1984*).

However, for lack of that option, we estimate the effect of seasonal depression using the instrumental variables method mentioned above, as indeed, the causal map demonstrates that all three conditions for doing so are present. Namely, (1) the length of nights affects the explanatory variable, i.e. seasonal depression;

(2) the length of nights affects stock index returns only indirectly through seasonal depression; and (3) there is no unobserved confounding variable between the length of nights and stock index returns. The causal map will thus enable us to verify the use of the SAD_t variable calculated from the length of nights by *Kamstra et al.* (*2003*) as an explanation of stock index returns, as in this case the length of nights means the instrumental variable used to estimate the size of the seasonal depression.

However, it is necessary to control for the D_t^T variable related to the close of the fiscal year and for the D_t^M variable implying the first trading day of the week, as presumably they affect returns directly rather than through risk-taking propensity. The causal map therefore enables us to estimate the effect of seasonal depression on returns more accurately, without endogeneity, by way of regression (5) below through influencing risk-taking propensity:

$$r_t = SAD_t + \rho_1 r_{t-1} + D_t^M + D_t^T + \epsilon_t \tag{5}$$

where SAD_t is the instrumental variable calculated from the length of nights, $\rho_1 r_{t-1}$ is the return lagged by one day, D_t^M is the first trading day of the week, and D_t^T is the variable associated with the close of the fiscal year.

4. Analysis of the effect of seasonal depression on financial markets

In this Section, in our analysis of the effect of seasonal depression on financial markets, we present the results of an estimation with a modified model compared to the one applied by *Kamstra et al.* (*2003*). Similar to the authors, we found a statistically significant relationship for three of the seven stock indices in our analysis. The findings also confirm that the issue is worthy of deeper analysis, and that even a causal relationship may well be observed with additional observations.

4.1. Findings and comparison

Although the causal map and the results obtained by *Kamstra et al.* (*2003*) both suggest that the inclusion of the variable related to the end of the fiscal year should be important to obtain a better estimate of stock market returns, this variable was not included in the final model because we did not have the resources required for calculating the values included in the variable. Consequently, the final model is the following:

$$r_t = SAD_t + \rho_1 r_{t-1} + D_t^M + \epsilon_t \tag{6}$$

Table 3 is obtained after regressing equation (6) on stock returns by country and includes all the coefficients for the stock indices included in the analysis except for the two Central European indices. The coefficient of the SAD_t variable is significant for all indices except for the returns on the S&P 500 and the OMX index.

Robust standard errors are estimated both in *Tables 3* and *4.* Comparing *Table 3* with the results obtained by *Kamstra et al.* (*2003*), there is a clear difference in the magnitude and significance of the coefficient associated with the SAD_t variable. The coefficient will be significant for NASDAQ, FTSE 100 and DAX with a p-value of at least 10 per cent. The coefficient associated with the D_t^M variable, which represents the start of the trading week, is negative for all indices except one, but will only be significant for NASDAQ (at a p-value of 1 per cent). The F-statistics will be significant at a p-value of at least 10 per cent in all cases except FTSE 100.

However, it should be noted that for DAX we obtained very similar results in terms of the magnitude of the coefficient. In the study by *Kamstra et al.* (*2023*), the coefficient of the SAD variable is 0.025, while in our current calculations it is 0.023.

For each trading day, we calculate the value of the SAD variable, multiply it by the coefficients obtained from the regression equation, and annualise the resulting return to obtain the annual return arising from seasonal depression. For example, *Kamstra et al.* (*2003*) calculated 8.2 per cent for DAX. According to our results, the return from seasonal depression is 7.98 per cent for Germany, 4.2 per cent for the UK and 5.43 per cent for NASDAQ. In other words, returns are that much higher relative to a situation without seasonal depression. These are very high values considering that the daily returns in *Table 2* correspond to annual returns of around 10, 5 and 12.5 per cent, respectively. However, the Monday effect, although significant in only one case, is associated with a negative sign and thus reduces annual returns.

Overall, of the indices included in *Table 3*, only NASDAQ shows a significant SAD_t coefficient and a strong F-statistic and accordingly, it is in the case of NASDAQ that the model is assumed to best capture the effect of seasonal depression on the risk-taking propensity reflected in stock returns.

Table 3
Regression results for selected stock indices in the US and Europe with robust standard errors

	Dependent variable:				
	Daily returns (per cent)				
	(S&P 500)	(NASDAQ)	(FTSE 100)	(DAX)	(OMX)
SAD_t	0.017 (0.010)	0.027** (0.013)	0.013* (0.007)	0.023** (0.009)	0.010 (0.009)
D_t^M	–0.033 (0.033)	–0.112*** (0.039)	–0.020 (0.033)	0.033 (0.041)	–0.024 (0.060)
Lagged variable	–6.566*** (2.286)	–1.772 (2.048)	–1.447 (1.862)	–1.198 (1.590)	–5.294** (2.463)
Constant	0.034** (0.015)	0.049*** (0.019)	0.010 (0.016)	0.007 (0.020)	0.034 (0.030)
Number of observations	9,922	9,627	8,658	8,918	3,611
R^2	0.005	0.002	0.001	0.001	0.003
Adjusted R^2	0.004	0.001	0.0003	0.001	0.002
F-statistics	15.443***	5.386***	1.795	2.505*	3.778**

*Note: *p<0,1; **p<0,05;***p<0,01.*
Source: Based on data from the Quantmod package (Ryan – Ulrich 2022)

Table 4 summarises the results of equation (6) run for the daily returns of the Polish and Czech WIG and PX indices. Apparently (with one exception), none of the coefficients associated with any of the variables will be significant, nor will the F-statistics be significant at a p-value of 5 per cent or above. It is likely that the effect of seasonal depression on returns cannot be detected through regression because the number of daily returns available for both countries is significantly smaller than for major stock markets.

This may also be supported by the fact that the SAD_t coefficient of OMX, which also has few observations on daily returns, did not turn out to be significant. In addition, it is possible that market integration is even greater, or that asymmetric returns are priced in on the market, or the analysis may not have taken into consideration an equity index or certain country-specific characteristics.

Table 4
Regression results for selected stock indices in Central Europe with robust standard errors

	Dependent variable:	
	Daily returns (per cent)	
	(WIG)	(PX)
SAD_t	0.002 (0.014)	0.011 (0.014)
D_t^M	0.084 (0.068)	0.006 (0.054)
Lagged variable	5.001 (4.683)	0.0001 (0.0002)
Constant	0.010 (0.032)	0.007 (0.028)
Number of observations	2,023	2,026
R^2	0.003	0.0004
Adjusted R^2	0.002	–0.001
F-statistics	2.247*	0.273

*Note: *p<0.1; **p<0.05; ***p<0.01.*
Source: Based on data from the Quantmod package (Ryan – Ulrich 2022)

5. Summary

As the results of the literature presented demonstrate, research focusing on investor sentiment and various seasonal patterns is a particularly important subfield of behavioural finance. Investor sentiment and seasonality may provide additional information, for example in financial market analyses, which may well make this approach a component of a successful investment strategy. Moreover, taking into consideration investor sentiment and observable seasonal effects may enable researchers to explain market anomalies that classical finance has previously observed, but failed to explain.

The results from the literature on sentiment and seasonal effects aptly demonstrate that, as we intend to explore the relationship between variables that are difficult to quantify and test, we need to be careful in our analysis. In addition to the empirical analysis, it is advisable to focus on processing subject-specific insight relevant to the analysis. Different statistically significant relationship analyses should be examined from different perspectives, as they do not necessarily explain causality on their own.

The analysis and reproduction of the Kamstra model suggests that the SAD_t variable applied in the model may be suitable to describe the effect of seasonal depression, as it showed a statistically significant relationship in the model constructed to explain the returns on several stock indices. Since in this form, the variable is used as a reduced form of the instrumental variable, no causal relationship can be detected between the reduced risk aversion reflected in stock market returns and the degree of seasonal depression.

We found significant effects on a long-term yet relatively recent database of three major stock exchanges (NASDAQ, UK, Germany). Since Škrinjarić found that a profitable trading strategy could be developed based on the SAD phenomenon on the Croatian stock market, our analysis may be used as a basis for further investigations on these three stock markets to see whether such portfolios can be established in their case.

Given the methodological soundness of the original paper and in consideration of the significant relationship, the analysis suggests that a causal relationship may well be measured by including observations regarding the magnitude of seasonal depression. The SAD_t variable may be used as a proxy to explain stock market returns for selected stock indices. Nevertheless, for a more extensive relational and causal analysis, the model needs to be developed further, and the application of a more complex time series approach is required. Moreover, by including more stock returns and applying the fiscal year variable, the effect of seasonal depression may be investigated further for the Central European stock market.

Our research provides useful information not only for academic researchers, but also for managers of financial companies, especially in the three affected countries we identified. Since seasonal depression is calculated to be responsible for 4 to 8 per cent of annual returns, it may be worthwhile to reduce risk aversion among employees by improving their working conditions. There are numerous ways to reduce seasonal depression that companies can offer to their employees (light therapy, vitamin D, psychological counselling, etc.). This may be the subject of a new research project.

References

Arkes, H.R. – Herren, L.T. – Isen, A.M. (1988): *The role of potential loss in the influence of affect on risk-taking behavior*. Organizational Behavior and Human Decision Processes, 42(2): 181–193. https://doi.org/10.1016/0749-5978(88)90011-8

Barberis, N.C. (2013*): Thirty years of prospect theory in economics: A review and assessment*. Journal of Economic Perspectives, 27(1): 173–196. https://doi.org/10.1257/jep.27.1.173

Barberis, N. – Thaler, R. (2003): *Chapter 18 a survey of behavioral finance*. In: Constantinides, G.M. – Harris, M. – Stulz, R.M. (eds.): Handbook of the Economics of Finance (Vol. 1, Part B.). Elsevier, Amsterdam, pp. 1053–1128. https://doi.org/10.1016/S1574-0102(03)01027-6

Cao, M. – Wei, J. (2005): *Stock market returns: A note on temperature anomaly*. Journal of Banking & Finance, 29(6): 1559–1573. https://doi.org/10.1016/j.jbankfin.2004.06.028

Chundakkadan, R. – Nedumparambil, E. (2022): *In search of COVID-19 and stock market behavior*. Global Finance Journal, 54, 100639. https://doi.org/10.1016/j.gfj.2021.100639

Cohen, R.M. – Gross, M. – Nordahl, T.E. – Semple, W.E. – Oren, D.A. – Rosenthal, N. (1992): *Preliminary data on the metabolic brain pattern of patients with winter seasonal affective disorder*. Archives of General Psychiatry, 49(7): 545–552. https://doi.org/10.1001/archpsyc.1992.01820070039006

De Bondt, W.F. – Thaler, R. (1985): *Does the stock market overreact?* The Journal of Finance, 40(3): 793–805. https://doi.org/10.1111/j.1540-6261.1985.tb05004.x

Dowling, M. – Lucey, B.M. (2008): *Robust global mood influences in equity pricing*. Journal of Multinational Financial Management, 18(2): 145–164. https://doi.org/10.1016/j.mulfin.2007.06.002

Duxbury, D. – Gärling, T. – Gamble, A. – Klass, V. (2020): *How emotions influence behavior in financial markets: a conceptual analysis and emotion-based account of buy-sell preferences*. The European Journal of Finance, 26(14): 1417–1438. https://doi.org/10.1080/1351847X.2020.1742758

Fama, E.F. (1970): *Efficient market hypothesis: A review of theory and empirical work*. Journal of Finance, 25(2): 28–30. https://doi.org/10.2307/2325486

Fömötör, B. – Parádi-Dolgos, A. – Sipiczki, Z. (2017): *Behavioural Finance and Consumer Loan Contracts.* Financial and Economic Review, 16(2): 156–169. https://doi.org/10.25201/FER.16.2.156169

Golovics, J. (2015): *Bounded rationality and altruism: behaviourism in economics*. Financial and Economic Review, 14(2): 158–172. https://en-hitelintezetiszemle.mnb.hu/letoltes/6-golovics-en.pdf

Goodell, J.W. – Kumar, S. – Rao, P. – Verma, S. (2023): *Emotions and stock market anomalies: A systematic review.* Journal of Behavioral and Experimental Finance, 37, 100722. https://doi.org/10.1016/j.jbef.2022.100722

Hirshleifer, D. – Shumway, T. (2003): *Good day sunshine: Stock returns and the weather*. The Journal of Finance, 58(3): 1009–1032. https://doi.org/10.1111/1540-6261.00556

Jacobsen, B. – Marquering, W. (2008): *Is it the weather?* Journal of Banking & Finance, 32(4): 526–540. https://doi.org/10.1016/j.jbankfin.2007.08.004

Jacobsen, B. – Marquering, W. (2009): *Is it the weather? Response.* Journal of Banking & Finance, 33(3): 583–587. https://doi.org/10.1016/j.jbankfin.2008.09.011

Joëts, M. (2012): *Mood-misattribution effect on energy finance: A biorhythm approach*. In: Barnett, W.A. – Jawadi, F. (eds.): Recent Developments in Alternative Finance: Empirical Assessments and Economic Implications (International Symposia in Economic Theory and Econometrics, Vol. 22). Emerald Group Publishing Limited, Bingley, pp. 213–233. https://doi.org/10.1108/S1571-0386(2012)0000022016

Johnson, E.J. – Tversky, A. (1983): *Affect, generalization, and the perception of risk*. Journal of Personality and Social Psychology, 45(1): 20–31. https://doi.org/10.1037/0022-3514.45.1.20

Kamstra, M.J. – Kramer, L.A. – Levi, M.D. (2003*): Winter Blues: A Sad Stock Market Cycle*. American Economic Review, 93(1): 324–343. https://doi.org/10.1257/000282803321455322

Kamstra, M.J. – Kramer, L.A. – Levi, M.D. (2009): *Is it the weather? Comment*. Journal of Banking & Finance, 33(3): 578–582. https://doi.org/10.1016/j.jbankfin.2008.09.013

Kamstra, M.J. – Kramer, L.A. – Levi, M.D. (2012): *A careful re-examination of seasonality in international stock markets: Comment on sentiment and stock returns*. Journal of Banking & Finance, 36(4): 934–956. https://doi.org/10.1016/j.jbankfin.2011.10.010

Kelly, P.J. – Meschke, F. (2010): *Sentiment and stock returns: The SAD anomaly revisited*. Journal of Banking & Finance, 34(6): 1308–1326. https://doi.org/10.1016/j.jbankfin.2009.11.027

Kuhnen, C.M. – Knutson, B. (2011): *The influence of affect on beliefs, preferences, and financial decisions*. Journal of Financial and Quantitative Analysis, 46(3): 605–626. https://doi.org/10.1017/S0022109011000123

Kutasi, G. – György, L. – Szabó, K. (2018): *Behavioural Factors in the Hungarian Retail Government Bond Market*. Financial and Economic Review, 17(1): 110–136. https://doi.org/10.25201/FER.17.1.110136

Lakatos, M. (2016): *A befektetői túlreagálás empirikus vizsgálata a Budapesti értéktőzsdén* (*An empirical test for investor over-reaction on the Budapest stock exchange*). Közgazdasági Szemle (Economic Review), 63(7–8): 762–786. https://doi.org/10.18414/KSZ.2016.7-8.762

Lanfear, M.G. – Lioui, A. – Siebert, M.G. (2019): *Market anomalies and disaster risk: Evidence from extreme weather events.* Journal of Financial Markets, 46, 100477. https://doi.org/10.1016/j.finmar.2018.10.003

Leonhardt, G. – Wirz-Justice, A. – Kräuchi, K. – Graw, P. – Wunder, D. – Haug, H.-J. (1994): L*ong-term follow-up of depression in seasonal affective disorder*. Comprehensive Psychiatry, 35(6): 457–464. https://doi.org/10.1016/0010-440X(94)90229-1

Loewenstein, G.F. – Weber, E.U. – Hsee, C.K. – Welch, N. (2001): *Risk as feelings*. Psychological Bulletin, 127(2): 267–286. https://doi.org/10.1037/0033-2909.127.2.267

Markowitz, H. (1952): *The utility of wealth*. Journal of Political Economy, 60(2): 151–158. https://doi.org/10.1086/257177

Miller, M.H. – Modigliani, F. (1961): *Dividend policy, growth, and the valuation of shares.* Journal of Business, 34(4): 411–433. https://doi.org/10.1086/294442

Molnár, M.A. (2006): *A hatékony piacokról szóló elmélet kritikái és empirikus tesztjei* (*Critiques and empirical tests of the efficient markets theory*). Hitelintézeti Szemle, 5(3): 44–62. https://www.bankszovetseg.hu/Content/Hitelintezeti/04.pdf

Naffa, H. (2009): *Eszközárazási anomáliák többváltozós modellje* (*A multivariate model of asset pricing anomalies*). Hitelintézeti Szemle, 8(6): 516–527. https://www.bankszovetseg.hu/Content/Hitelintezeti/HSZ6_2009_naffa_helena.pdf

Nagy, B. – Ulbert, J. (2007): *Tőkepiaci anomáliák* (*Stock market anomalies*). Statisztikai Szemle (Hungarian Statistical Review), 85(12): 1013–1032. https://www.ksh.hu/statszemle_archive/2007/2007_12/2007_12_1013.pdf

Neszveda, G. (2018): *The Contribution of Thaler to Behavioural Economics*. Financial and Economic Review, 17(1): 153–167. http://doi.org/10.25201/FER.17.1.153167

Palinkas, L.A. – Wong, M. (2020): *Global climate change and mental health*. Current Opinion in Psychology, 32: 12–16. https://doi.org/10.1016/j.copsyc.2019.06.023

Pearl, J. – Mackenzie, D. (2018): *The Book of Why: the New Science of Cause and Effect*. Basic Books, New York.

Pesaran, M.H. – Taylor, L.W. (1999): *Diagnostics for iv regressions*. Oxford Bulletin of Economics and Statistics, 61(2): 255–281. https://doi.org/10.1111/1468-0084.00128

Peillex, J. – El Ouadghiri, I. – Gomes, M. – Jaballah, J. (2021): *Extreme heat and stock market activity*. Ecological Economics, 179, 106810. https://doi.org/10.1016/j.ecolecon.2020.106810

Ruan, Q. – Zhang, M. – Lv, D. – Yang, H. (2018): *SAD and stock returns revisited: Nonlinear analysis based on MF-DCCA and Granger test.* Physica A: Statistical Mechanics and its Applications, 509: 1009–1022. https://doi.org/10.1016/j.physa.2018.06.075

Ryan, J.A. – Ulrich, J.M. (2022): *quantmod: Quantitative financial modelling framework* [Computer software manual]. (R package version 0.4.20). https://www.quantmod.com/. Downloaded: 3 March 2022.

Shanaev, S. – Shuraeva, A. – Fedorova, S. (2022): *The Groundhog Day stock market anomaly*. Finance Research Letters, 47(Part A), 102641. https://doi.org/10.1016/j.frl.2021.102641

Škrinjarić, T. (2018): *Testing for Seasonal Affective Disorder on Selected CEE and SEE Stock Markets*. Risks, 6(4), 140. https://doi.org/10.3390/risks6040140

Škrinjarić, T. (2022): *Let's make some profits on seasonal depression on the stock market.* Zbornik Radova, 28: 7–36. https://doi.org/10.46458/27121097.2022.28.7

Škrinjarić, T. – Marasović, B. – Šego, B. (2021): *Does the Croatian Stock Market Have Seasonal Affective Disorder?* Journal of Risk and Financial Management, 14(2), 89. https://doi.org/10.3390/jrfm14020089

Slovic, P. – Finucane, M.L. – Peters, E. – MacGregor, D.G. (2004): *Risk as analysis and risk as feelings: Some thoughts about affect, reason, risk, and rationality*. Risk Analysis, 24(2): 311–322. https://doi.org/10.1111/j.0272-4332.2004.00433.x

Subramaniam, S. – Chakraborty, M. (2021): *Covid-19 fear index: does it matter for stock market returns?* Review of Behavioral Finance, 13(1): 40–50. https://doi.org/10.1108/RBF-08-2020-0215

Thaler, R.H. (1999): *The end of behavioral finance*. Financial Analysts Journal, 55(6): 12–17. https://doi.org/10.2469/faj.v55.n6.2310

Tversky, A. – Kahneman, D. (1974*): Judgment under Uncertainty: Heuristics and Biases: Biases in judgments reveal some heuristics of thinking under uncertainty*. Science, 185(4157): 1124–1131. https://doi.org/10.1126/science.185.4157.1124

Zuckerman, M. (1984): *Experience and desire: A new format for sensation seeking scales*. Journal of Behavioral Assessment, 6: 101–114. https://doi.org/10.1007/BF01350166

Zuckerman, M. (2007): *The sensation seeking scale V (SSS-V): Still reliable and valid*. Personality and Individual Differences, 43(5): 1303–1305. https://doi.org/10.1016/j.paid.2007.03.021