BULLETIN
OF
ECONOMIC THEORY AND ANALYSIS

Journal homepage: https://dergipark.org.tr/tr/pub/beta

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To cite this article: Ergün, Z., C. (2024). Seasonal Affective Disorder (SAD) on Borsa Istanbul. *Bulletin of Economic Theory and Analysis*, *9*(1), 71-88.

Received: 10 Jul 2023

Accepted: 10 Oct 2023

Published online: 29 Feb 2024

Bulletin of Economic Theory and Analysis

Volume 9, Issue 1, pp. 71-88, 2024

https://dergipark.org.tr/tr/pub/beta

Original Article / Araştırma Makalesi

Received / Alınma: 10.07.2023 Accepted / Kabul: 10.10.2023

Seasonal Affective Disorder (SAD) on Borsa Istanbul

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ABSTRACT

Seasonal Affective Disorder (SAD) is a severe depression that stems from the decreased daylight hours in the autumn and winter. The SAD makes investors more risk-averse, which in turn affects the financial markets. This study aims to examine the effect of SAD on Borsa Istanbul (BIST) for the period January 2015 - May 2023. The BIST-100 index is used to represent the overall stock market, and the BIST-Industrials, Financials, Technology, and Food Beverage indices are used to evaluate any sectoral disparities. Furthermore, autumn, tax-loss selling, Mondays, and COVID-19 outbreak effects are included in the model. The results show that there is a statistically significant and positive SAD effect on BIST-100 index returns. The SAD also has an impact on every sectoral index, except for BIST-Food Beverage. Moreover, there is no asymmetrical effect of the autumn in any indices. Among the control variables, the Monday effect is determined to be statistically significant and positive for BIST-100, BIST-Industrials, and BIST-Technology indices. Finally, only for the BIST-Industrials index the COVID-19 dummy is statistically significant and positive. Additionally, the GARCH model has also been used as a robustness test, and consistent findings with the previous analysis are found.

Keywords
Seasonal Affective Disorder, Seasonal Anomalies, Behavioral Finance, Borsa Istanbul

JEL Classification
G10, G40, G41

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Borsa İstanbul'da Mevsimsel Duygulanım Bozukluğu

ÖZ

Mevsimsel Duygulanım Bozukluğu (SAD), sonbahar ve kış aylarında gün ışığının azalmasından kaynaklanan şiddetli bir depresyondur. SAD, yatırımcıları daha riskten kaçınır hale getirmekte ve bu da finansal piyasaları etkilemektedir. Bu çalışma, SAD'nin Borsa İstanbul (BIST) üzerindeki etkisini Ocak 2015 - Mayıs 2023 dönemi için incelemeyi amaçlamaktadır. BIST-100 endeksi genel hisse senedi piyasasını temsil etmek için, BIST-Sınai, Mali, Teknoloji ve Gıda İçecek endeksleri ise sektörel farklılıkları değerlendirmek için kullanılmıştır. Ayrıca sonbahar, vergi kaybı satışı, pazartesi günleri ve COVID-19 salgını etkileri de modele dahil edilmiştir. Sonuçlar, BIST-100 endeks getirileri üzerinde istatistiksel olarak anlamlı ve pozitif bir SAD etkisi olduğunu göstermektedir. SAD, BIST-Gıda İçecek hariç tüm sektörel endeksler üzerinde de etkili olmaktadır. Ayrıca, hiçbir endekste sonbaharın asimetrik etkisi görülmemektedir. Kontrol değişkenlerinden Pazartesi etkisinin BIST-100, BIST-Sınai ve BIST-Teknoloji endeksleri için istatistiksel olarak anlamlı ve pozitif olduğu tespit edilmiştir. Son olarak, sadece BIST-Sınai endeksi için COVID-19 kuklası istatistiksel olarak anlamlı ve pozitiftir. Ayrıca, sağlamlık testi olarak GARCH modeli de kullanılmış ve önceki analizlerle tutarlı bulgular elde edilmiştir.

Anahtar Kelimeler
Mevsimsel Duygulanım Bozukluğu, Mevsimsel Anomaliler, Davranışsal Finans, Borsa İstanbul

JEL Kodu
G10, G40, G41

1. Introduction

Seasonal Affective Disorder (SAD) is a kind of major depression, which is commonly known as winter depression. During the winter, when there are fewer daylight hours, this kind of depression usually appears. The longer nights make people more pessimistic, which may cause severe depression, sleep disorders, concentration problems, and anxiety and in turn, impacts individuals' propensity for taking risks (Lu & Chou, 2012). During these times, the risk aversion of the individuals tends to be sharpened (Garrett et al., 2005). The SAD effect starts at the beginning of autumn (the 21st of September) and decreases until the end of the winter (the 21st of March). The effect is more apparent in countries with extreme latitudes, such as Sweden and Australia (Hammami & Abaoub, 2011; Kamstra et al., 2003).

According to Kamstra et al. (2003), investing decisions may vary as a result of investors' higher risk aversion in the fall and winter, which could have an impact on the stock market. Based on this premise, they investigated how the SAD affected the financial markets of various countries, and the findings were consistent with the theory that the SAD affects stock returns. Kamstra et al. (2003) argued that at the beginning of autumn, investors' risk aversion is at its peak, and they tend to avoid risky investments by preferring safer assets. As a result, the returns are lower in the fall until the longest night of the year. However, as their depression tends to be diminished at the end of winter, investors buy back their risky assets over the winter, which results in higher returns on the stock markets (Kamstra et al., 2003). This type of stock market seasonality contradicts the Efficient Market Hypothesis (EMH) of Eugene Fama (1970). According to the EMH, it is impossible to predict future prices by analyzing historical data. However, by taking advantage of SAD's predominance on particular days in the financial markets, investors may be able to exceed the market. EMH also makes the supposition that stock market participants are rational and that their emotions have no impact on stock prices. However, behavioral finance implies that investors' optimism and pessimism levels may have a major impact on the financial markets, supporting the likelihood that SAD will have a large impact. In light of these arguments, many studies examined the effect of SAD on various stock market returns (i.e., Gerlach, 2010; Raut and Kumar, 2020; Ruan et al., 2018; Skrinjarić, 2018; Skrinjarić et al., 2021). However, to the author's knowledge, the SAD effect has previously been studied for the Turkish stock exchange only in a multi-country context, and the findings are not particularly clear. For that reason, the primary goal of this study is to figure out how the SAD has affected Borsa Istanbul (BIST). Furthermore, not all industries may be affected by these anomalies, their effects can vary depending on the sectors, or investors' emotional reactions might change depending on the industry. Prior research that examined investor sentiment on a sectoral basis supported that conclusion (such as Uygur & Taş, 2014; Khan et al., 2020; Niu et al., 2021). Additionally, plenty of research observed variations in sectors for seasonal anomalies (i.e., Jacobsen & Visaltanachoti, 2009; Mbululu & Chipeta, 2012; Carrazedo et al., 2016; Musnadi et al., 2018), but not for SAD. For that reason, the second aim of this study is to reveal whether the SAD effect differs based on the sectors.

The contribution of this study is threefold. First, by extending the time frame from January 2015 to May 2023, the SAD effect is investigated on the BIST-100 index, which is the primary stock index used to reflect the entire market. Second, the SAD effect is analyzed for the BIST-Industrials, Financials, Technology, and Food Beverage to investigate any sectoral differences. Third, following Kamstra et al. (2003) some control variables such as the autumn effect, tax-loss selling effect, and Monday effect are included in the model. Additionally, the influence of the COVID-19 epidemic is also controlled following Skrinjarić et al. (2021).

The next sections of the study will first summarize the related literature. Second, the data and methodology will be explained. Third, the empirical results will be discussed. Finally, the paper concludes with a discussion and the implications of the findings.

2. Literature Summary

In the literature, although numerous types of research about stock market anomalies have been conducted (i.e., Cao & Wei, 2005; Durham, 2001; Wuthisatian, 2022), the studies about the impact of SAD on the stock markets are fewer. Kamstra et al. (2003) were the first to bring up the idea that this mental disorder may impact investors' behavior throughout particular periods of the year, which may then affect stock returns. Their research examined how SAD affected the financial markets of various countries, in both the southern and northern hemispheres. They observed a substantial SAD impact on stock markets, highlighting that countries in higher latitudes have a more severe SAD effect (Kamstra et al., 2003). Following the calculation and findings of Kamstra et al. (2003) several studies investigated the SAD effect on different stock markets which are summarized in Table 1.

Table 1

Literature Summary

Author(s)	Countries	Period	SAD Effect
Garrett et al. (2005)	The USA, Sweden, New Zealand, the UK, Japan, Australia	1962-2000	Yes
Bhattarai & Joshi (2007)	Nepal	1995-2005	No
Jacobsen & Marquering (2008)	48 Countries	1970-2004	No
Gerlach (2010)	The USA	1992-2005	No
Hammami & Abaoub (2011)	Tunisia	1998-2008	No
Stefanescu & Dumitriu (2011)	Romania	2002-2011	Yes
Lu & Chou (2012)	China	2003-2008	Yes, for Turnover and Liquidity
Frühwirth & Sögner (2015)	The USA	2002-2006	No
Murgea (2016)	Romania	2000-2014	Yes
Ruan et al. (2018)	China	2006-2016	Yes
Skrinjarić (2018)	11 Countries	2010-2018	Yes for 6 markets
Magnusson (2019)	75 Countries	2000-2014	Weak

Thach et al. (2019)	Vietnam	2002-2017	Yes
Kapalczynski (2022)	34 Countries	1973-2015	Yes
Raut & Kumar (2020)	India	2003-2016	Yes (summer type SAD)
Skrinjarić et al. (2021)	Crotia	2010-2021	Yes

Similar to Kamstra et al. (2003), a few studies examined the SAD effect in a multi-country context. By incorporating the Capital Asset Pricing Model (CAPM), Garrett et al. (2005) evaluated the SAD effect on six different stock markets and found that the SAD has an impact on the price of risk. This outcome supports the claim that during the winter months, investors are more risk averse. Additionally, Skrinjarić (2018) investigated the impact of SAD on the returns and risks of 11 Central and Southeast European markets and found that 6 of them are affected.

Besides, Jacobsen & Marquering (2008) and Magnusson (2019) analyzed the Halloween effect together with the SAD. Jacobsen & Marquering (2008) considered 48 different stock markets and even though they observed seasonal trends in stock returns during the summer and winter, they claimed that these patterns are not directly related to the investors' mood and SAD. Similarly, Magnusson (2019) analyzed the Halloween effect together with the SAD in 75 countries and found weak evidence. Alternatively, Gerlach (2010) and Kapalczynski (2022) included several macroeconomic variables in their analyses. Gerlach (2010) examined the New York Stock Exchange and included four macroeconomic announcements, but the stock market returns, and SAD is found to be unrelated. Similarly, Frühwirth & Sögner (2015) focused on the USA stock market (S&P 500 index) and individual stocks and bonds, and consistent with Gerlach (2010) the SAD effect was not captured. Moreover, Kapalczynski (2022) revealed a significant effect of SAD on stock market returns, but when the macroeconomic factors are added the effect has diminished.

The remaining studies have focused on the single stock markets. Bhattarai & Joshi (2007) and Hammami & Abaoub (2011) investigated the SAD effect on Nepalese and Tunisian stock markets, respectively, and they could not find a significant impact. In contrast, Stefanescu & Dumitriu (2011) and Murgea (2016) concentrated on the Romanian stock market, divided the period according to economic crises and they both found a substantial effect of SAD. In addition, Lu & Chou (2012) and Ruan et al. (2018) concentrated on the Chinese stock market. Lu & Chou (2012) analyzed the SAD effect not only for stock returns but also for turnover and liquidity, and they revealed significant results only for the turnover and liquidity of the Shanghai Stock

Exchange. Ruan et al. (2018), on the other hand, differentiated the stock market as small and large-cap stock indices and found a stronger SAD effect for the small-cap stocks.

Moreover, Thach et al. (2019) and Skrinjarić et al. (2021) examined the SAD on the Vietnam and Croatia stock markets, respectively, and they found significant results in both markets. In contrast to the previous studies, Raut & Kumar (2020) found a summer-type SAD in the Indian stock market which indicates that heat and humidity have a crucial impact on the investors' mood. Overall, it could be observed that the results in the whole literature differ based on the latitude of the city and analyzed the period.

3. Data and Methodology

To represent the Turkish stock exchange market, BIST-100 index closing prices are used. To represent the sectoral indices, BIST – Industrials, Financials, Technology, and Food Beverage are chosen. The daily data covers the period from January 2015 to May 2023. For the empirical analysis, the natural logarithmic returns of the indices are calculated with the following equation:

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

$r_{i,t}$ is the logarithmic return of index i on day t, $p_{i,t,}$ and $p_{i,t-1}$ are the closing price of index i on trading day t and t-1, respectively.

SAD_t, on the other hand, is computed following Kamstra et al. (2003). For trading days in the winter and fall, SAD_t is (H_t-12), and zero otherwise. The autumn and winter period spans from September 21 until March 20. There, H_t stands for the number of hours of the night, which at a specific latitude is the time between sunrise and sunset.

Since the Turkish stock exchange is located in the city of Istanbul, the latitude of Istanbul is used which is specified as 41,01384. To determine H_t at a given latitude δ, primarily, the sun's declination angle has to be identified as follows:

$$\lambda_t = 0.4102x \sin[(2\pi/365)x(julian_t - 80.25)] \quad (2)$$

λ_t is the declination angle of the sun, $julian_t$ is the number of days in a year that ranges from 1 to 365 (or 366 in leap years). Next, H_t is determined as follows:

$$H_t = 24 - 7.72xarccos[-tan(2\pi\delta/360)xtan(\lambda_t)] \quad (3)$$

H_t is the length of the night, arccos is the inverse cosine, δ denotes the latitude of Istanbul, and λ_t is the sun's declination angle.

As highlighted by Kamstra et al. (2003); the SAD causes investors' risk aversion to rise towards the start of autumn (September 21), which results in reduced returns. The end of winter is when investors' risk aversion is predicted to decline, and greater returns are anticipated. As a result, the control variable needs to be used to control the impact of autumn because it may have an asymmetrical impact compared to winter. The autumn season spans from September 21 until December 20. The dummy variable $FALL_t$ equals SAD for trading days in the autumn, and 0 otherwise.

Moreover, Kamstra et al. (2003) emphasized that some other popular calendar anomalies should be controlled in the model. The first anomaly is the Monday (or weekend) effect. The Monday effect refers to the substantial drop in stock values following weekends (French, 1980). To control the Monday anomaly, the dummy variable is added to the model which takes the value of 1 on Mondays, and 0 otherwise. The second anomaly is the tax loss selling effect. As highlighted by Wachtel (1942); to avoid paying hefty taxes, investors often sell their stock holdings at the end of December and repurchase them at the start of January. Stock values fluctuate throughout the year, declining towards the end of the year and increasing at the beginning because of this behavior, which is known as a tax loss selling anomaly. To control this anomaly, the dummy variable (TAX_t) is used which is 1 on the last trading day and the following five trading days; and 0 otherwise.

Lastly, in addition to these control variables, following Skrinjarić et al. (2021), the influence of the COVID-19 pandemic is also controlled by employing a dummy variable which is equal to 1 starting from 11 March 2020 to 17 May 2021. These dates were chosen specifically because the World Health Organization officially designated the COVID-19 outbreak as a global pandemic on March 11, 2020, and Turkiye began to stretch restrictions toward the pandemic on 17 May 2021[1].

To gauge the impact of SAD on BIST-100 index returns, the regression equation model is defined followingly:

$$r_{i,t} = \alpha + \beta_1 r_{i,t-1} + \beta_2 r_{i,t-2} + \beta_3 SAD_t + \beta_4 MON_t + \beta_5 TAX_t + \beta_6 COV_t + \varepsilon_t \tag{4}$$

[1] Retrieved from www.icisleri.gov.tr (Accessed on 01.06.2023).

$r_{i,t}$ is the return of index i on day t; $r_{i,t-1}$ and $r_{i,t-2}$ are the one and two lagged returns (where it is required to control for residual autocorrelation), respectively; SAD_t represents the seasonal affective disorder on day t; MON_t is a dummy variable for the Monday effect; TAX_t is a dummy variable for the tax-loss selling effect; and COV_t is a dummy variable for the COVID-19 pandemic.

To analyze the asymmetrical effect of the autumn, the dummy variable $FALL_t$ is included in the model which equals SAD_t when it is autumn, and 0 otherwise:

$$r_{i,t} = \alpha + \beta_1 r_{i,t-1} + \beta_2 r_{i,t-2} + \beta_3 SAD_t + \beta_4 FALL_t + \beta_5 MON_t + \beta_6 TAX_t + \varepsilon_t \qquad (5)$$

The regression equations (4) and (5) are examined for each index with the Ordinary Least Squares (OLS) method using the EViews software after the diagnostic tests. Since investors have higher risk aversion in winter and fall, they require higher expected returns. Risk-averse investors typically sell their risky investments in the fall, which results in lower returns. In contrast, after the longest night of the year (December 21), they start buying riskier investments again, which results in better returns in the months that follow. So, if there is an effect of SAD on BIST, we expect a statistically significant and positive SAD_t coefficient; and if there is an asymmetrical effect of autumn, we expect a statistically significant and negative $FALL_t$ coefficient.

4. Empirical Results

Before implementing diagnostic tests, the descriptive statistics for the BIST-100 (XU100), BIST-Industrial (XUSIN), BIST-Financials (XUMAL), BIST-Technology (XUTEK), and BIST-Food Beverage (XGIDA) indices logarithmic returns are examined in Table 2. There are 2108 observations for the period January 2015 to May 2023. The returns of the BIST-100 index range between -0.103068 (on 22 March 2021) to 0.094219 (on 15 February 2023), and the mean is 0.000795. The returns of the BIST-Industrial index range between -0.10154 (on 22 March 2021) to 0.09231 (on 15 February 2023). The returns of the BIST-Financials index range between -0.10310 (on 22 March 2021) to 0.09033 (on 15 February 2023). These three indices reached their minimum and maximum values on the same dates with similar values. Moreover, although the BIST-Technology index reached its minimum and maximum values on 16 November 2017 and 24 March 2020, the second lowest and highest values were observed again on 22 March 2021 and 15 February 2023, respectively. Similarly, the lowest value of the BIST-Food Beverage Index was recorded on July 18, 2016, while its second-lowest value was recorded on March 22, 2021, and it again reached its highest value on February 15, 2023. These dates are significant because on 19

March 2021, the president of the Central Bank of the Republic of Turkiye changed, and on the first trading day after the change (22 March 2021) the stock exchange market dropped severely[2]. On the other side, after the huge earthquake struck Southeast of Turkiye on February 6, 2023, Borsa Istanbul was closed for five days until February 15, when the stock market recorded a significant increase[3].

When the standard deviations of the indices are compared, the BIST-Technology index has the highest value (0.01996), which indicates the highest volatility and the BIST-Industrial index has the lowest value (0.01469), which indicates the lowest volatility among others. According to the Jarque-Bera test statistics, all the variables are statistically significant at a 1% level, demonstrating that they are not normally distributed (which is expected for the large financial dataset[4]). Moreover, the stationarity of the variables is controlled using the Augmented Dickey-Fuller (ADF) test, because the use of nonstationary data may result in misleading regressions (Brooks, 2014: 354). The findings indicate that all series are stationary at level.

Table 2

Descriptive Statistics

	XU100	**XUSIN**	**XUMAL**	**XUTEK**	**XGIDA**
Mean	0.00079	0.00107	0.00063	0.001177	0.000577
Maximum	0.09422	0.09231	0.09033	0.093632	0.089880
Minimum	-0.10307	-0.10154	-0.10310	-0.15152	-0.09847
Standard Dev.	0.01551	0.01469	0.01775	0.01996	0.01599
Jarque-Bera	3054.74***	3682.80***	1458.17***	3067.77***	2420.53***
Observations	2108	2108	2108	2108	2108

Notes. The 1%, 5%, and 10% levels of statistical significance are denoted by ***, **, and *, respectively.

In the second phase, the diagnostic tests (i.e., multicollinearity, heteroscedasticity, and autocorrelation) are controlled, and required corrections are made for each equation before concluding regression results[5]. First, the multicollinearity between variables is controlled with the Centered Variance Inflation Factor (VIF). There is no multicollinearity between the variables in any of the equations for each index because the VIF values of the variables are all close to 1. Second, heteroscedasticity and autocorrelation of the series are checked with the White and

[2] https://www.bbc.com/turkce/haberler-turkiye-56489505.
[3] https://www.bloomberght.com/borsa-gunu-sert-yukselisle-tamamladi-2325288.
[4] As indicated by Brooks (2014:210) for the large sample size the violation of normality assumption is insignificant.
[5] The detailed results could be shared upon request.

Breusch-Godfrey Serial Correlation LM Tests, respectively. The heteroscedasticity is found to be present in all equations (with the probability chi-square of 0.000), and the Huber-White correction is used to regulate it. On the other hand, for the BIST-100, BIST-Financials, and BIST-Technology datasets, there is no autocorrelation problem since the Breusch-Godfrey Serial Correlation LM Test result is found not to be statistically significant (with the probability chi-square of 0.422, 0.6801 and 0.9322, respectively). However, for the BIST-Industrials and BIST-Food Beverage datasets, the results of the Breusch-Godfrey Serial Correlation LM Test indicate an autocorrelation problem. Therefore, one and two lagged returns of both indices are included in the equations to control for residual autocorrelation.

After the required corrections are made, the regression equations (4) and (5) are estimated for each index return. The results for the BIST-100 index are presented in Table 3. According to F-statistics, models (4) and (5) are statistically significant at 10% and 5% levels, respectively. The regression models (4) and (5) account for 0.23% and 0.30%, respectively, of the total variation in the returns, according to the adjusted R-squares. When the coefficients of the variables are evaluated, the SAD effect on BIST-100 index returns is statistically significant and positive, which is expected previously. The significance level and effect of SAD disappeared by the inclusion of the autumn dummy, and since the coefficient of the FALL variable is not significant, it appears that autumn has no asymmetrical impact on the returns. Moreover, some popular calendar anomalies (Monday and tax loss selling anomalies) and the effect of the COVID-19 outbreak have been controlled in the model. Among them, only the coefficient of the Monday dummy variable is positive and statistically significant for both models. Therefore, in contrast to French (1980), on Mondays BIST-100 index returns tend to be higher. Besides, there is no impact of tax loss selling and the COVID-19 outbreak on the BIST-100 index.

Table 3

Regression Analysis Results for BIST-100 Index

Variables	**w/o FALL dummy (Model 4)**	**with FALL dummy (Model 5)**
α	-0.000224 [-0.507488]	-0.000205 [-0.465415]
SAD_t	0.000694 [2.095095]**	0.000253 [0.552868]
$FALL_t$	-	0.000801 [1.484733]
MON_t	0.001694	0.001693

	[1.760815]*	[1.762180]*
TAX_t	-0.000519 [-0.205098]	0.000674 [0.251975]
COV_t	0.000574 [0.563689]	0.000561 [0.551581]
Adj. R-Square	0.002374	0.003074
F-Statistics	2.253237*	2.299172**

Notes. This table presents the results of the regression equations (4) and (5). The dependent variable is the logarithmic return of the BIST-100 index, and the independent variables are seasonal affective disorder, the dummies for autumns (for equation (5)), Mondays, tax-loss selling, and the COVID-19 outbreak. The 1%, 5%, and 10% levels of statistical significance are denoted by ***, **, and *, respectively. The t statistics are given in parentheses.

To evaluate whether the effect of SAD varies based on the sector, the regression models 4 and 5 are applied separately for each selected sectoral index. BIST-Industrials (XUSIN), BIST-Financials (XUMAL), BIST-Technology (XUTEK), and BIST-Food Beverage (XGIDA) are included in the analyses and the results of models 4 and 5 are shared in Table 4 and Table 5, respectively. F-statistics of both tables show that all of the regression equations are statistically significant. When the coefficients of the variables are evaluated in Table 4, the SAD is statistically significant and positive for all indices except for the BIST-Food Beverage index. As shown in Table 5, similar to the BIST-100 index, the significance level and effect of SAD disappeared by the inclusion of the autumn dummy, and the coefficient of the FALL variable is not significant. Therefore, autumn has no asymmetrical impact on the returns of any indices. Among the calendar anomalies, consistent with the BIST-100 index, the Monday dummy variable is positive and statistically significant only for BIST-Industrials and Technology indices. On the other hand, tax loss selling does not affect any index, and the COVID-19 outbreak dummy is statistically significant and positive only for the BIST-Industrials index. Overall, the SAD has a substantial impact on almost the entire market, but only the Food and Beverage industry seems not to be affected by it.

Table 4

Regression Analysis Results for the Sectoral Indices (Model 4)

Variables	XUSIN	XUMAL	XUTEK	XGIDA
α	-0.000187 [-0.450503]	-0.000402 [-0.778906]	-9.49E-05 [-0.168520]	-0.000178 [-0.384982]
SAD_t	0.000603 [1.855319]*	0.000840 [2.320266]**	0.000778 [1.848037]*	0.000346 [1.077539]
MON_t	0.001959 [2.231862]**	0.001652 [1.477152]	0.002382 [2.010028]**	0.001348 [1.385337]
TAX_t	-5.42E-05	-0.001726	0.001828	-8.73E-05

	[-0.022375]	[-0.639945]	[0.581753]	[-0.030437]
COV_t	0.001802	-1.39E-05	0.000445	0.001091
	[1.701849]*	[-0.011631]	[0.329732]	[0.946727]
Adj. R-Square	0.007501	0.001943	0.002739	0.002728
F-Statistics	3.651542***	2.025654*	2.446716**	1.959632*

Notes. This table presents the results of the regression equation (4). The dependent variables are the logarithmic return of the BIST-Industrial, BIST-Financials, BIST-Technology, and BIST-Food Beverage index, and the independent variables are seasonal affective disorder, the dummies for Mondays, tax-loss selling, and the COVID-19 outbreak. To control for residual autocorrelations the one- and two-lagged returns are added to the equation as r_{t-1} and r_{t-2} for XUSIN and XGIDA (The statistics results of these variables are not included in the table). The 1%, 5%, and 10% levels of statistical significance are denoted by ***, **, and *, respectively. The t statistics are given in parentheses.

Table 5

Regression Analysis Results for the Sectoral Indices (Model 5)

Variables	XUSIN	XUMAL	XUTEK	XGIDA
α	-0.000171	-0.000386	-6.90E-05	-0.000161
	[-0.411153]	[-0.747801]	[-0.122620]	[-0.348641]
SAD_t	0.000229	0.000448	0.000172	-4.98E-05
	[0.510103]	[0.942633]	[0.319863]	[-0.109026]
$FALL_t$	0.000682	0.000712	0.001100	0.000720
	[1.320134]	[1.238886]	[1.618463]	[1.405445]
MON_t	0.001959	0.001652	0.002382	0.001349
	[2.233166]**	[1.477756]	[2.009866]**	[1.386424]
TAX_t	0.000960	-0.000665	0.003467	0.000983
	[0.373970]	[-0.235109]	[1.058418]	[0.326798]
COV_t	0.001795	-2.54E-05	0.000428	0.001081
	[1.694557]*	[-0.021274]	[0.316276]	[0.938094]
Adj. R-Square	0.007975	0.002178	0.003602	0.003143
F-Statistics	3.417575***	1.919653*	2.523582**	1.948271*

Notes. This table presents the results of the regression equation (5). The dependent variables are the logarithmic return of the BIST-Industrial, BIST-Financials, BIST-Technology, and BIST-Food Beverage index, and the independent variables are seasonal affective disorder, the dummies for autumns, Mondays, tax-loss selling, and the COVID-19 outbreak. To control for residual autocorrelations the one- and two-lagged returns are added to the equation as r_{t-1} and r_{t-2} for XUSIN and XGIDA (The statistics results of these variables are not included in the table). The 1%, 5%, and 10% levels of statistical significance are denoted by ***, **, and *, respectively. The t statistics are given in parentheses.

For the last step, following Kamstra et al. (2003), the robustness of the results is checked by employing the generalized autoregressive conditional heteroscedasticity (GARCH) model to capture the heteroscedasticity of the data which was previously regulated by Huber-White specification. The GARCH (1,1) model is estimated for all indices, and the results of Models 4 and 5 are shared in Tables 6 and 7, respectively. When the results of the GARCH model are compared with the original findings in Tables 4 and 5, it can be observed that the values are very close to each other for all variables. When the heteroscedasticity of the data is controlled with a GARCH approach, the SAD effect is found to be statistically significant and positive in BIST-100, BIST-

Industrials, BIST-Financials, and BIST-Technology indices. Moreover, similar to the original model, Table 7 shows that the fall dummy is not statistically significant for any index demonstrating that autumn has no asymmetrical effect. The only difference in the GARCH model appeared for two control variables. With the GARCH model, the impact of Monday is statistically significant and positive for all indices (in the original model it was significant only for BIST-100, Industrials, and Technology indices). The impact of the COVID-19 epidemic is also positive for the food and beverage industry as well as the industrials index, contrary to the initial model (in the initial results it was significant only for BIST-Industrials). Therefore, it could be concluded that the robust results for the effect of SAD support the original findings of the model.

Table 6

Robustness Test GARCH (1,1) Results (Model 4)

Variables	**w/o FALL dummy (Model 4)**				
	XU100	XUSIN	XUMAL	XUTEK	XGIDA
α	-1.83E-05 [-0.042971]	4.04E-05 [0.101643]	-0.000225 [-0.470444]	0.000376 [0.738728]	-7.32E-05 [-0.166414]
SAD_t	0.000649 [2.274993]**	0.000535 [2.017206]**	0.000798 [2.457300]**	0.000763 [2.197763]**	0.000411 [1.436404]
MON_t	0.001547 [2.464423]**	0.001489 [1.689132]*	0.002099 [2.078599]**	0.002618 [2.500940]**	0.001525 [1.717318]*
TAX_t	-0.000963 [-0.564829]	-0.000301 [-0.156945]	-0.001738 [-0.831845]	0.000738 [0.394784]	0.000171 [0.065258]
COV_t	0.001425 [1.499829]	0.002651 [1.735620]*	0.000894 [0.863444]	0.000774 [0.729846]	0.002535 [2.022001]**

Notes. This table presents the results of the GARCH(1,1) specification for model 4. The dependent variable is the logarithmic return of the BIST-100 index, and the independent variables are seasonal affective disorder, Mondays, tax-loss selling, and the COVID-19 outbreak. The 1%, 5%, and 10% levels of statistical significance are denoted by ***, **, and *, respectively. The z statistics are given in parentheses.

Table 7

Robustness Test GARCH (1,1) Results (Model 5)

Variables	**with FALL dummy (Model 5)**				
	XU100	XUSIN	XUMAL	XUTEK	XGIDA
α	-1.75E-05 [-0.041052]	4.47E-05 [0.111565]	-0.000224 [-0.464110]	0.000378 [0.743472]	-6.58E-05 [-0.148406]
SAD_t	0.000632 [1.546671]	0.000458 [1.389813]	0.000770 [1.832788]*	0.000475 [1.035295]	0.000143 [0.340773]
$FALL_t$	3.10E-05 [0.065614]	0.000144 [0.333013]	4.90E-05 [0.094517]	0.000535 [0.929163]	0.000448 [0.962524]
MON_t	0.001548 [2.464636]**	0.001494 [1.683068]*	0.002100 [2.076696]**	0.002629 [2.511111]**	0.001538 [1.729421]*
TAX_t	-0.000916	-8.19E-05	-0.001664	0.001537	0.000858

	[-0.481405	[-0.041437]	[-0.757696]	[0.750205]	[0.310281]
COV_t	0.001424	0.002651	0.000896	0.000785	0.002524
	[1.497696]	[1.702215]*	[0.863098]	[0.733113]	[2.001331]**

Notes. This table presents the results of the GARCH(1,1) specification for model 5. The dependent variable is the logarithmic return of the BIST-100 index, and the independent variables are seasonal affective disorder, the dummies for autumns, Mondays, tax-loss selling, and the COVID-19 outbreak. The 1%, 5%, and 10% levels of statistical significance are denoted by ***, **, and *, respectively. The z statistics are given in parentheses.

5. Conclusion

This paper investigated whether there is an effect of SAD on Borsa Istanbul for the period January 2015 to May 2023. The BIST-100 index is used to represent the overall stock market, and the BIST-Industrials, Financials, Technology, and Food Beverage indices are utilized to examine any sectoral disparities. Following Kamstra et al. (2003), the multiple regression model has been employed by incorporating several control variables (dummies for fall, Mondays, and tax-loss selling) separately for each index. Additionally, following Skrinjarić et al. (2021), the influence of the COVID-19 pandemic is also controlled. The findings, which are in line with those of Skrinjarić (2018), Thach et al. (2019), and Skrinjarić et al. (2021), demonstrate that there is a statistically significant and positive SAD effect on BIST-100 index returns. Furthermore, every sectoral index, except BIST-Food Beverage, is affected by the SAD. Autumn does not, however, have an asymmetrical impact on the returns of any indices. The Monday impact is statistically significant and positive for BIST-100, BIST-Industrials, and BIST-Technology indices, which contradicts French's (1980) claim that returns are often lower on Mondays. Lastly, the COVID-19 dummy is statistically significant and positive only for the BIST-Industrials index. As a robustness test, the GARCH model has also been employed and consistent results are obtained.

To sum up, the BIST-100 index represents the majority of the Turkish stock market, so it could be stated that there is a significant SAD effect on Borsa Istanbul. This result shows that BIST violates the weak form of EMH, and arbitrageurs could benefit from seasonal return patterns by employing profitable trading strategies. Before September 2020, foreign investors had constituted the majority of the market. Therefore, because they may prefer mostly the stocks on the BIST-100 index, their SAD influence may be large on the market. On the other hand, sectoral analysis demonstrates that SAD is effective for all examined indices except for the food and beverage sector. In light of this result, investors may divide their portfolios among several industries while taking the SAD effect variations into account, thereby lowering the risk associated with their investments. However, considering most sectoral indices are impacted by the SAD, it might be argued that the SAD effect is equivalent in strength across all industries. As a result, investors might profit from this result by preferring alternative investments other than stocks during these seasonal times. But to properly comprehend these findings, more sectors or marketplaces may need to be included in the analysis in future studies.

Future research may also separate the period based on changes in the ratio of domestic and foreign investors. Additionally, the SAD effect may differ according to the capitalization size of the firm, so the sector-based SAD effect in the market might be examined for small- and large-cap stocks separately. Moreover, the period might be divided based on financial crises, allowing the influence of SAD to be seen throughout these difficult times. Finally, the present study employed a linear model, but further studies may apply non-linear models to capture the non-linear patterns of the dataset.

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