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THE IMPACT OF SEASONAL AFFECTIVE DISORDER ON GREEN CRYPTOCURRENCIES

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ABSTRACT
Purpose- Seasonal Affective Disorder (SAD) which arises during the winter when there are fewer daylight hours is a form of the major depressive disease. SAD affects most of the financial markets. Since there is scarce research on the relationship between SAD and cryptocurrency returns, this study is aimed to examine the impact of SAD on green cryptocurrencies. To the best of the author's knowledge, this is the first study that investigates the relationship between SAD and the returns of green cryptocurrencies, so the study is expected to fill the gap in the related literature.
Methodology- Cardano (ADA), Tron (TRX), and Stellar (XLM) are considered for the analysis, which covers the period spanning from January 2018 to March 2023. The multiple regression model has been implemented by including dummies for autumn, Mondays, and tax-loss selling. A specific location must be specified for the latitude information to determine how many hours are spent at night. The latitude of New York City is considered for that calculation because the majority of cryptocurrency users are concentrated in the USA.
Findings- The findings demonstrate that the SAD, autumn, Monday, and tax-loss selling effects have no impact on green cryptocurrencies. Due to the worldwide spread of cryptocurrency investors, these effects are probably mitigated.
Conclusion- According to the results, arbitrageurs are unable to benefit from generating abnormal returns using seasonal return patterns. Future studies might use non-linear techniques, change the location that is considered when calculating latitude, and include more cryptocurrencies in their examinations.

Keywords: Seasonal affective disorder, cryptocurrencies, green finance, behavioral finance, anomalies.
JEL Codes: G10, G40, G41

1. INTRODUCTION

Based on the clinical psychology literature, Seasonal Affective Disorder (SAD), commonly referred to as "winter depression," is a form of the major depressive disease. This type of depression tends to arise during the winter when there are fewer daylight hours. People are more pessimistic since the nights are longer, which may lead to severe depression, and in turn, it affects the risk-taking behavior of individuals. Kamstra et al. (2003) argued that because individuals are more risk-averse during the autumn and winter times, their investment decisions may also be changed which may result in negative returns in the stock markets. They analyzed the SAD effect on various financial markets, and the results supported the idea that there is a SAD effect on stock returns. After that conclusion, many studies examined the effect of SAD on various stock market returns (i.e., Gerlach, 2010; Kelly and Meschke, 2010; Ruan et al., 2018; Škrinjarić, 2018; Raut and Kumar, 2020; Škrinjarić et al., 2021). However, there is not much study that covers the SAD effect on other financial markets, such as the cryptocurrency market.

Reviewing the literature on cryptocurrencies reveals that few studies examined the several seasonality effects on cryptocurrency returns. Aharon and Qadan (2019) and Ma and Tanizaki (2019) investigated the day-of-the-week effect on returns and volatilities of Bitcoin, and they both found a significant effect. Besides Bitcoin, Caporale and Plastun (2019) included LiteCoin, Ripple, and Dash in their analysis, and consistent with the previous studies only Bitcoin is found to be affected by that anomaly. Together with the day-of-the-week effect, Baur et al. (2019) investigated intra-day time-of-day and month-of-year effects for the returns and trading volume of Bitcoin, but they do not find significant results. Moreover, Kaiser (2019) examined the day-of-the-week, January, and Halloween effects on the ten largest cryptocurrency returns. Except for Bitcoin, their findings are not statistically significant for others. Similarly, Kinateder and Papavassiliou (2021) analyzed the day-of-the-week, Halloween, and month-of-the-year effects on Bitcoin returns and volatility. While there is no significant Halloween and day-of-the-week effects, a significant month-of-the-year effect is detected. Dumrongwong (2021) also analyzed Monday, January and Halloween effects on Bitcoin, Ethereum, Ripple, Tether and Litecoin, and it is found that January effect is present for Ethereum, and Monday effect is present for Litecoin. Different from the previous research, Lopez-Martin (2022) examined the Ramadan effect on Bitcoin, Ethereum, Ripple, Stellar, Litecoin, and Binance Coin, and they found significant evidence of the Ramadan effect on most of the cryptocurrencies.

On the other hand, Qadan et al. (2022) conducted a comprehensive study and investigated several anomalies including SAD on cryptocurrency (Bitcoin, Ethereum, Litecoin, Ripple, Dash, Monero, Nem, and Ethereum Classic) returns. Their findings indicate that there is no statistically significant effect of SAD on analyzed cryptocurrencies. In light of the above explanations, it is noticeable that there is still a gap in the literature about the impact of SAD on the cryptocurrency market. Thus, this study aims to analyze the effect of SAD on green cryptocurrency returns. As of April 2023, based on their market capitalizations, the top seven green cryptocurrencies are Cardano, Tron, Avalanche, Stellar, Near, Algorand, and Cosmos[1] . Cardano, Tron, and Stellar offer the most historical information. Therefore, these three green cryptocurrencies are considered for the analysis, which covers the period spanning from January 2018 to March 2023. Because they are brand new, there is not much literature on green cryptocurrencies in general, necessitating more research.

It is beneficial to introduce the green side of cryptocurrencies before proceeding to the methodological section. In addition to being the most well-known cryptocurrency, Bitcoin also has the worst environmental impact. According to the Bitcoin Energy Consumption Index, the estimated yearly energy consumption for mining Bitcoins climbed quickly from 9.59 TWh (Terawatt hours) in February 2017 to 98.67 TWh in April 2023, which is comparable to Kazakhstan's power consumption. Additionally, it is estimated that a single Bitcoin transaction will require up to 802,15 kWh of electricity, which is more energy than the average American household uses in more than 27.49 days[2]. The inefficient Proof-of-Work (PoW) mining method used by Bitcoin, which requires the utilization of incredibly powerful and energy-intensive devices, is responsible for its excessive energy consumption. As a result, non-PoW cryptocurrency techniques have increased in popularity recently. The significance of sustainability and a greener global economy has increased in connection with recent worries about climate change, such as global warming. As a result, an increasing number of environmentally friendly cryptocurrencies have been produced with the market's growing demand for them (Ren and Lucey, 2022). When compared with mining conventional cryptocurrencies, mining green cryptocurrencies consumes fewer non-renewable resources (such as coal and fossil fuels) and less electricity (Ul Haq et al., 2022). Green cryptocurrencies are built on the energy-efficient Proof-of-Stake (PoS) method, which offers validating devices rather than mining computers to protect the network without using a lot of power (Košťál et al., 2018).

To the best of the author's knowledge, this is the first study that investigates the relationship between SAD and the returns of green cryptocurrencies, so the study is expected to fill the gap in the related literature. The next sections will first define the data and methodology. Second, the explanation of the empirical findings will be presented. Subsequently, the paper will be concluded with a discussion and the implications of the findings.

2. DATA AND METHODOLOGY

As a representative of green cryptocurrencies US dollar daily closing prices of Cardano (ADA), Tron (TRX), and Stellar (XLM) coins are taken into consideration which is obtained from www.investing.com. Cardano (ADA) has the biggest market capitalization among them, and overall, as of April 2023, it is the seventh-largest cryptocurrency. Cardano is created by the co-founder of Ethereum[3]. Tron (TRX), the fastest-growing public chain in the world, is also the sixteenth-largest cryptocurrency overall[4]. The Stellar (XLM), the twenty-fifth largest cryptocurrency overall, claims to be quicker, less expensive, and more energy-efficient than conventional blockchain systems like Bitcoin and Ethereum[5].

The data covers the period from January 2018 to March 2023. For the empirical analysis, the natural logarithmic returns of each cryptocurrency are calculated as follows:

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

where $r_{i,t}$ indicates the logarithmic return of cryptocurrency i on day t, $p_{i,t}$ shows the closing price of cryptocurrency i on trading day t, and $p_{i,t-1}$ denotes the closing price of cryptocurrency i on trading day t-1.

On the other hand, following Kamstra et al. (2003) SAD_t is calculated. SAD_t is (H_t-12) for trading days in winter and autumn, and zero otherwise. The autumn and winter period starts on the 21st of September and ends on the 20th of March. There, H_t is the time from sunrise to sunset at a particular location (or latitude), in other words, it is the number of hours of the night. There are approximately 420 million cryptocurrency users worldwide, and the USA constitutes the majority of them[6].

[1] For the list of green cryptocurrencies see: https://finance.yahoo.com/news/15-environmentally-sustainable-cryptocurrencies-invest-224849569.html?guccounter=1&guce_referrer=aHR0cHM6Ly9tYWlsLmdvb2dsZS5jb20v&guce_referrer_sig=AQAAACS0ZF41p_zjOl4Q7T8WSEGDEf73f58255mifq2igSl7Cs1c5eCg_B5iBmw5BElxMq1cU6KZQdtKh9Pbjm1yA4XbwDvT3BG4LCD-DUB1Fjzlvwa5I9XTup46KivhuLrhcAL9SApAiAeKVOE1gQGruq43jtQhC1ULfaSihZo4mnUP (Accessed on 09.04.2023).
[2] Retrieved from https://digiconomist.net/bitcoin-energy-consumption (Accessed on 12.04.2023).
[3] Retrieved from https://cardano.org/ (Accessed on 13.04.2023).
[4] Retrieved from https://tron.network/index?lng=en (Accessed on 13.04.2023).
[5] Retrieved from https://www.stellar.org/learn/intro-to-stellar (Accessed on 13.04.2023).
[6] Retrieved from: https://triple-a.io/crypto-ownership-data/ (Accessed on 10.04.2023).

Thus, for the latitude information, the location is selected as the USA, New York City (NYC), which is specified as 40,71278[7]. To calculate H_t at specific latitude δ, primarily, the sun's declination angle has to be gauged as follows:

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

where λ_t is the sun's declination angle, $julian_t$ is the number of days in the year which takes the value of 1 to 365 (or 366 based on the leap year). Secondly, H_t could be calculated as follows:

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

where H_t is the number of hours at night, arccos is the inverse cosine, δ is the latitude of NYC, and λ_t is the sun's declination angle.

As emphasized by Kamstra et al. (2003), due to the SAD, investors' risk aversion increases at the beginning of autumn (September 21) which causes lower returns. In contrast, the risk aversion of investors is expected to decrease at the end of winter and resulted in higher returns. Therefore, the control variable must be included in the analyses to control the effect of autumn because there is a possibility that it will have an asymmetric effect relative to the winter. The autumn season is started on the 21st of September and ends on the 20th of December. The dummy variable $FALL_t$ is 1 for trading days in the autumn, and zero otherwise. A Monday and a tax-loss selling dummy variables are also included in the model to control for these calendar anomalies. In addition, Kamstra et al. (2003) included temperature, precipitation, and cloud cover as control variables; however, this study follows Qadan et al. (2022) and does not include these variables in the model.

To estimate the SAD effect on green cryptocurrencies, the following regression equation model is defined for each cryptocurrency:

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

where $r_{i,t}$ is the logarithmic return of cryptocurrency i on day t; $r_{i,t-1}$ and $r_{i,t-2}$ are the one and two lagged returns, respectively (to control for residual autocorrelation); SAD_t represents the seasonal affective disorder on day t; $FALL_t$ is a dummy variable that equals one when the period t is in the autumn and zero otherwise; MON_t is a dummy variable that equals one on Mondays and zero otherwise; and TAX_t is a dummy variable that equals one on the last trading day (31st of December) and the first five trading days (1st, 2nd, 3rd, 4th, 5th of January) and zero otherwise. The regression equations for each cryptocurrency are examined using the Eviews software after the diagnostic tests.

3. EMPIRICAL RESULTS

First, the descriptive statistics for the returns of Cardano (ADA), Tron (TRX), and Stellar (XLM) are examined in Table 1. The sample consists of 1916 observations for the period January 2018 to March 2023.

Table 1: Descriptive Statistics

Variables	Mean	Maximum	Minimum	Standard Dev.	Jarque-Bera	Observations
R_{ADA}	-0.000301	9.559110	-9.339492	0.677262	2756821***	1916
R_{TRX}	0.000221	0.755590	-0.570850	0.061927	31338.91***	1916
R_{XLM}	-0.000600	0.553585	-0.440312	0.058652	10736.27***	1916

This table presents the results of the descriptive statistics. RADA is the return of Cardano, RTRX is the return of Tron, and RXLM is the return of Stellar. **, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively.

The returns of Cardano range between 9.559 (on the 3rd of January 2018) to -9.339 (on the 23rd of February 2021), and the mean is -0.0003. The returns of Tron range between 0.756 (on the 4th of January 2018) to -0.571 (on the 12th of March 2020), and the mean is 0.0002. The returns of Stellar range between 0.554 (on the 6th of January 2019) to -0.440 (on the 12th of March 2020), and the mean is -0.0006. The standard deviations are 0.677, 0.062 and 0.059 for Cardano, Tron and Stellar, respectively. Cardano has the highest volatility among the other cryptocurrencies since its returns have the largest standard deviation. Additionally, according to the Jarque-Bera test statistics, the variables are statistically significant at a 1% level, proving that none of the variables are all normally distributed.

Brooks (2014: 354) indicated that the non-stationary data may lead to spurious regression, hence in the second step the stationarity of the variables is controlled with the Augmented Dickey-Fuller (ADF) test, and all series are found to be stationary at level[8]. After the required corrections are made for the heteroscedasticity problem[9], the regression equation (4) is estimated, and the results are presented in Table 2.

Table 2 shows the results of the relationship between the returns of each cryptocurrency and SAD. F-statistics show that the model is statistically significant at a 1% level for ADA and TRX, and a 10% level for XLM. Moreover, the adjusted R-squares reflect how much of the overall variation in the returns is explained by the regression model, and they are 9.3%, 53%, and 0.28% for ADA, TRX, and XLM, respectively. When the coefficients of the variables are evaluated, SAD does not have a significant effect on the examined cryptocurrency returns. Moreover, there is no asymmetrical effect of autumn. These results are consistent with the findings of Qadan et al. (2022). On the other hand, Qadan et al. (2022) found a significant tax effect for Bitcoin, Monero, and Ethereum, and found a significant Monday effect for Bitcoin, which are not statistically significant for Cardano, Tron, and Stellar.

[7] Retrieved from https://www.mapsofworld.com/lat_long/nyc.html (Accessed on 10.04.2023).
[8] The results could be shared upon request.
[9] Newey-West Test is applied for the corrections.

Table 2: Results of the Regression Analysis

Variables	Cardano (ADA)	Tron (TRX)	Stellar (XLM)
α	0.009309	0.000639	-0.000435
	[0.632388]	[0.387977]	[-0.259868]
SAD_t	-0.006682	-0.001143	-0.000707
	[-0.343880]	[-0.643614]	[-0.421052]
$FALL_t$	0.004181	0.000226	0.000193
	[0.204727]	[0.125830]	[0.085852]
MON_t	-0.060824	-0.002562	-0.001374
	[-1.392371]	[-1.090415]	[-0.386069]
TAX_t	0.182293	0.041681	0.017630
	[0.510641]	[0.2054]	[1.426955]
Adj. R-Square	0.093534	0.532168	0.002847
F-Statistics	33.89884***	363.6793***	1.910467*

This table presents the results of the regression equation: $r_{i,t} = \alpha + \beta_1 r_{i,t-1} + \beta_2 r_{i,t-2} + \beta_3 SAD_t + \beta_4 FALL_t + \beta_5 MON_t + \beta_6 TAX_t + \varepsilon_t$. The dependent variable is the return of ADA, TRX, and XLM, respectively, and the independent variables are seasonal affective disorder, and the dummies for autumns, Mondays, and tax-loss selling. To control for residual autocorrelations the one and two-lagged returns are added to the equation as $r_{i,t-1}$ and $r_{i,t-2}$. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively. t statistics are in parentheses.

4. CONCLUSION

Seasonal Affective Disorder (SAD) is a major depressive disease that is caused by the shortened daylight in the winter season. The financial markets are impacted by this disease because it impacts how investors take risks. Although earlier studies showed that SAD influences stock markets in the majority of countries, there has only been one study that examined the SAD effect on the cryptocurrency market (Qadan et al., 2022). Different from the previous study, this paper is aimed to examine the SAD effect on green cryptocurrencies. Policymakers have recently encouraged more environmentally friendly funding, therefore closely examining the green cryptocurrency market would reveal information about its effectiveness. Based on market capitalization and data availability, Cardano (ADA), Tron (TRX), and Stellar (XLM) are taken into consideration for the analyses as a representation of green cryptocurrencies.

The multiple regression model has been implemented following Kamstra et al. (2003) by integrating several control variables (dummies for autumn, Mondays, and tax-loss selling). A specific location must be specified for the latitude information to determine how many hours are spent at night. The latitude of New York City is considered for that calculation because the majority of cryptocurrency users are concentrated in the USA. The results show that the green cryptocurrencies under consideration are not affected by the SAD, autumn, Monday, or tax-loss selling effects which are in line with the findings of Qadan et al. (2022). Such effects are probably diminished by the fact that cryptocurrency investors are dispersed around the world. Therefore, due to these results, arbitrageurs are unable to benefit from producing abnormal returns using seasonal return patterns. Future research may alter the location that is considered to determine latitude, apply non-linear approaches, and assess more cryptocurrencies in their analyses.

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