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LET'S MAKE SOME PROFITS ON SEASONAL DEPRESSION ON THE STOCK MARKET

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Abstract

This paper observes the possibilities of exploiting a behavioural anomaly on the stock market. Previous literature confirms the existence of Seasonal Affective Disorder (SAD) in return series on the Zagreb Stock Exchange. However, a comprehensive set of investment guidance based on such findings is lacking in the related literature. That is why after the confirmation of the existence of SAD effects in this research, the focus is on simulation of trading strategies that take such information into account. The results indicate that there exist SAD and fall effects on the Croatian stock market, alongside precipitation and temperature having significant effects on stock returns as well. Based on daily data ranging from January 2010 until December 2020 for the Croatian stock market index CROBEX, several strategies are observed and compared via performance measures aimed at beating the market. Even with the inclusion of transaction costs, it is shown and commented on possibilities for speculators aiming to obtain extra profits in certain situations. Simpler strategies are considered in the study. However, they provide a starting point for future strategies that combine different (mostly calendar) anomalies with the SAD anomaly. This is due to showing that SAD-driven investors who aim to apply the contrarian strategies against the herd can obtain profits due to the changing risk-aversion of others over the year.

Keywords*: seasonal affective disorder, stock market, COVID-19, emerging market, winter blues, weather anomaly, behavioural finance*

JEL*:* C01, C63, G1, G4

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Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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1. INTRODUCTION

Empirical investor sentiment and its effects on the financial markets is a hot topic in the last two decades (Baker and Wugler, 2006, 2007; Wang, Keswani, and Taylor, 2006; Škrinjarić and Čižmešija, 2019; Su, Cai, and Tao, 2020; Schneller, et al., 2018). This is due to the development of the methodology of how to observe and measure specific sentiment and feeling variables. Such research follows in the area of behavioral finance (Shleifer, 1999 which tries to explain anomalies in financial return and risk series, that cannot be explained via rational models. Theoretical models explain how the investor mood affects risk aversion over time. These are the affect infusion model (AIM) developed in Forgas (1995 and the mood maintenance hypothesis (MMH[1] developed in Isen, Nygren, and Ashby (1988) and Isen and Patrick (1983). The AIM approach is mostly agreed in the literature (see Kramer and Weber, 2011 due to it explaining that negative moods increase risk aversion, whereas the MMH approach explains that positive mood is the one in charge of avoiding additional risk (greater risk aversion). Thus, it is not debatable anymore if the sentiment affects the financial variables within the modeling process; the questions remain on how this information can be used and exploited (Baker and Wugler, 2007). Moreover, Chau, Deesomsak, and Koutmos (2016) found that already approximately 600 papers exist on the SSRN (Social Science Research Network) at the date of writing the research.

Part of the literature focuses on the weather effects on investor sentiment and the decision-making process. The psychiatry literature found that the seasonal affective disorder (SAD henceforward, Rosenthal et al. 1984; Rosenthal, 1998) is a mood disorder affecting ordinary people and investors as well. In essence,

[1] For more theory on AIM and MMH, please refer to Mayer and Hanson (1995), Nasby and Yando, (1982), Schwarz and Clore (1983), Wright and Bower (1992), Forgas (1999).

it affects the investor's risk aversion over the year[2]. Thus, the SAD effects fall within the AIM theoretical explanations. Different markets over the world have been examined if SAD affects the return and/or risk series (48 countries in Jacobsen and Marquering, 2008; developed markets in Garett, Kamstra and Kramer, 2005); IPOs (initial public offerings) under and over-pricing have been found to be affected due to the SAD effects (Dolvin and Fernbaher, 2014; Keef, Keefe O'Connor, and Khaled, 2015); less-risky assets are under these effects as well, such as the government treasury yields (Kamstra, Kramer, and Levy, 2014). It is not a new thing to empirically evaluate the SAD and weather effects on the financial markets. However, the majority of the literature focuses solely on estimating an econometric model and commenting on the significance of selected variables, as well as giving general conclusions based on the results. Due to the speculative nature of some stock market participants, who aim to obtain profits due to exploiting some violation of the EMH (efficient market hypothesis, see new examples in Dimpfl and Jank, 2016; Titan, 2015; Hirshleifer, Hsu, and Li, 2013; or theory in Timmerman and Granger, 2004 it is important to evaluate the SAD estimation results to see if this anomaly can be utilized to obtain extra profits[3]. However, there is a lack of literature focusing on the SAD anomaly and possible exploitations of these effects on the stock market.

Thus, the contribution of this research compared to existing ones is as follows. Previous literature estimates the model in which the SAD effects are observed in return and/or risk series. Exploiting the results as an investor is rarely found. The calendar effects, in general, are rarely explored in such a way, as already stated in Gebka, Hudson, and Atanasova (2015). The results of the analysis here are used in simulating the trading strategies for those speculators who aim to beat the market. Many contrarian strategies exist today which try to beat the market by exploiting one anomaly or the other. However, the focus of this research will be on the possibilities of trading strategies that exploit the time-varying risk aversion of the majority of investors. The transaction costs are, of course, included in the simulation part, and the portfolio performance measures are estimated for the contrasting strategies. The importance of this research lies in the fact that the SAD-induced trading on the stock market can provide certain profits, due to not following the herd[4], and trading against it. Specific investment guidance is given and commented on, which is lacking in related research as well. As the research shows that the SAD anomaly can be exploited over the year, it contributes to

[2] See Cohen et al. (1992) for a psychiatric point of view within human behavior and feelings and full explanations within financial applications with references please refer to Škrinjarić, Marasović, and Šego (2021).

[3] For other anomalies and possible strategies, please see Xavier and Machado (2018) or Schwert (2003).

[4] See details in: Scharfstein and Stein (1990); Christie and Huang (1995); Devenow and Welch (1996), Cote and Sanders (1997) or Bikhchandan, Hirshleifer, and Welch (1998).

the technical trading strategies aimed to beat the market. The empirical analysis will be made on the Croatian stock market index, for the Zagreb stock exchange, whose headquarters are in the capital city Zagreb. The interest of the readership regarding the selected market should be due to the following. First of all, several papers previously proved that the SAD effects exist on this market (please see literature review and the empirical results section, alongside the results in Milošević Avdalović and Milenković, 2007; or Radovanov and Marickić, 2017). Furthermore, the international diversification possibilities regarding the inclusion of this market to the portfolio still exist, as Baele, Bekaert, and Schäfer (2015) shown that this market has a lower Hurdle rate for the exact purpose of the international diversification; as well as lower correlation to the World market index, European market index, Russian index and the Emerging market index (data collected from MSCI). Next, the investor sentiment was found to be greatly affected via external events, such as political and economic uncertainty (Škrinjarić and Orlović, 2020). Finally, this market is one of those that provide attractive risk-adjusted returns, found in Golab, Allen, and Powell (2015).

The second section discusses the related literature, regarding anomalies in general, investor sentiment, and trading strategies. The third section describes the used methodology used in the study. A brief glance through the econometric model of estimating SAD effects is made here, due to it not being the focus of the research. Greater attention is given to the trading strategies aimed to exploit the SAD effects. The fourth section is the empirical one with the results of the simulation, and the final, fifth section, concludes the paper.

2. LITERATURE OVERVIEW

The general SAD and weather effects have been investigated in empirical research, as well as general sentiment proxies that affect the financial markets over a longer run. Thus, part of the research focuses on the investor sentiment overall, via survey measures (Brown and Cliff, 2005; Škrinjarić, Lovretin Golubić, and Orlović, 2020 volume premium, number of IPOs (initial public offering) in Baker, Wurgler, and Yuan (2012 macroeconomic variables based constructed indices in Abdelhédi-Zouch, Abbes, and Boujelbène (2015 Lee (2019 consumer confidence indicators in Jansen and Nahius (2003) or Schmeling (2009); dictionary-based sentiment construction in Jiang et al. (2019 Mangee (2018, 2014 and Chen et al. (2014). Other approaches can be found in McGurk, Nowak, and Hall (2019). The sentiment is even found to predict return series better than macroeconomic variables, such as in Uhl (2014 and it affects the way stock market participants forecast future returns (Frydman, Mangee, and Stillwagon, 2020 and the way assets are allocated within portfolios (Hilliard, Narayansamy, and Zhang, 2020).

Even mathematical frameworks have been constructed, which formalize the expectations of economic agents about future prices, where econometric models are combined with sentiment and non-fundamental factors (Frydman et al., 2017). However, these mentioned approaches observe the sentiment, return, and volatility interaction in the longer-run. For those who aim to speculate on the market, the short-term changes on the market present potentials for gains, to exploit the inefficiencies, if possible.

By focusing on the research regarding the SAD and weather effects in general, the following results are the most prominent ones. Some papers focus on one effect or the other, whereas others observe them simultaneously (e.g. Worthington, 2006; or Kaustia and Rantapuska, 2013). Temperature is one of the examined weather variables in Lu and Chou (2012); Kang et al. (2010); Dowling and Lucey (2008); Cao and Wei (2005); humidity in Tetteh and Amoah (2020); Sheikh, Ali Shah, and Mahmood (2017); Yoon and Kang (2009); Floros (2011); precipitation and wind in Edwards et al. (2015); or Kang et al. (2010); daylight savings effects in Worthington (2003); intraday weather effects on stock returns in Pizzutilo and Roncone (2016); lunar effects on REIT returns in Lee et al. (2014). Probably the most common variable is the SAD one, constructed based on the length of the day (i.e. photoperiod). Usual findings are that those stock markets whose latitudes are more distant from the equator have greater SAD effects throughout the year. This is not surprising, due to greater changes in the length of the day or night hours at such latitudes. Some popular early work includes Saunders (1993) for the New York stock exchange and the effects of cloudiness on the return series. In this research, the author observed some irrational behavior due to the effects of lack or surplus of cloudy hours. 26 stock markets from different countries have been in the focus of Hirshleifer and Shumway (2003 where the sunshine hours or lack of are found significant in determining the return series on the observed markets. Even more countries (37) were in the focus of Dowling and Lucey (2008 in which the daily returns asked for inclusion of the GARCH (generalized autoregressive conditional heteroskedasticity) model, as will be done in this research as well. This research is an example of greater risk aversion variations on the stock markets with greater distance from the equator. Other more developed markets are in the focus of Kaplanski and Levy (2009, 2017 or Xu (2016). In recent years, experience growth in the number of papers dealing with less developed markets. The Romanian stock market is popular in research, as seen in Stefanescu and Dumitru (2011) and Murgea (2016). Both papers found significant SAD effects in the Bucharest stock exchange. The Croatian as well: in Škrinjarić (2018 where the analysis included 10 other Central and South East European (CESEE) markets (11 markets in total (Bosnia and Herzegovina, Bulgaria, Czechia, Hungary, Poland, Serbia, Slovakia, Slovenia, Romania, and Ukraine); or Škrinjaić, Marasović and Šego (2021 where SAD effects were found in return and risk series as well.

As a final important group of papers important for evaluating the possibilities of such findings are those that are focused on the trading strategies that try to use such information. Comments on the inefficiencies of the stock markets, especially those in the development are found throughout the literature. Some of the newer studies include Heininen and Puttonen (2008); Barbić (2010); Alajbeg and Bubaš (2011); Georgantopoulos, Kenourgios, and Tsamis (2011); Stoitsova-Stoykova (2017); Dragotă and Ţilică (2014). The herding behavior is linked to the investor sentiment on the market, due to overreactions and under reactions (Blasco, Corredor, and Ferreruela, 2011). Thus, the contrarian strategies could potentially exploit such behavior. The herding behavior, although weak evidence is found, exists on the Croatian market (Škrinjarić and Šego, 2018b which is of interest here as well. The majority of the mentioned research finds inefficiencies in the CESEE markets, but open questions remain on if these inefficiencies can be exploited. Some research that examines trading strategies calculates simple measures, such as average return series of strategies of interest (Dzhabarov and Zeimba, 2010). Other measures, such as the *t*-test and number of positive returns are included in Gebka, Hudson, and Atanasova (2015 where authors contrast the technical trading strategies. Due to research missing on simulation of the trading strategies related to the SAD anomaly, let us briefly mention some recent papers dealing with the comparisons of the speculative and technical trading strategies: Ratner and Leal (1999); Bajgrowitz and Scaillet (2012); or Manahov, Hudson, and Gebka (2014). Finally, seasonality was observed in Zaremba (2017 and how it affects trading, but this regarded the cross-sectional stock characteristics; put options as saving the value of the portfolio due to seasonal changes have been observed in Muller and Ward (2015);

3. METHODOLOGY DESCRIPTION

3.1. Econometric estimation of SAD effects

The usual approach of estimating the SAD effects on a stock market is as follows (Kamstra, Kramer, and Levi, 2003; and Jacobsen and Marquering, 2008). The SAD measure on day *t* is calculated for the fall and winter days, with being equal to 0 otherwise. SAD_t in fall and winter is calculated as H_t – 12 and interpreted as photoperiod, where H_t is the average number of hours of the night at a location of specific latitude. Thus, the values of SAD_t differ for different latitudes, with oscillations being greater, the location is further from the equator. The value of H_t is estimated within the area of spherical trigonometry as follows:

$$H_t = \begin{cases} 24 - 7.72 \arccos\left(-\tan\left(\frac{2\pi\delta}{360}\right)\tan\gamma_t\right), & \text{Northern hemisphere} \\ 7.72 \arccos\left(-\tan\left(\frac{2\pi\delta}{360}\right)\tan\gamma_t\right), & \text{Southern hemisphere} \end{cases}. \quad (1)$$

In (1) it should be noted that if one observes latitude on the Northern or Southern hemisphere, γ_t is the sun's declination angle at latitude δ calculated via formula $\gamma_t = 0.4102\sin\left(\frac{2\pi}{365}\left(D_t - 80.25\right)\right)$. Finally, the values of D_t represent the day of the year (1 to 365 or 366). Due to asymmetric effects of the winter solstice on the risk aversion, an additional variable is defined, $Fall_t$, which is equal to 1 for days regarding fall time, and 0 otherwise. Due to several calendar anomalies being prominent in the literature, but markets as well, the following ones are included in the analysis. The main idea is that the risk aversion increasing towards the winter solstice. This reflects in lower returns before the solstice and Fall effects should be negative on the return series (Palinkas, Houseal and Rosenthal, 1996; and Palinkas and Houseal, 2000). Control variables have to be included in the analysis as well. Thus, the Monday (or weekend) effects will be included, Mon_t, due to this effect not being one of the most popular ones in the literature (Keim, 2008; Silva, 2010; Siegel, 2008; Škrinjarić, 2012 but it is still present on the Croatian market (Stoica and Diaconasu, 2011; Andries, Ihnatov and Sprincean 2018; Škrinjarić 2018; Škrinjarić and Šego, 2018a). Furthermore, the tax-loss selling of stocks at the end of the year is found to be prominent on stock markets as well (Fountas and Segredakis, 2002; Silva, 2010; Sias and Starks, 1997; Poterba and Weisbenner, 2001). That is why a binary variable Tax_t is included in the model, with the value being equal to 1 for the last trading day of the tax year and the next 4 days in the new tax year (zero value is otherwise). Another variable that needs to be added is the binary one regarding the pandemic of COVID-19, as the sample in the empirical analysis includes this period as well (Cov_t). Previous literature found that short-term negative effects are found in return series during the COVID-19 breakout throughout the world, with increases in the stock market risk (Corbet et al., 2020; Liu et al., 2020; Sansa, 2020; Haroon and Rizvi, 2020). This variable is equal to 1 for the period from 2 January – 30 April 2020. The data on the percentage of cloud cover ($Cloud_t$ daily average temperature ($Temp_t$ and millimeters of precipitation ($Prec_t$) are included as in Kamstra, Kramer, and Levi (2003). Interested readers can refer to the mentioned studies for references regarding the mentioned variables affecting the investment decisions over the year. Finally, the ARMA(p,q)-GARCH(p,q) (autoregressive moving average – generalized autoregressive conditional heteroskedasticity) specifications are included in estimation of the model, so that these specifications are taken into consideration, due to the nature of daily data. Thus, the following general model will be observed:

$$\begin{aligned} r_t &= \alpha + \sum_{i=1}^{p} \phi_i r_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \beta_M MON_t + \beta_{Tax} Tax_t + \beta_{\text{cov}} Cov_t + \beta_{SAD} SAD_t + \beta_{Fall} Fall_t \\ &+ \beta_{temp} Temp_t + \beta_{Cloud} Cloud_t + \beta_{Perc} Prec_t + \varepsilon_t \end{aligned}$$

$$\sigma_t^2 = \gamma + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \beta_i \sigma_{t-i}^2 + \gamma_{\text{cov}} Cov_t + \gamma_{SAD} SAD_t + \gamma_{Fall} Fall_t$$
$$+ \gamma_{temp} Temp_t + \gamma_{Cloud} Cloud_t + \gamma_{Perc} Prec_t \quad (2)$$

in which the first equation is the conditional return r_t with all included control variables alongside the *SAD* and *Fall* ones, the second equation is the conditional volatility, σ_t^2 , one, and ε_t is the error term. Model (2) includes all possibilities of the weather and SAD effects on the return and risk series.

3.2. Trading strategies simulation

The focus of the research are the trading strategies to see if the speculator can beat the market when knowing that there exist the SAD effects in the return series. To keep things simple, two benchmark strategies will be compared to the SAD ones: the value of the market index itself, for those who mostly follow the market (tracking and indexing strategies, see Frino, Gallagher, and Oetomo, 2005) and the stop-loss strategy as one popular technical strategy. The basic idea of the stop-loss strategy is to buy or sell a financial asset when a certain price is achieved. The sell-stop order is focused on selling the asset when the price falls below a certain threshold, whereas the buy-stop order is one in which the investor enters the short position when the price increases over a certain threshold. Return series can be observed as well (Acar and Satchell, 2002). Thus, the two benchmark strategies are: "bench" and "stop-loss". In both the investor starts with a monetary unit invested in both strategies. The "bench" strategy is, in essence, a *buy-and-hold* one, due to its passiveness. The "stop-loss" strategy is based on buying or selling with respect to the 0 return value as a threshold one.

The SAD strategies are formed as follows (with a starting point of one monetary unit):

- „SAD" – due to positive effects of the *SAD* variable on return series in the model (2 the investor buys the stock market index before winter arrives, holds the index during the winter, as returns are on average greater, and sells the index at the end of the winter. The obtained value is held until the new winter season comes. Then, the investor buys the value of the index with money obtained during the last selling transaction.
- „SAD + Mon" – as the previous strategy, but the investor is active during the non-winter time. This means that he is buying the index on Mondays during spring, summer and fall, and selling the index on the next trading

day. Due to the return series being negative on Mondays, the investor expects to obtain extra profits during the non-winter time as prices fall on Mondays compared to other trading days of the week.

- „SAD + Fall" – as the *Fall* variable has negative effects on the return series in the model (2 the investor buys the index at the beginning of the fall, due to prices going down, and sells the index when fall ends, due to prices going up in the winter solstice. Then, the investor holds the gained money until the next fall.
- „SAD + Fall + Mon" – as the previous strategy, but with included Monday strategy during winter, spring and summer, similar to strategy "SAD + Mon".
- „SAD + COVID" – for complete contrarians[5] who follow the market trends in order to exploit the COVID-19 pandemic effects alongside the first strategy "SAD". When WHO (2020a, b) announced Public Health Emergency of International Concern (PHEIC) and afterward on 11 February 2020 the name "COVID-19", it is supposed that on the next day investor decided to sell the current value of the market index. This is due to expectations of a short-term decline of the index value, as it happened consequently. The investor holds the portfolio and observes when the short-term effects disappear and sells the portfolio at the beginning of April (10 April 2020) when the market starts to recover.

Of course, all of the strategies are simulated based on the inclusion of the transaction costs forever buy or sell transaction, with the assumption of the costs being equal to 1% of the transaction value, as well as high 10%. This is to compare better and worse scenarios. As the SAD effects are not new in the literature, the contrarian (see LeBaron and Vaitilngam, 1999; or Siegel, 2002) who follows such studies should have been aware of such possibilities.

4. EMPIRICAL RESULTS

In order to empirically confirm the results of previous studies (Škrinjarić, 2018; Škrinjarić, Marasović, and Šego, 2018, 2021 daily data on the Croatian stock market index[6], CROBEX, was collected from Investing (2021 for the period 4 January 2010 – 31 December 2020. The daily weather data was retrieved from the Croatian Meteorological and Hydrological Service (2021) on-demand:

[5] For more details on contrarian strategies, please see Lakonishok, Shleifer and Vishny (1994); Lakonishok and Schmidt (1984, 1989).

[6] Unfortunately, the data on dividend payouts was not available to the author. Thus, the results contain some effects of dividend payouts as well, that should be taken into consideration when interpreting these results.

percentage of cloud cover, daily average temperature, and millimeters of precipitation for Zagreb. This city was chosen due to the Croatian stock market, the Zagreb Stock Exchange, having its headquarters in Zagreb. Finally, the *SAD* and *Fall* variables were constructed based on the description in the Methodology section, as well as Tax, Monday, and the COVID-19 variable. Daily return series have been calculated via formula $r_t = \ln (P_t / P_{t-1}$ where r_t denotes the return series and P_t the index value on day *t*. In total, the analysis includes 2740 daily observations for all variables.

The focus of this research is not on the estimation of the model (2 as the SAD effects are already proven to be present on the Croatian market, as already mentioned in the previous sections. However, the results need to be confimed. The Box-Jenkins (1970) approach was used to determine the appropriate ARMA-GARCH model for the return and risk series. AR(1) was sufficient enough to achieve no autocorrelation of the residuals of the model (up to the lag length of 30); alongside GARCH(1,1) with the assumption of the GED (generalized error distribution) to obtain no residual ARCH effects (again, up to lag length of 30). The maximum likelihood method of estimation was utilized to obtain the estimation results. Thus, a brief comment is given in Table 1, as the focus is the possibilities of exploiting the results via trading strategies in the next part of the subsection. The results are in line with previously mentioned research of the Croatian market, with the *SAD* variable being significant and having a positive impact on the return series. Moreover, the *Fall* variable is found to be significant here. This could be due to including the *Cloud*, *Prec*, and *Temp* variables as well[7]. As the *Monday* variable is found to be significant as usual for this market, the trading strategies will include (as previously described) these effects to some extent.

Table 1. Estimation results of SAD effects, model (2) estimation results

Coefficient	Conditional return equation	Coefficient	Variance equation
Const	0.0006 (0.0004)*	Const	3.36·10-6 (1.37·10-6)***
Monday	-0.0015 (0.0002)***	ARCH(1)	0.0976 (0.0158)***
Tax	0.0007 (0.0008)	GARCH(1)	0.8574 (0.0204)***
COVID	-0.0005 (0.0010)	COVID	3.58·10-6 (1.04·10-6)***

[7] The insignificance of these variables is in line with Dowling and Lucey (2008), Goetzmann and Zhu (2005).

AR(1)	0.0524 (0.0183)***	SAD	-4.47·10-7 (3.03·10-7)*
SAD	0.0002 (0.0001)*	Fall	2.32·10-7 (2.19·10-7)
Fall	-0.0003 (0.0001)***	Cloud	-7.72·10-8 (1.43·10-7)
Cloud	-4.49·10-5 (3.18·10-5)	Perc	9.35·10-8 (7.67·10-8)
Perc	1.08·10-6 (1.6·10-5)	Temp	-7.62·10-8 (4.25·10-8)**
Temp	-2.19·10-7 (1.79·10-5)	-	-

Source: author's calculation

Note: standard errors are given in parenthesis. *, ** and *** denote significance on 10%, 5% and 1% (one sided test).

The results of the simulation of the trading strategies are in the following figures and tables. First of all, the simulated strategies are shown in Figures 1 and 2. The 1% and 10% transaction costs are divided, so greater comparability can be made between the strategies. Figure 1 contrasts the 1% costs included. The best performing was the "SAD_1%" and the "stop-loss_1% strategies when comparing the portfolio value over the observed period. The "bench" strategy is the worst one, with the lowest values. This means that the passive investors that follow the market index to obtain diversification of the overall portfolio would have suffered the greatest losses. Due to the stock market index being stagnant at best in the observed period overall, none of the strategies provided an increasing trend over the years. However, the idea of beating the market is proven in Figure 1 for the majority of the strategies, due to their values being greater than the "bench" strategy which represents the market itself. Similar conclusions arise when observing Figure 2, in which all strategies are compared, but now with 10% transaction costs. Of course, the profits are lower, but the overall conclusions still hold. Although there were more transactions in the case of those strategies which included the Monday effect trading, there were still profitable in terms of beating the market. The COVID-19 crisis is prominent in all strategies, due to the majority of the markets all over the world being affected by this pandemic. For true contrarians, the additional simulation was made within the best strategies in Figures 1 and 2, namely, the solely "SAD" ones. The original strategies are compared to the same ones with the inclusion of COVID-19 contrarian strategies in Figure 3, for the data in 2020. If the speculator was not panicking as other market participants, he would have saved his portfolio value during the short-term market decline and obtained even better profits at the end.

Table 2. Performance measures of selected trading strategies

Strategy	Mean	Total	SD	CE		
				1	5	10
Bench	$-8.37\cdot10^{-5}$	$-2.29\cdot10^{-1}$	$7.57\cdot10^{-3}$	$-1.12\cdot10^{-4}$	$-2.27\cdot10^{-4}$	$-3.70\cdot10^{-4}$
SAD_10%	$-3.85\cdot10^{-5}$	$-1.05\cdot10^{-1}$	$6.69\cdot10^{-3}$	$-6.08\cdot10^{-5}$	$-1.50\cdot10^{-4}$	$-2.62\cdot10^{-4}$
SAD_1%	$-3.67\cdot10^{-6}$	$-1.01\cdot10^{-2}$	$5.74\cdot10^{-3}$	$-2.01\cdot10^{-5}$	$-8.60\cdot10^{-5}$	$-1.68\cdot10^{-4}$
SAD+Covid_10%	$-6.63\cdot10^{-5}$	$-1.82\cdot10^{-1}$	$6.82\cdot10^{-3}$	$-8.96\cdot10^{-5}$	$-1.83\cdot10^{-4}$	$-2.99\cdot10^{-4}$
SAD+Covid_1%	**$1.08\cdot10^{-4}$**	**$2.95\cdot10^{-1}$**	$4.36\cdot10^{-3}$	**$9.81\cdot10^{-5}$**	**$6\cdot10^{-5}$**	**$1.24\cdot10^{-5}$**
SAD+Mon_10%	$-5.31\cdot10^{-5}$	$-1.45\cdot10^{-1}$	$6.67\cdot10^{-3}$	$-7.53\cdot10^{-5}$	$-1.64\cdot10^{-4}$	$-2.75\cdot10^{-4}$
SAD+Mon_1%	$-1.83\cdot10^{-5}$	$-5.02\cdot10^{-2}$	$6.38\cdot10^{-3}$	$-3.87\cdot10^{-5}$	$-1.20\cdot10^{-4}$	$-2.22\cdot10^{-4}$
SAD+Fall_10%	$-5.34\cdot10^{-5}$	$-1.46\cdot10^{-1}$	$3.94\cdot10^{-3}$	$-6.12\cdot10^{-5}$	$-9.23\cdot10^{-5}$	$-1.31\cdot10^{-4}$
SAD+Fall_1%	$-1.86\cdot10^{-5}$	$-5.11\cdot10^{-2}$	**$3.44\cdot10^{-3}$**	$-2.45\cdot10^{-5}$	$-4.82\cdot10^{-5}$	$-7.77\cdot10^{-5}$
SAD+Fall+Mon_10%	$-5.52\cdot10^{-6}$	$-1.51\cdot10^{-2}$	$5.13\cdot10^{-3}$	$-1.87\cdot10^{-5}$	$-7.13\cdot10^{-5}$	$-1.37\cdot10^{-4}$
SAD+Fall+Mon_1%	$2.93\cdot10^{-5}$	$8.02\cdot10^{-2}$	$4.75\cdot10^{-3}$	$1.80\cdot10^{-5}$	$-2.72\cdot10^{-5}$	$-8.36\cdot10^{-5}$
stop-loss_10%	$2.89\cdot10^{-5}$	$-1.30\cdot10^{-2}$	$4.93\cdot10^{-3}$	$1.67\cdot10^{-5}$	$-3.18\cdot10^{-5}$	$-9.24\cdot10^{-5}$
stop-loss_1%	$2.89\cdot10^{-5}$	$8.23\cdot10^{-2}$	$4.93\cdot10^{-3}$	$1.67\cdot10^{-5}$	$-3.18\cdot10^{-5}$	$-9.24\cdot10^{-5}$

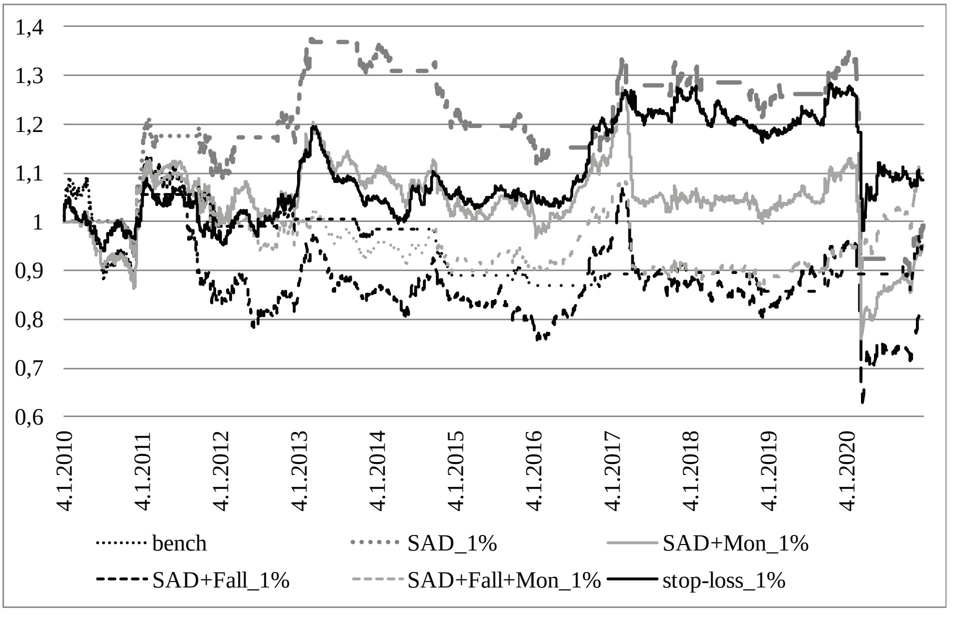
Strategy	LPM	HPM	Skew	Non neg (%)	> market (%)	Break even costs	No times best
Bench	$4.65 \cdot 10^{-3}$	$4.58 \cdot 10^{-3}$	-2.199388	50.5	-	-	0
SAD_10%	$4.65 \cdot 10^{-3}$	$1.50 \cdot 10^{-3}$	–4.223188	77.2	89.1	2.64	0
SAD_1%	$8.75 \cdot 10^{-3}$	$1.46 \cdot 10^{-3}$	–4.729718	77.2	**96.6**	0.27	1
SAD+Covid_10%	$5.42 \cdot 10^{-3}$	$1.45 \cdot 10^{-3}$	–5.652290	77.4	89.1	2.88	0
SAD+Covid_1%	$5.25 \cdot 10^{-3}$	$\mathbf{4.73 \cdot 10^{-3}}$	2.579351	77.4	**96.6**	0.29	**7**
SAD+Mon_10%	$4.93 \cdot 10^{-3}$	$2.34 \cdot 10^{-3}$	–4.354367	67.1	84.9	59.20	0
SAD+Mon_1%	$5.31 \cdot 10^{-3}$	$2.34 \cdot 10^{-3}$	-3.520626	67.1	90.2	5.89	0
SAD+Fall_10%	$\mathbf{1.27 \cdot 10^{-3}}$	$6.53 \cdot 10^{-4}$	-2.666741	**87.1**	39.7	2.08	1
SAD+Fall_1%	$4.97 \cdot 10^{-3}$	$6.53 \cdot 10^{-4}$	**5.268789**	**87.1**	76.8	**0.21**	4
SAD+Fall+Mon_10%	$4.84 \cdot 10^{-3}$	$1.58 \cdot 10^{-3}$	-1.707375	74.4	43.6	54.60	0
SAD+Fall+Mon_1%	$4.86 \cdot 10^{-3}$	$4.61 \cdot 10^{-3}$	1.370507	74.4	89.9	4.98	0
stop-loss_10%	$4.58 \cdot 10^{-3}$	$4.65 \cdot 10^{-3}$	-1.896565	75.2	84.6	150.4	0
stop-loss_1%	$4.63 \cdot 10^{-3}$	$4.65 \cdot 10^{-3}$	-1.896565	75.2	90.5	15.03	0

Source: author's calculation

Note: bolded values in shaded cells indicate the best performance in the column. Mean – average return, Total – total return, SD – standard deviation, CE – certainty equivalent, LPM – lower partial measure, HPM – higher partial measure, Skew – coefficient of skewness, Non neg (%) – the percentage of nonnegative returns, > market (%) – the percentage of days the strategy outperforms the market (i.e. the "bench" strategy Break even costs – total costs to be covered in the entire period to break even at the end, No times best – number of times the strategy is best when compared to others across columns.

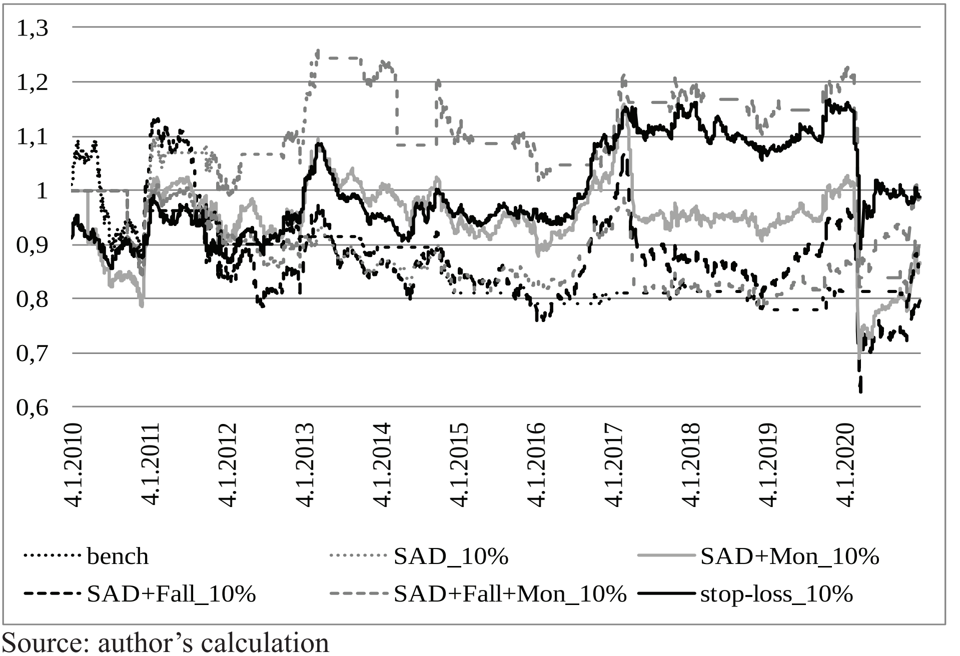
Next, specific portfolio performance measures have been calculated in Table 2. The mean is the average return for the entire observed period for a strategy. Due to the positive effects of the COVID trading, the best strategy in terms of the mean return was "SAD+Covid_1%". This is true for the second column, i.e. for the total return. SD, i.e. the standard deviation of the portfolio return series indicates that many strategies were less volatile compared to the "bench" one. Although speculators are more interested in the profit measures, this also is a good indicator for those who pay attention to the risk as well. CE is the certainty equivalent (Varian, 1992; Guidolin and Timmermann, 2008; Cvitanić and Zapatero, 2004 is estimated as the following value CE ≈ $E(\mu)$-0.5$\gamma\sigma^2$, where $E(\mu)$ and σ^2 represent the mean return and the variance of the portfolio, whereas the coefficient of absolute risk aversion is denoted with γ. The values of γ are changed from 1 and 5, to 10 to represent higher to lower risk tolerance. Again, the "SAD+Covid_1%" strategy dominates the others. If the focus is made on the losses and excesses separately, the LPM, i.e. the lower partial moment and HPM (higher partial moment) for every strategy have been calculated as follows (Shadwick and Keating, 2002): $LPM = \frac{1}{\tau}\sum_{t=1}^{\tau}\left[\max\left\{0, E(r) - r_t\right\}\right]$, where τ is the number of below average return series; $HPM = \frac{1}{\eta}\sum_{t=1}^{\eta}\left[\max\left\{0, r_t - E(r)\right\}\right]$, and η is the number of above average return series. For the LPM, the results are mixed. Some strategies provided lower losses than the "bench" but were not better than the "stop-loss" ones. However, those aiming to obtain extra profits can observe that HPM is best for several SAD combinations, either with the Fall variable or the COVID one. To obtain a better insight into the asymmetry of the return distribution, the coefficient of skewness column indicates that the best strategies are SAD in combination with Fall and COVID. These two provided the greatest extreme abnormal returns. Some of the usual performance measurements include the last three. The market has overall achieved 50.5% of non-negative returns ("bench"). All other strategies are much better performing. Thus, it is not always best to be passive. The "SAD+Fall" strategies achieved the best results in this column, due to holding the unchanged value of the portfolio in this contrarian strategy. Although already seen in Figures 1 and 2, the best performing strategies that were beating the "bench" one majority of the time are the "SAD" and the "SAD_Covid" combination. Next, due to transaction costs being a prominent problem in many previous discussions on the possibilities of exploiting the anomalies found on the market, the break-even costs are calculated. This is the value in the entire period, the investor needed to cover just the costs to obtain zero profit. Due to the "stop-loss" strategy being the one with the most transactions, it has the highest costs. Thus, although this strategy outperformed others regarding certain criteria in Table 2, the costs are those that could turn off the investor. In this column, one can see that the lowest break-even costs are found for those strategies in which the least amount of transactions were made. However, due to potential gains, there needs to be a balance between observing the costs and the profits. Finally, in order to avoid data snooping bias, the White's (2000) reality check for data snooping test was performed, in which the null hypothesis assumes that the SAD strategies produced non-positive returns, where for the 10 SAD strategies and 1342 daily return series, length of the block bootstrap of 1, and 1000 bootstrap replications were made following the White (2000) paper and *R* script preparation on cristiandima (2014) website. The resulting *p*-value is close to zero, indicating that the null hypothesis can be rejected on usual levels of significance.

Figure 1. Portfolio value of simulated trading strategies, 1% transaction costs



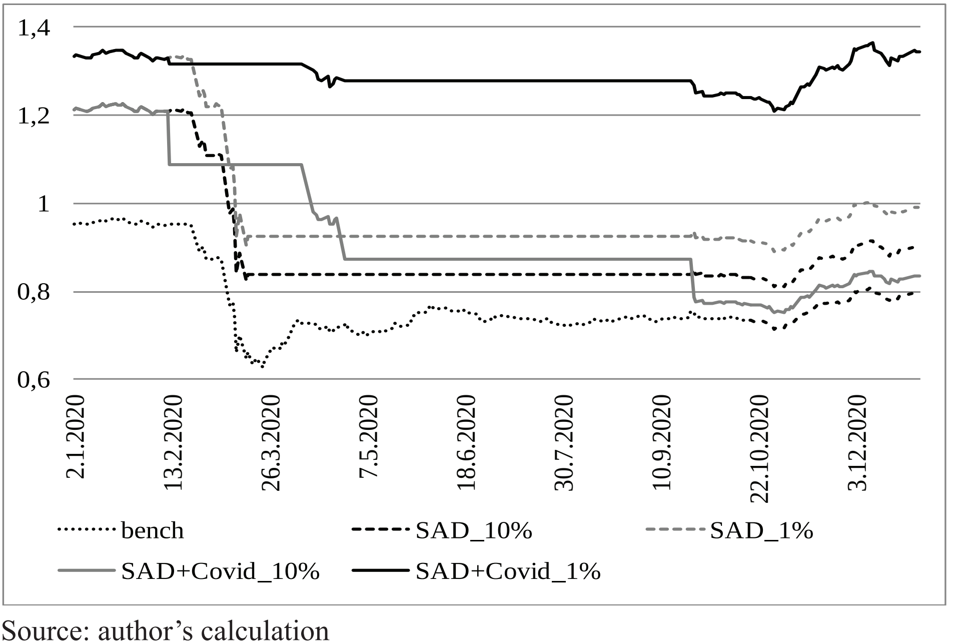
Source: author's calculation

Figure 2. Portfolio value of simulated trading strategies, 1% transaction costs



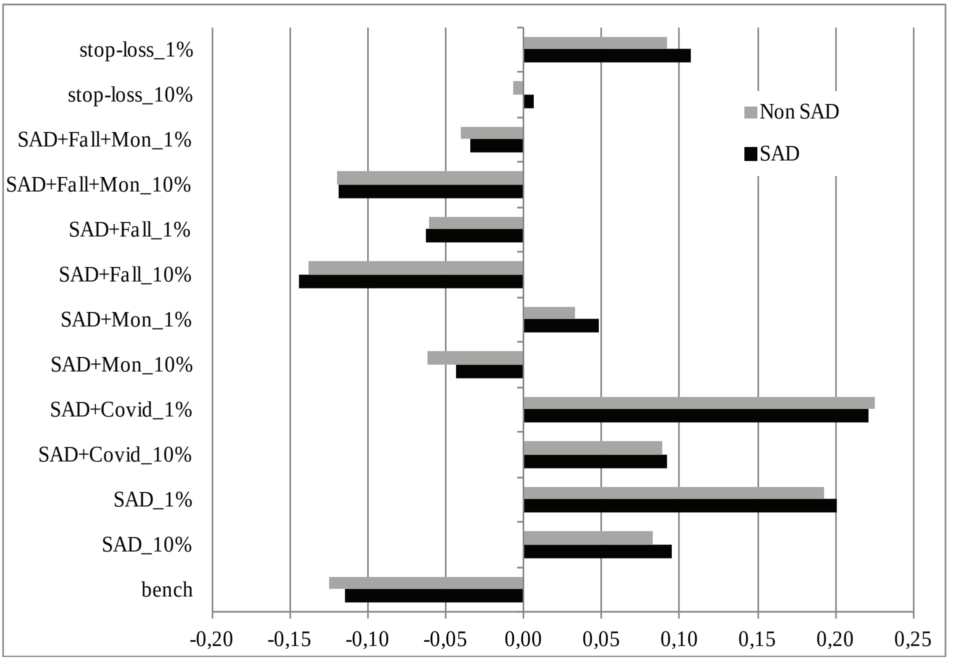
Source: author's calculation

Figure 3. Portfolio value of simulated trading strategies, 2020 data, included COVID-19 exploitation



Source: author's calculation

Figure 4. Mean value of each trading strategy, SAD time VS non-SAD time



Source: author's calculation

Note: values are multiplied with 1000 so that the decimal places are reduced.

Before the conclusion, additional average returns were calculated for the specific part of the year, i.e. the SAD part (fall and winter) and the rest of the year. These mean returns are shown in Figure 4. This visualization summarizes the previous comments on the returns and profits of the observed strategies, with the SAD strategy (in combination with COVID, and without it) being the best one. With the inclusion of the Fall part in trading, the opposite is achieved. Namely, the investor is better without including the variability of the return series around the winter solstice. By focusing on the SAD effects of the winter alone, one could be much better off.

5. CONCLUSION

The importance of research such as this one can be found in tailoring contrarian strategies so that the possibilities of obtaining extra profits could be observed. If the speculator is focusing to behave against the herd, there could be possibilities to beat the market. Due to the SAD effects being found on many stock markets, the question remained if this can be exploited. Namely, finding certain anomalies in the return series does not mean that the Efficient Market Hypothesis is violated if no profits can be made. Research usually lacks the simulation of the strategies. Thus, this paper wanted to fill that gap. As the SAD effects do not ask for many transactions over the year, they could be attractive for those who do not want to follow the market daily. The implications of the results are as follows. If the speculator or the investor chooses not to be entirely passive, he could beat the market. A balance should be made between the number of transactions and the profit desires. The Monday effects prominent for many years and on many markets are not suggested to be exploited, as too many transactions resulted in lowering the portfolio value and the possibility to beat the market. Suggestions for the stock market participants include to at least trying to include the SAD (just the winter) effects to some extent in existing strategies, especially the technical ones.

The shortfalls of the study include the following ones. Firstly, relatively simple strategies were simulated; in some of the investor does nothing during the periods of non-winter or non-fall. In order to exploit other (calendar) anomalies during the year, a greater analysis needs to be done in the future (for calendar anomalies, please see, Škrinjarić, 2012). Not having data on dividend free index also makes the results somewhat muddled. Future work should try to include cleaner data as well. Next, no other financial assets were examined to combine into the strategies, so that a portfolio is formed. This could be explored as well, to see the diversification possibilities, or simply to see if the idea of beating the market could be achieved in a greater manner. Finally, a simultaneous analysis can be made for other country indices as well, so that international investors obtain better insights into trading possibilities. Although data snooping has been addressed many times in the literature (see extensive research in Park and Irwin, 2007 there are some possible ways to evaluate the results of these findings in the future. One is to replicate the findings with newer data, as suggested in Lo and MacKinlay (1990) or Schwert (2003). The White procedure was performed in this study, but another robustness checking of the results would always be welcomed.

This research contributes to the area of asset pricing models, in terms of anomalies and exploiting the "irrational" behavior within the rational models. Due to the return and risk series being, at least partially affected by the SAD on the selected markets. This does not mean that the "old" models are wrong (Ying et al., 2018). However, evidence on the anomalies that cannot be explained via those "old" models is piling up. Thus, future models, in theory, and practice should at least consider the possibilities of nonrational behavior, and people behavior in general.

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IDEMO ZARADITI NA SEZONSKOJ DEPRESIJI NA TRŽIŠTU DIONICA

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Sažetak

Ovaj članak razmatra mogućnosti iskorištavanja bihevioralne anomalije vezane uz sezonsku depresiju (engl. SAD – seasonal affective disorder) u prinosima dionica na Zagrebačkoj burzi. Prethodna literatura potvrđuje postojanje ovog učinka u prinosima dionica, no ne postoje obuhvatne analize koje se bave trgovinskim strategijama koje iskorištavaju tu činjenicu. Zato se u ovome radu nakon potvrde postojanja SAD učinaka u prinosima dionica vrši fokus na simulaciju trgovinskih strategija koje takve informacije uvažavaju. Rezultati upućuju da postoje SAD učinci, kao i učinci jeseni, temperature i količine kiše na predviđanje prinosa dionica. Temeljem dnevnih podataka od siječnja 2010. do prosinca 2020. godine za tržišni indeks CROBEX, simulira se nekoliko strategija u svrhu pobjeđivanja tržišta. Čak i uz uključivanje transakcijskih troškova u analizu, pokazano je da postoje mogućnosti za špekulante da zarade dodatne profite u određenim situacijama. Razmatraju se jednostavne strategije trgovanja u radu, no ovdje se pruža polazna točka za buduća istraživanja, u kojima se mogu kombinirati strategije trgovanja temeljene na kalendarskim učincima kao i SAD anomalijom. To je zbog toga što oni špekulanti koji odluke donose temeljem SAD učinaka u suštini rade suprotne strategije (engl. contrarian) u odnosu na ostatak krda i mogu ostvariti profite upravo zbog promjene averzije prema riziku kroz godinu.

Ključne riječi*: učinak sezonalne depresije, tržišta dionica, COVID-19, tržište u nastajanju, zimska depresija, anomalija vezana uz vrijeme, bihevioralne financije*

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