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Article

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Reference: Trifan, Ruxandra (2020). Behavioural biases and stock market reaction : evidence from six post-communist countries. In: Ekonomický časopis 68 (8), S. 811 - 826. https://www.sav.sk/journals/uploads/0903124608%2020%20Trifan%20+%20SR.pdf. doi:10.31577/ekoncas.2020.08.03.

Behavioural Biases and Stock Market Reaction: Evidence from Six Post-communist Countries[1]

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Abstract

This article investigates the relationship between several behavioural biases and stock market reactions. We analyse six post-communist countries (Romania, Poland, Hungary, Slovenia, the Slovak Republic and the Czech Republic) for the January 2012 – September 2019' time period. We test for any effect of different measures used in behavioural finance literature (investors' optimism, respectively pessimism, spontaneous behaviour and the anchoring effect) on stock market's trading volume. Our empirical findings suggest that judgement and emotions are a significant driver of the stock market, not all market players acting rationally when investing. Investors are susceptible to behavioural biases which influence significantly their decision making process. Polish investors are pessimistic individuals, while in Romania, Hungary and the Czech Republic the optimistic sentiment exercises a greater influence on the trading activity. Spontaneous behaviour characterizes the Romanian, Hungarian and Slovak investors. Lastly, the anchoring effect is found significant in 5 out of 6 countries analysed, no effect being observed in the Czech Republic.

Keywords: *behavioural biases, trading volume, stock market behaviour*

JEL Classification: G12, G14, G41

DOI: https://doi.org/10.31577/ekoncas.2020.08.03

Introduction

The psychological component of the investors' behaviour has gained a lot of interest among researchers in the last decades. An extensive body of literature proves that investors' behaviour contradicts the traditional theories and is influenced

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[1] This paper was co-financed by The Bucharest University of Economic Studies during the PhD program.

by several factors such as psychological biases, heuristics, demographic variables, etc. (Kumar and Lee, 2006; Baker and Wurgler, 2007; Babajide and Adetiloy, 2012).

The rational expectations theory failed to explain the financial market behaviour, investors reacting non-rational when making financial decisions. Smith, Suchanek and Williams (1988) is representative here for his analysis on the evolution of market prices and beliefs over a longer time horizon, within a market for a long-lived asset. The investor trading behaviour is based on beliefs, "which is not fully justified by fundamental rational valuation" (Dragotă and Mitrică, 2004). Oprean (2014) and Dhaoui (2015a,b) complemented the existing literature with evidence to support a spontaneous behaviour of the market players.

The main goal of this article is to determine the extent to which behavioural biases such as optimism, pessimism, spontaneous behaviour and the anchoring effect, exercise an influence on the stock market, through the trading volume. The analysis focuses on post-communist countries within the Central Eastern Europe zone, namely Romania, Poland, Hungary, Slovenia, the Slovak Republic and the Czech Republic. As small emerging and frontier markets, they are characterized by lower levels of liquidity in comparison with their peers and larger institutional trades strongly affect or, in some cases, dictate the market trend. Furthermore, they face greater levels of uncertainty and weaker regulatory systems. Therefore, we expect to see an increased degree of spontaneous reactions, which are not necessarily in accordance with the information available related to stock market evolution or to fundamentals. Hence, this study contributes, firstly, to the existing literature on the domestic market through a better understanding on the behavioural biases and how they affect trading, but also to a better understanding of the investors' actions. Secondly, it complements the research done on former socialist countries (Chelley-Steeley, 2005; Beckmann, Belke and Kühl, 2011; Peterle and Berk, 2016) and provides evidence to support the assumption of irrational behaviour (Shefrin, 2002; Barberis and Thaler, 2003).

This research can be helpful for both theoreticians and active practitioners through a better comprehension of how investor's psychology has a say in the global functioning of the financial markets, as well as to integrate these sentiments and emotions in the macroeconomic analysis. Thus, it may provide possible explanations for certain economic events that affect greatly the economy health state.

The remainder of this paper is structured as follows. Section 1 presents a literature overview on the behavioural factors. The second section describes the variables' computation and the methodology used in order to investigate the impact of behavioural errors on the stock market, through the trading volume.

The third section shows the data used to perform the equation model and to estimate some preliminary results. Section 4 presents the main empirical findings and the last section states the conclusions drawn after the analysis.

1. Literature Review

The efficient market hypothesis (Fama, 1970; 1991; 1998) and the rational expectations theory (Muth, 1961) have been intensively analysed when explaining the behaviour of stock market returns, trading volume and volatility in both developed and emerging economies. Several definitions were proposed to better explain the rational agent. From an economic point of view, a rational behaviour relates to the decision-making process in accordance with the choice that brings the optimal level of utility or benefit, monetary or emotional, for an individual. In other words, rationality is the internal consistency of a specific individual, seen as a sum of his needs, desires, obstacles, motivation, responsibilities, environment and so on and so forth, ultimately indicating to a certain predictability the investor's moves (Robbins and Judge, 2007). Two significant theories derived from this concept. First, the rational choice theory states that all individuals are "homo economicus", thus making logical decisions which result in the highest satisfaction. Second, there is the bounded rationality theory. The assumption here is limited rationality, an individual making a choice based on the information he currently has and on the way he processes it (Mullainathan and Thaler, 2000).

From a traditional finance perspective, an investor is rational if he makes a decision after evaluating all the information available to him, pursuing as an objective his return maximization for a given level of risk (Sanfey et al., 2003). It assumes that people are unaffected by biases or emotions. Behavioural finance complements the definition so far, by adding the psychological to the standard economic theories. It focuses on how individuals interpret the amount of data flooding them, how they sort between relevant and non-relevant information and how they act upon it. Hence, it provides a better explanation for irrational investment decision-making process (Shefrin, 2002).

The relationship between biases, heuristics, investors and markets' trading behaviour has been largely studied throughout the literature (Smith, Suchanek and Williams, 1988; Puri and Robinson, 2007; Angelini and Cavapozzi, 2017; Roger, Roger and Schatt, 2018; Marquardt, Noussair and Weber, 2019; etc.). There is no classical approach here on how to better determine the errors of investors' behaviour. There were proposed several measures for behavioural biases. One approach is based on the survey method, which quantifies and models the

responses of individual investors regarding expected movement of the stock market and the aggregate economy (Puri and Robinson, 2007; Kinari, 2016; Angelini and Cavapozzi, 2017; Gabbi and Zanotti, 2019). Others, used market related implicit sentiment proxies like the Thomson Reuters Market Psych Indices, consumer confidence indices, investor sentiment indices and so on and so forth (Nooijen and Broda, 2016; Griffith, Najand and Shen, 2020). Donelly (2014) determined the market players' optimism/pessimism through earnings forecast, by examining the forecast errors and revisions. Satt (2016) proposed as measure for investor behavioural biases the difference between analyst recommendations and last month's consensus recommendations. Other researchers linked investors behavioural errors to the weather condition, namely to the level of sunshine or clouds (see Hirshleifer and Shumway, 2003; Goetzmann et al., 2014).

Under the influence of sentiment, preferences and beliefs, market players behave differently. Their financial decisions are driven to a certain extent by their optimism or pessimism, amongst other factors.

Investors' trading activity is asymmetrically affected by their optimistic, respectively pessimistic expectations for future earnings. While optimists are sensitive to positive results, the pessimists are more sensitive to negative results. On one hand, an optimistic investor expects an increase in stock returns to be followed by another new increase, offering the possibility of realizing future gains. Therefore, the more optimistic a market player is, the more he will increase his trading volume, underestimating his risk exposure. If the market is not in accordance with his expectations and there is a decrease in stock prices, he will trade normally, being less affected by the negative results. On the other hand, a pessimistic investor expects a decrease in stock returns to be followed by another new decrease and he will diminish his exposure by trading less, fearing potential losses. If, contrary to his expectations, there is a positive trend of the stock returns, he will trade normally.

Puri and Robinson (2007) showed that optimism is strongly related to the investment amount allocated in stocks. Moreover, Christelis, Jappelli and Padula (2010) found a positive effect of several cognitive factors (amongst them, the optimism bias) on the investing probability in information intensive assets. Rocciolo, Gheno and Brooks (2019) linked optimism to investors' expectations regarding the market risk, political and economic events.

Consistent results were also obtained by Angelini and Cavapozzi (2017) and Benhabib and Spiegel (2019). Roger, Roger and Schatt (2018) observed the behaviour of financial analysts, who tend to process differently large and small figures: "*when they are optimistic (pessimistic), analysts issue more optimistic (pessimistic) target prices for small price stocks than for large price stocks"*.

Summing up all of the above findings, market players are not always rational and their financial decisions are based on sentiment and beliefs. As such, behavioural biases play an important part in financial markets and their use in macroeconomic models helps to better explain and control for what drives the market.

2. Variables Computation and Methodology

This paper examines the effect of behavioural biases on the stock market. To do so, we defined the variables of the study and proposed the equation models, later used to estimate the results for the suggested relationship. Our analysis focuses on six stock markets within the Central Eastern Europe, namely Romania, Poland, Hungary, Slovenia, the Slovak Republic and the Czech Republic. We considered as Dependant variable the market index trading volume, which serves as proxy for the stock market behaviour. This indicator is of great relevance, being the basis of many trading strategies. It makes investors aware of the stock's market activity and its liquidity in terms of order execution and connection between the buyers and the sellers. We calculated this variable as the natural logarithm of the total number of transactions within a trading day.

In terms of behavioural biases that may affect investors' actions, we chose to include in our analysis the following: optimism, pessimism, spontaneous behaviour and the anchoring effect, as defined by Dhaoui (2015a,b), described in the following lines. Even though approaches have been made to model the market players' behaviour and incorporate their judgemental errors, there has not been conceived so far a standard manner to define the variables. In this paper, we chose to compute the behavioural factors based upon the daily stock market indices returns and values, as it is presented below.

We first proceeded with the calculations of daily returns of the market indices, as follows:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{1}$$

where

R_t – the daily stock market index return on day t,
P_t – the closing value of the market index on day t,
$P_{t\text{-}1}$ – the closing value of the market index on day t-1.

Based on the returns of the stock index for each of the six markets in our analysis, we estimated the investors' optimism, pessimism and spontaneous

behaviour. These biases reveal the financial market movements which are significantly influenced by market players' psychological perception of determined trades, leading to mispricing situations.

The optimism shown by investors in relation with the information they have at a certain moment in time leads to over-reaction from their side, thus increasing the volume of their transactions when expecting a rise in the stock prices. An optimistic investor is the one who expects an increase in stock returns to be followed by another new increase. Thus, having in mind the possibility of realizing future gains, he will increase his trading volume. If the market moves in the opposite direction with respect to the optimistic investor's expectations, he will trade normally or postpone, being more sensitive to positive results than to negative ones.

Connecting market positive returns with a certain level of profit individuals previously reached, would make them overestimate the probability of good outcomes and invest more.

Dhaoui (2015a,b) defined the optimistic investor as the one who "*expects an above average stock price level to which a standard deviation is added at any given time"*. On the assumption of investors being return seekers and risk adverse, he modelled the optimism variable by using an average stock price level and standard deviation, creating, thus, a benchmark level $\left(\overline{R}+\sigma\right)$.[2] If optimistic investors' previous gains (identified through the returns in the previous day) are higher than the benchmark level, they will expect further increases in stock returns and trade aggressively. If this is not the case, they will trade normally or they would postpone.

In our study, we defined the optimism variable by taking into account the approach of Dhaoui (2015a,b). However, instead of subtracting the standard deviation from the average return, calculated for the entire time period as Dhaoui, we computed the average return and standard deviation on the previous 52 weeks, as can be seen below. We considered a period of 52 weeks to be representative as per its use in the technical analysis by traders and investors when determining an asset's behaviour and identifying investment opportunities. It is significant as well for potential investors as it shows them how much a share price fluctuated within this period, but it also gives an overview on the company's current state (bullish earning prospects, an unplanned management of debts or unnecessary costs that are not controlled for, etc.).

[2] Dhaoui (2015a,b) used the average stock price to illustrate that investors were return seekers and the average standard deviation to estimate their exposure to risk. Combining the two, the average stock return augmented by the standard deviation, he estimated the lowest high return as the fixed level over which, if reached, optimistic investors would overreact and trade aggressively.

$$\text{Optimism} = \max\left\{\left[R_{t-1} - \left(\overline{R}_{52week} + \sigma_{52week}\right)\right]; 0\right\} \quad (2)$$

where

R_{t-1} – the return registered in the previous day (t-1),

$\left(\overline{R}_{52week} + \sigma_{52week}\right)$ – the lowest high level of return that an optimistic investor would accept.

Adversely, pessimism occurs when the estimations stipulate a decrease in the stock prices. A pessimistic investor expects a decrease in stock returns to be followed by another new decrease and he will diminish his exposure by trading less or postponing, fearing potential losses.

In the same manner as in the case of optimism, Dhaoui (2015a,b) computed the benchmark, that quantifies the minimum level of loss that investors would accept, as $\left(\overline{R} - \sigma\right)$. Specifically, if the returns registered in the previous day are higher than the benchmark $\left(\overline{R} - \sigma\right)$, pessimistic investors would continue on trading. If, on the contrary, returns in the previous day are lower than the benchmark value, they would postpone or abstain from trading, being more fearful and doubtful about future results.

When computing the pessimism variable, we determined the benchmark by using the average return and standard deviation on the previous 52 weeks:

$$\text{Pessimism} = \max\left\{\left[R_{t-1} - \left(\overline{R}_{52week} - \sigma_{52week}\right)\right]; 0\right\} \quad (3)$$

where

R_{t-1} – the return registered in the previous day (t-1),

$\left(\overline{R}_{52week} - \sigma_{52week}\right)$ – the highest low level of return that a pessimistic investor would tolerate.

Spontaneous behaviour illustrates the reactions of investors who trade randomly, in a chaotic manner, without previously investigating the market behaviour. They are neither optimistic nor pessimistic. They would trade if the returns registered in the just last day exceed the critical level of acceptance defined as $\left(\overline{R}_{52week} - \sigma_{52week}\right)$ and get closer to the profit benchmark $\left(\overline{R}_{52week} + \sigma_{52week}\right)$. If previous day's returns are not within this range, investors would abstain from trading.

$$\text{Spontaneous behaviour} = \begin{cases} R_t, if \left(\overline{R}_{52week} - \sigma_{52week}\right) < R_{t-1} < \left(\overline{R}_{52week} + \sigma_{52week}\right) \\ 0, otherwise \end{cases} \quad (4)$$

where

R_{t-1} – the return registered in the previous day (t-1),

$\left(\overline{R}_{52week} - \sigma_{52week}\right)$ – the highest low level of return that a pessimistic investor would tolerate,

$\left(\overline{R}_{52week} + \sigma_{52week}\right)$ – the lowest high level of return that an optimistic investor would accept,

R_t – the return registered on current day (t).

Lastly, we also controlled for any influence of a price anchor on the evolution of the market trading volume. Thus, we constructed the 52-week high variable to assert how market players react on the proximity of the current market stock price to its recorded 52-weeks high. According to Lee and Piqueira (2019) and Huddart, Lang and Yetman (2009), it would call on "momentum" investors to know that if a stock trades in approximation to its 52-weeks high, it would most probably maintain its upward trend on the medium term. Thus, we expect an increase in the trading volume once the stock market price exceeds the past price extreme. We defined the 52-week high as:

$$52 \text{ week high value of the market index} = \frac{P_t}{P_{52weekHigh_t}} \tag{5}$$

where

P_t – the stock market value on day t,

$P_{52wkHight}$ – the stock market's highest value over the last 52 weeks ending on day t.

In addition to these behavioural errors, we also considered for some calendar effects in our regression models, to test for the existence of trading anomalies: namely the Monday effect, the Friday effect, the Turn-of-the-Month effect and the Turn-of-the-Year effect (Kunkel, Compton and Beyer, 2003; Berument and Dogan, 2012; Sander and Veiderpass, 2013).

Given the focus of our analysis, post-communist countries, which are still frontier and emerging markets, they are more prone to both behavioural errors and market anomalies. We computed these effects as dummy variables which take the value 1 if the trading day coincides with the investigated period, and 0 otherwise. We defined the Turn-of-the-Month effect as Thaler (1987) and Kunkel, Compton and Beyer (2003), considering a 4-day investigated period defined as trading days –1 through +3. With respect to the Turn-of-the-Year effect, there is no optimal event window length for this. We considered as time interval (–5 market days, +5 market days) as in Sander and Veiderpass (2013). We expect a positive influence of this calendar effect on the stock market behaviour.

In terms of control variables, taking into account the explanatory power on stock market trading activity and the data frequency (daily), we used the market trend as well as the change (%) in the gold price, respectively the change (%) in the exchange rate.

We computed the market trend, following Dhaoui and Kraief (2014), as the difference between the market index closing value minus its lowest value observed in the last x days, divided by the difference between the market index highest value in the last x days minus its lowest value observed in the last x days.

Given the fact that our analysis is daily, we considered the x to be 1.

$$\text{Market Trend} = \frac{Market\ Index\ Closing\ Value - Market\ Index\ Lowest\ Value_{(t,t-1)}}{Market\ Index\ Highest\ Value_{(t,t-1)} - Market\ Index\ Lowest\ Value_{(t,t-1)}} \quad (6)$$

The market trend can be seen as a reference point for investors, offering signals that may influence their decisions in terms of buy, sell or just hold, ultimately impacting their trading activity.

With respect to the change (%) in the gold price, respectively the change (%) in the exchange rate, we expect negative relationships between these 2 control variables and the stock market trading volume.

The motivation behind is as follows: investors would opt for safer investments such as gold in more turmoil times; a strong domestic currency would represent positive signals of a strong economy, leading to an optimistic sentiment towards investments.

Having all variables defined as per the above methodology, we proceeded to the estimation of the regression model:

$$\begin{aligned} Trading\_Volume_t &= \beta_0 + \beta_1 * Trading\_Volume_{(t-1)} + \\ &+ \beta_{i=2}^{4} * Behaviour\_factors_{(t-1)} + \beta_5 * Market\_trend_{(t-1)} + \\ &+ \beta_6 * \Delta Exchange\_rate_t + \beta_7 * \Delta Gold\_price_t + \\ &+ \beta_{i=8}^{11} * Calendar\_effects_t + \varepsilon_t \end{aligned} \quad (7)$$

where Behaviour factors are: optimism, pessimism, spontaneous behaviour and the 52 week high value of the market index; the Calendar Effects are: The Monday and Friday effect, the turn of the month effect and the turn of the year effect and ε_t is the error term of the equation.

We estimated OLS equations, for each country separately, to test the impact of these behavioural biases and the calendar effects on the stock market trading volume.

3. Data

To perform our analysis, we first gathered information about stock market indices values (open, close, high and low) and trading volume for a time period of approximately 8 years (from January 2012 to September 2019). We collected daily data from the Thomson Reuters Database. The data sample consists of six countries, namely Poland, Hungary, Slovenia, the Slovak Republic, the Czech Republic and Romania. We considered as representative benchmarks stock indices which encompass the most liquid shares traded on these 6 regulated markets and which cover the time period under investigation: BET-XT (Romania), WIG20 (Poland), BUX (Hungary), SBITOP (Slovenia), SAX (Slovak Republic) and PX (Czech Republic). They can be seen as relevant proxies for the markets, covering distinct industry sectors and showing a good overview of stock market's movements.

We chose to examine the impact of behavioural biases on investors' trading within CEE countries for a couple of reasons. As former socialist states, they are still small emerging markets, characterized by lower levels of liquidity in comparison with their pears, together accounting for less than 5% of the global stock market capitalization (Köke and Schröder, 2003). They are considered, still, highly speculative and larger institutional trades affect the market trend (Dragotă and Ţilică, 2014; Dragotă and Ciobanu, 2017).

Some descriptive statistics for the stock markets' returns and trading volumes are reported in Table 1. The statistics for the stock indices' returns are representative for the regression model's behavioural variables (optimism, pessimism and spontaneous behaviour), the latter being computed based upon the stock indices' returns, as defined in the methodology section.

In terms of stock market's trading volume, the Polish and Romanian stock markets exhibit larger trading volumes than their peers. Slovenia and the Slovak Republic stock markets display the lowest trading volume, while, at the same time the highest correspondent volatility. This is not surprising as they are still frontier markets in comparison with their counterparties Poland, Hungary, Czech Republic and Romania,[3] being characterized by higher levels of uncertainty and unreliability, with little investments coming from the institutional sector. Hence, Slovenia and the Slovak Republic are the least liquid stock markets, quantified through volume and market capitalization, amongst the six ones analysed.

With respect to the stock market returns, results show that Poland has the lowest mean of returns, close to 0.006%, while at the opposite side, Hungary

[3] Romania has been recently upgraded (end of September 2019) from frontier to emerging market by FTSE Russell, after a 3 years' time monitoring.

registers the greatest mean of returns between 2012 and 2019 (0.06%). Also, in terms of standard deviation, Poland, Hungary and the Slovak Republic exhibit a higher standard deviation of returns, approximately 1.1%, in comparison with Romania, Slovenia and Czech Republic, approaching 0.9%.

To proceed to the estimation of the regression model, we first checked for the stationarity of the variables. Further on, we addressed the multi-collinearity issue, by establishing the correlations between the model's factors. We considered as benchmark a 40% maximum level of correlation between the variables.

We have also verified the regression models defined for each country for serial autocorrelation, heteroscedasticity and normality among the error terms. To see if the models are free from serial correlation, we performed Correlogram – Q-statistics and Breusch-Godfrey Serial Correlation LM Test (Breusch, 1978; Godfrey, 1978). With respect to the heteroscedasticity, we used the White's test (White, 1980). Serial correlation and heteroscedasticity were present among all equation models, thus we applied the Newey-West correction (Newey and West, 1987).

All the six regression models are statistically significant and the results obtained are in line with expectations. Investors are prone to psychological factors which influence their decision-making when investing. Findings are in line with previous research and suggest the existence of non-rational investors in the six analysed markets (Dhaoui, 2015a,b; Kinari, 2016; Angelini and Cavapozzi, 2017; Benhabib and Spiegel, 2019; Roger, Roger and Schatt, 2018; Rocciolo, Gheno and Brooks, 2019).

T a b l e 1

Descriptive Statistics

Variables	Country											
	Romania		***Poland***		***Hungary***		***Slovenia***		***Slovak Republic***		***Czech Republic***	
	Returns (%)	Trading volume	Returns (%)	Trading volume	Returns (%)	Trading volume	Returns (%)	Trading volume	Returns (%)	Trading volume	Returns (%)	Trading volume
Mean	0.045	16.70	0.006	16.96	0.06	14.91	0.02	10.05	0.02	6.59	0.01	14.53
Median	0.051	16.69	0.02	16.92	0.06	14.88	0.01	10.01	0	6.88	0.05	14.46
Minimum	–10.71	14.70	–6.19	15.70	–6.07	11.62	–5.18	5.99	–9.33	0	–4.71	12.59
Maximum	6.55	19.26	5.23	19.07	6.77	17.96	3.53	13.22	9.12	13.57	4.47	17.75
Standard Deviation	0.88	0.60	1.11	0.41	1.08	0.52	0.842	0.70	1.083	2.47	0.86	0.59
Kurtosis	19.96	0.28	1.74	2.64	2.28	1.87	3.36	0.99	8.74	–0.88	2.44	2.26
Skewness	–1.53	0.08	–0.18	0.89	0.01	0.18	–0.24	0.18	–0.22	–0.44	–0.34	0.93
Obs.	**1 940**		**1 932**		**1 921**		**1 922**		**1 917**		**1 940**	

Source: Own calculations.

4. Empirical Results

Table 2 synthesizes the findings of the analysed relationship between behavioural biases, some calendar effects, control variables and the stock market trading volume, by country.

T a b l e 2

Effects of Behavioural Biases on Trading Volume

Dependent variable: Trading volume						
Independent variables	***Romania***	***Poland***	***Hungary***	***Slovenia***	***Slovak Republic***	***Czech Republic***
Constant	9.732***	7.174***	4.991***	4.260***	6.016***	4.236***
Trading Volume (–1)	0.353***	0.406***	0.427***	0.277***	0.383***	0.413***
Optimism (–1)	5.982*	5.398**	6.352***	3.785	1.657	3.189*
Pessimism (–1)	–2.449	–7.206***	–4.926	–5.769	–1.477	–2.991
Spontaneous behaviour (–1)	6.630*	0.236	4.288**	1.640	2.656*	0.479
52 week high value of the market index (–1)	1.054***	0.273***	0.361*	1.177***	4.827***	0.291
Market trend (–1)	0.210***	0.043	0.026	0.110**	0.239*	0.067
ΔExchange_rate	2.437	–6.885**	0.360	–2.366	–8.010	–1.245
ΔGold_price	–0.289	–0.162	0.541	1.039	–3.384	–0.567
Monday effect	–0.232***	–0.342***	–0.290***	–0.117***	–0.194**	–0.270***
Friday effect	0.119***	0.088***	0.109***	0.022	0.236**	0.046
Turn of the month effect	0.014	0.024	–0.007	0.007	0.033	0.073**
Turn of the year effect	0.012	–0.022	0.054	0.262***	–0.050	0.160**
R^2 (%)	**18.32**	**38.50**	**36.58**	**20.66**	**54.48**	**38.29**
Adj. R^2 (%)	**17.75**	**38.03**	**36.09**	**20.05**	**54.09**	**37.81**

Note: *, ** and *** represents significance at 90%, 95% and 99% confidence levels; regression models are statistically significant at 99% confidence level.

Source: Own calculations.

As a robustness check, we also estimated the behavioural factors (optimism, pessimism and spontaneous behaviour) as in Dhaoui's (2015a,b) methodology, using average return and standard deviation for the entire time period under analysis, instead of the 52 weeks' time horizon. There is no significant change in the results. Independent variables maintain their explanatory power in stock market's trading volume and their signs.

Spontaneous behaviour is statistically significant only for Romania, the Slovak Republic and Hungary at 90%, respectively 95% confidence level, positively impacting market trading volume. Results are consistent with our expectations, stock markets being still underdeveloped and exhibiting a limited contribution to the economic growth, due to lack of financial depth (Rault et al., 2014).

With respect to the investors' optimism/pessimism, it appears as the optimistic/ pessimistic market players exhibit a great influence on the trading volume, especially in Romania, Poland, Hungary and Czech Republic. Results show a positive influence of the optimistic sentiment on the market trading volume, being statistically significant for Romania, Poland, Hungary and the Czech Republic.

Hungary is found to be more optimistic than their counterparties. This outcome is not surprising. Looking over the last 10 years' Economic Sentiment Indicator[4] computed by Eurostat, as to have an overview of how the current economic situation is assessed and what are the expectations with respect to future developments, Romania and Poland appear to have lower values than Hungary.

However, in Poland's case the pessimism exhibits a greater impact on the trading volume. Moreover, according to Gallup International Global Survey,[5] Poland is characterized as a pessimistic country in terms of hope with respect to future economic development, joined by Italy, Greece, Iran, Mexico or Turkey.

With respect to Slovenia and the Slovak Republic, there is no effect of optimism, nor pessimism on the dependant variable.

In line with previous research (Lee and Piqueira, 2019) is also the pricing anchor (measured by the 52, findings showing a positive influence on the stock market trading volume. However, the impact is smaller in comparison with the rest of the behavioural variables. Results are statistically significant for all countries except the Czech Republic. Market trend is found to have a positive effect on investors' trading volume in Romania, Slovenia and the Slovak Republic, while no influence in the case of Poland, Hungary and the Czech Republic.

The exchange rate modification is significant only for Poland, showing a negative impact on the market trading volume, while the gold price change is found to be statistically significant for no country in our analysis.

In terms of calendar effects, only the Monday effect was statistically significant for all countries, while the Friday effect was statistically significant for Romania, Poland and Hungary and the Slovak Republic. The turn of the month appears to have explanatory power only in the Czech stock market as per our results, while the turn of the year effect is statistically significant for Slovenia and the Czech Republic. Results are in line with previous research (Kunkel, Compton and Beyer, 2003; Berument and Dogan, 2012).

Conclusions

We analysed the relationship between behavioural biases, some calendar effects and market trading volume in six post-communist countries: Romania, Poland, Hungary, Slovenia, the Slovak Republic and the Czech Republic. Results

[4] The Economic Sentiment Indicator (ESI), computed by Eurostat, is a composite indicator that takes into account five sectoral confidence indicators: Industrial confidence indicator, Services confidence indicator, Consumer confidence indicator, Construction confidence indicator Retail trade confidence indicator.

[5] Gallup International's Annual Global End of Year Survey on happiness, hope and economic optimism, 2017.

indicated a significant impact of the behavioural biases on the evolution of the stock market trading volume. Polish investors are pessimistic individuals, while in Romania, Hungary and the Czech Republic the optimistic sentiment exercises a greater influence on the trading activity. Further on, spontaneous behaviour is found to influence the stock market trading volume in Romania, Hungary and the Slovak Republic. The anchoring effect has also a positive say in the stock markets in 5 out of the six countries analysed, Czech Republic being the sole country where there has been found no impact.

Results are in line with previous research that sustains investors' irrationality and recommend taking into account, into the macroeconomic models, the emotions and psychological factors that may affect investors' decision making and ultimately their trading within the stock markets, but not only limited to that. With respect to the control variables, market trend was found significant for Romania, Slovenia and the Slovak Republic, while the exchange rate modification was found as significant only in Poland. Results indicated no statistically significant effect of the gold price modification.

In terms of calendar effects, the Monday effect is present in all countries, while the Friday effect is significant only for Romania, Poland, Hungary and the Slovak Republic. Furthermore, the day-of-the week effect has proven to be significant for Romania, Poland and Hungary. Finally, the turn of the year influenced positively the evolution of the dependant variable in the cases of Slovenia and the Czech Republic, while the turn of the month effect is significant only for the Czech stock market.

This study contributes to the existing literature through a better understanding of the investors' behavioural errors and their impact on the financial market with application to former socialist countries. Moreover, the results obtained indicate that investors are not fully rational when making decisions, their judgement and emotions being a significant driver of the market.

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