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Exploring the Relationship Between the Put Call Ratio and Market Indices: A Comparative Analysis of S&P 500 and BET

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Abstract: *The equity put/call ratio (PCR) from the Chicago Board Options Exchange (CBOE) is widely regarded by market participants as an indicator of market sentiment and positioning. While frequently used as a contrarian signal for traders, long-term investors often adjust their positions based on extreme PCR levels. This paper evaluates the relevance of the PCR as a sentiment indicator by examining its correlations, causal relationships, and responsiveness with the S&P 500 and BET indices. By conducting an empirical analysis across two distinct markets developed market and a frontier market, the study sheds light on the behavior of the PCR in these contrasting contexts, with particular emphasis on the structural limitations and behavioral nuances of the BET index. The findings reveal that while the PCR demonstrates limited predictive capacity for market movements, shocks to the S&P 500 significantly influence the PCR. Conversely, the relationship between the PCR and the BET index is negligible, reflecting the unique constraints of the Romanian market, such as its low liquidity and the absence of derivative markets. These results underscore the need to adapt sentiment indicators to the specific characteristics of frontier markets*

JEL classification: F65, G15, G24

Key words: putcallratio; betindex; sp500; sentimentindicator.

1. INTRODUCTION

This study aims to explore the relationship between the put-call ratio (PCR) and two major market indices: the S&P 500, representing one of the most influential global markets, and the Bucharest Exchange Trading Index (BET), providing insights from a European frontier market. The Romanian stock market, represented by the Bucharest Exchange Trading Index (BET), is characterized by several unique features that set it apart from developed markets. These include low trading volumes, a limited number of listed companies, and the dominance of a few key industries, such as energy and financial services. Additionally, the absence of a well-developed derivatives market limits the availability of advanced financial instruments like futures and options. These structural constraints significantly influence market dynamics and the applicability of sentiment indicators like the Put-Call Ratio (PCR). Understanding these characteristics is crucial for interpreting the results of this study and evaluating the relevance of sentiment indicators in frontier markets like Romania. Beyond direct forecasting, the Put-Call Ratio (PCR) offers numerous applications in financial decision-making. In risk management, the PCR can signal shifts in market sentiment, allowing portfolio managers to adjust their hedging strategies or conduct stress tests under extreme market scenarios.

Additionally, PCR can inform portfolio optimization by serving as a sentiment-based input for dynamic asset allocation and behavioral adjustments. Finally, as a tactical tool, the PCR can act as a contrarian indicator or aid in market timing, helping traders exploit overbought or oversold conditions. These alternative applications highlight the broader utility of PCR in modern financial markets. Understanding the correlation between market indices and the PCR offers valuable information about how derivatives trading reflects broader market performance. This analysis not only helps in predicting market trends but also contributes to a deeper understanding of economic indicators and their impact on financial markets.

The unique context of the Romanian market, characterized by the absence of derivative instruments and a relatively illiquid stock market, presents an underexplored opportunity to examine the limitations of sentiment indicators like the PCR. Unlike developed markets, the structural constraints of frontier markets such as BET provide new insights into the PCR's relevance and predictive capabilities. In the intricate world of finance, identifying the dynamics between market indices and derivative indicators like the PCR is crucial for both investors and policymakers. Investors rely on a few critical figures to make informed decisions. Among these, PCR provides a measurable indicator of market sentiment, which is often dominated by two psychological forces: fear and greed. By studying such metrics, investors can identify opportunities for speculation or protection against potential losses caused by abrupt market changes.

Options, which are financial contracts used by speculators and hedgers alike, play a key role in this analysis. These contracts grant the buyer the right, but not the obligation, to buy (call options) or sell (put options) an underlying asset at a set price before a specific expiration date. The PCR, which measures the ratio of traded put options to call options, serves as a gauge of market sentiment. Traditionally, a high PCR suggests bearish market sentiment, while a low PCR indicates bullish conditions. This study draws on foundational works such as Fisher Black (Fisher Black; Myron Shcoles, 1973), who find that writing covered options often leads to profits, and the analysis by Easley, O'Hara, and Srinivas (1998), which examined the informational value of option trading volumes (David Easley; Maureen O'Hara; P.S. Srinivas, 1998). However, the limited application of these theories to markets like BET, where options trading is absent, underscores the need for context-specific investigations. More recent studies show conflicting views on the PCR's predictive power. For example, Houlihan and Creamer (Houlihan & Creamer, 2019) found that changes in asset prices could be predicted by the volume of options trading, while Gang et al. (Gang;Jianhua;Huang Nan;Song Ke; Zhang Ruyi, 2020) argue that the PCR lacks a consistent correlation with index returns.

These inconsistencies highlight the importance of examining the PCR's utility within distinct market environments, particularly in frontier markets where trading volume and sentiment dynamics differ significantly from developed markets. Contagion effects from developed markets like the U.S. to emerging markets in Europe, including Romania, have been explored in the literature, as seen in the works of Davidescu et al. (Davidescu et al., 2023) and Nica et al. (Nica et al., 2024). While these studies address broader market dynamics, they lack a focused analysis of how sentiment indicators such as the PCR interact with indices like BET. Our study aims to fill this gap by investigating the specific influence of PCR on Romania's frontier market. The findings of our analysis are in line with Vijh (1990), which examines the liquidity of the CBOE options market and contradicts popular belief when concluding that informational influences on the liquidity of options are not substantial (Vijh, 1990). In addition, they find that the volume of the options market does not significantly influence the spread of the options market, the same finding being also reported later by Cho and Engle (Cho & Engle, 1999). Furthermore, we critically evaluate prior findings that suggest the PCR is moderately effective in developed markets, like S&P 500 (Blau & Brough, 2015) but lacks consistent correlations with returns in emerging or frontier markets (Gang;Jianhua;Huang Nan;Song Ke; Zhang Ruyi, 2020). This juxtaposition provides a foundation for understanding the limitations and potential adaptations of the PCR as a sentiment indicator.

The structure of this paper stands as follows: the introduction and literature review present the theoretical foundations and synthesize previous studies on PCR and market indices. The data section describes the dataset and descriptive statistics. The methodology outlines the models used in the empirical section, including the VAR model, correlation matrix, impulse-response function, and Granger causality tests. Finally, the results section discusses the empirical findings, followed by a conclusion that highlights the study's major insights, implications, and directions for future research. The Chicago Board Options Exchange (CBOE) provides key statistics for the options market, with the put/call ratio (PCR) being one of the most widely used and easy-to-interpret indicators. A high PCR typically signals a bearish market, indicating uncertainty, while a low PCR suggests optimism and a bullish environment. As a contrarian indicator, extreme PCR values are often used by traders to anticipate market reversals—a high PCR may signal a market bottom, while a low PCR may indicate a market peak. Understanding the correlation between the PCR and stock indices is particularly useful for investors seeking to better navigate market sentiment.

2. LITERATURE REVIEW

This study aims to fill a gap in the literature by examining the efficiency of the PCR in relation to both the S&P 500 and BET indices. Our findings indicate that while the PCR is not always a reliable predictor of major market movements, shocks to the S&P 500 can influence the PCR. In contrast, the impact on the BET index remains insignificant. Through a comparative analysis of these indices and the PCR, this research seeks to understand how market sentiment, as reflected in the PCR, correlates with market performance under varying economic conditions. Using statistical techniques to analyze historical data, this study will quantify the strength and nature of these correlations over time, contributing to the literature by providing new insights into market dynamics and their implications for decision-makers and investors.

The informational role of transaction volume in options markets and its predictive power for stock prices has been extensively studied as well. According to Easley, O'Hara, and Srinivas (1998), the causal relationship between stocks and derivatives exists only in an ideal market (David Easley; Maureen O'Hara; P.S. Srinivas, 1998). Additionally, research shows that short sales are more informative than regular sales transactions and understanding the constraints on short sales can provide valuable insights (Aitken et al., 1998). The simplicity of the PCR as a sentiment indicator is emphasized by Baker and Wurgler (2007), who link it to future cash flows and investment risk (Baker & Wurgler, 2007). Blau and Brough (2015) also find an inverse relationship between the PCR and future stock returns in the U.S. market, suggesting that PCR can be a useful proxy for short-sale constraints (Blau & Brough, 2015).

The empirical relationship between the PCR and stock indices has been explored in various markets. For instance, Hu and Yang (2015) apply an asymmetric VARX-MGARCH model to analyze the correlation between the PCR and the SSE50 index. While no direct relationship between returns and the PCR was found, the model gives useful insights for the analysis of trading volatility (Gang;Jianhua;Huang Nan;Song Ke; Zhang Ruyi, 2020). Similarly, Hameed and Jeon (2020) show that disagreement-based options trading volume has a negative impact on future stock returns, especially in the presence of stock misevaluation (Hameed & Jeon, 2020). Analyzing the S&P 500 index, Bandopadhyaya and Jones (2008) find that the PCR outperforms the VIX as a market sentiment indicator, using residuals from a random-walk regression (Bandopadhyaya & Jones, 2008). However, other studies, such as Son (2012), found little evidence to support a significant relationship between spot prices and PCR (Son, 2012). Fang et al. (2014) also find minimal predictive power from technical and sentiment indicators, including the PCR, when considering broader economic cycles (Fang et al., 2014).

The study also incorporates insights from recent research into sentiment indicators during periods of economic instability. For instance, Amazouz (Amazouz, 2022) analyzed market sentiment during the COVID-19 pandemic, finding that the PCR captured a significant portion of sentiment variation. These findings raise questions about whether PCR effectiveness is amplified during periods of heightened market volatility, a particularly relevant consideration for less stable markets like BET. Another study (Tsukahara & Tsuchimura, 2021) using a VAR model to assess the spillover effects of sentiment indices, such as the consumer confidence index and PCR, on the Nikkei Index, suggests that the PCR had a significant impact. On the other hand, Zhou (2003) applies a VAR model to examine the equity put/call ratio and S&P 500 index over a five-year period, concluding that the PCR lacks predictive power and cannot effectively synchronize with market movements (Zhou, 2003).

In a novel approach, Houlihan and Creamer (2017) explore the connection between social media sentiment and PCR, finding that sentiment derived from Stocktwits could enhance the model's performance in predicting market movements (Houlihan & Creamer, 2017). Blau and Brough (2015) confirm a negative relationship between PCR and future returns, supporting the approach that options can act as substitutes for short selling, being unaffected by short-sale constraints (Blau & Brough, 2015). By situating the analysis within Romania's unique market context, characterized by low liquidity, concentrated industry dominance, and the absence of futures and options markets, this study contributes to the literature on adapting sentiment indicators to market-specific conditions.

The selection of the S&P 500 and BET indices is central to this study as they represent two contrasting market environments: a mature, developed market (S&P 500) and a frontier market (BET). The S&P 500 serves as a benchmark for global market performance due to its depth, liquidity, and role in reflecting macroeconomic trends. Conversely, the BET index provides insights into a less liquid and structurally constrained market, characterized by the dominance of a few industries and the absence of derivative trading mechanisms. This research is conducted with the future establishment of a derivatives market in Romania in mind, emphasizing the importance of understanding the limitations of sentiment indicators like the Put-Call Ratio (PCR). The findings highlight that the PCR lacks consistent relevance even in a mature market such as the United States, making it even less suitable as a key sentiment indicator in Romania. Investors should be cautious not to overemphasize the importance of such indicators in the Romanian context. To further contextualize this research, additional studies on emerging markets and their interconnections with other asset classes, such as the work by K. Chen (Chen, 2024), will be referenced to highlight broader dynamics influencing market behavior.

3. METHODOLOGY

There is a strong belief among the participants in capital markets that the options market, and particularly the volume of trade, can be used as an indicator of market movement, having a high predictive power. We aim to test here this hypothesis by applying an autoregressive VAR model handling the causality relationship, in the Granger sense, between the PCR variables, S&P500 and the representative index of the Bucharest Stock Exchange (BSE), BET. These methods were selected to provide a nuanced understanding of bidirectional relationships, considering both short-term impacts and long-term dynamics between the indices and the PCR. This is especially important to identify the impact that the developed US stock market has on emerging and frontier markets, such as like the Romanian one. We remind you that at this point the Bucharest Stock Exchange Market received the status of an emerging market, therefore becoming a part of the FTSE Russell global indices, as of September 21, 2020. The choice of these methods was guided by the aim to understand the relevance and limitations of the PCR in an emerging market like Romania, where derivative markets are absent. The VAR model, Granger causality tests, and impulse-response functions allow us to evaluate these dynamics effectively.

To evaluate the predictive power of the Put-Call Ratio (PCR) for the S&P 500 and BET indices, we employed Granger causality tests and impulse-response functions (IRFs) derived from the vector autoregressive (VAR) model. These methods are well-suited for capturing short-term dynamics and bidirectional relationships between variables. The Granger causality tests assess whether past values of one variable contribute to predicting another, while IRFs provide insights into the magnitude and duration of shocks in one variable on another. Our results indicate that the PCR lacks consistent predictive capacity, particularly in the context of the Romanian market, emphasizing the limited utility of sentiment indicators like the PCR in such environments. These findings reinforce the need for caution when interpreting PCR as a reliable sentiment measure in either developed or frontier markets.

The vector autoregressive (VAR) model was selected due to its ability to capture bidirectional relationships and short-term dynamics in a straightforward and interpretable manner. This makes it particularly suitable for an exploratory analysis in a structurally simple and low-liquidity market like Romania. However, we acknowledge its limitations in capturing non-linear relationships, which are often observed in financial markets. These limitations will be addressed in the discussion section.

Our study uses data starting from July 6, 2016, until October 4, 2019. The data was obtained from different sources as follows: The data for S&P500 are from the Bloomberg database, the data for BET was obtained from the official BSE website, and the data for PCR was obtained from the Chicago Board of Trade official website. The timeframe of 2016-2019 was selected to focus on a relatively stable economic period, free from major disruptions such as the COVID-19 pandemic. This choice allowed us to examine standard market dynamics without the influence of extraordinary events, providing a clearer view of the relationships between the PCR and market indices. While this approach offers valuable insights, the exclusion of more recent data represents a limitation that will be addressed in the conclusions. The data set contains the daily closes over more than 3 years between July 6, 2016, and October 4, 2019. The data has been processed to include common trading data, excluding weekends and legal holidays in both the US and Romania. The sample period was chosen to encompass various market conditions, providing a comprehensive view of potential correlations between the variables. This approach aligns with the context of the establishment of the Central Counterparty (CCP) and the introduction of futures and options markets in Romania. The aim is to understand correlations not only during periods of high volatility but also under regular market conditions, which are vital for the early stages of derivatives market development.

3.1. Stationarity

To check the stationarity of our series, we apply the augmented Dickey-Fuller test, which was created by Dickey-Fuller in 1979 (David A. Dickey and Wayne A. Fuller, 1979). The variable always has a unit root, indicating that it is non-stationary, according to the null hypothesis (H0). The alternative assumption (H1) implies that the unit root does not exist, leading to stationarity. Additionally, to reject the null hypothesis and establish the series as stationary, the p-value should be less than the significance level (0.05). We use ADF statistics (Augmented Dickey-Fuller statistic) which compares critical values to determine whether to reject the null hypothesis. The significant levels are 1%, 5% and 10%. We reject non-stationarity if the test statistic's value is less than or equal to the 5 percent critical value. The stationarity of the variables was tested using the augmented Dickey-Fuller (ADF) test. The results indicate that the PCR is stationary, while the S&P 500 and BET indices are non-stationary at their levels but become stationary when transformed into returns. This ensures that the variables are suitable for further analysis within the vector autoregressive (VAR) framework. We obtain the new variables in terms of returns for indices and deviation for PCR: SPr, BETr and PCRr. Put-Call ratio (PCR) is defined as the ratio of the trading volume of put options to call options:

$$\text{PCR} = \frac{\text{Volume of Put Options}}{\text{Volume of Call options}}$$

To standardize PCR, S&P 500 Index and BET Index, we calculate:

- The log-return of PCR as follows:

$$\text{PCRr}= \ln \left(\frac{\text{PCRt}}{\text{PCRt}-1}\right),$$

where PCRt is Put-call ratio at time t and PCRt-1 is Put-Call Ratio at time t-1.

- The log-return of the S&P500 Index is given by:

$$\text{SPr}=\ln \left(\frac{\text{SPt}}{\text{SPt}-1}\right),$$

where SPt is closing price of S&p500 at time t and SPt-1 is closing price of S&p500 at time t-1

- The log-return of the BET Index is calculated similar:

$$\text{BETr}= \ln \left(\frac{\text{BETt}}{\text{BETt}-1}\right),$$

where BETt is closing price of BET Index at time *t* and BETt-1 is closing price of BET Index at time *t-1*.

3.2. VAR Model

The vector autoregressive model (VAR) is known as a flexible model in the analysis of time series with several variables, being a continuation of the univariate autoregressive model. The model is mainly used in the description and estimation of the dynamics of time series, being popularized by Christopher A. Sims who suggested that the method with finite parameters used is only part of a dimensional space of infinite parameters (Sims, 1980). Thus, this approach treats all variables as endogenous and can only be applied under conditions of their stationarity. Helmut Kuchenhoff underlines the advantages of VAR models over vector error connection models by the fact that they can be used even if the cointegration structure is not known (Lederer & Küchenhoff, 2006). James H. Stock and Mark W. Watson bring to light the fact that, although dynamic macroeconomic stochastic general equilibrium models provide an intellectually coherent framework for policy analysis, they do not fit the data well (Watson, 2001). Zha, Tao, Waggoner, Daniel F., and Juan F. Rubio-Ramírez provide a general theory that can be used for both linear and non-linear restrictions, including impulse-response ones, to identify SVAR globally (Rubio-Ramírez, Juan F.; Waggoner, Daniel F.; Zha, 2008).

The equations that make up a VAR model are functions of a set of variables, each of which represents a variable in the system as a function of both its own and the other variables' lagged values. An error term's constant covariance matrix, linearity, and stationarity are the three main presumptions of a VAR model. To further capture the dynamic interactions within the system, VAR models also assume that variables in the system have a contemporaneous effect on one another. Parameter estimation and model order selection are two essential steps in the estimation of VAR models.

The model order selection process establishes a suitable lag length for the VAR model. Three popular criteria for choosing the most appropriate model order are the Hannan-Quinn Information Criterion (HQIC), the Bayesian Information Criterion (BIC), and the Akaike Information Criterion (AIC). Parameters are estimated using methods such as maximum likelihood estimation (MLE), ordinary least squares (OLS), or Bayesian methods after the lag order has been established. When interpreting VAR models, the impulse response analysis becomes particularly important. It allows us to study how changes in one variable, such as shocks or innovations, affect the system over time. We can evaluate the system's dynamic interactions and transmission mechanisms by simulating the response of variables to a brief change in one while keeping the others constant. Identifying potential feedback loops and interdependencies, this analysis sheds light on both the short- and long-term effects.

3.3. Granger Causality test

To determine the direction of causality, we use the Granger causality test. Finding the variables that influence another variable in a determinative way is also helpful. The Granger causality allows us to assess the correlation between the present values of one variable and the historical values of other variables (Engel & Granger, 1987). The Granger causality test's null hypothesis is that x is not caused by the lag values of y's. The excluded variables cause the equation variable when the p-value is equal to or less than 0.05, indicating a causal relationship between the variables. However, when the p-value is greater than 0.05, the null hypothesis cannot be rejected at the 5 percent significance level, indicating that the excluded variables do not cause the equation variable and that there is no Granger cause. The Granger Causality Test is particularly suited to the study's objective, as it helps identify potential predictive relationships in the absence of a well-developed options market. For example, it allows us to evaluate whether the S&P 500 significantly influences the PCR or if the BET index reacts to changes in the PCR.

3.4. Impulse responses

Impulse-response analysis becomes particularly important in this context. It allows us to study how shocks to one variable, such as S&P 500 or BET, propagate through the system, capturing the system's resilience to shocks and interdependencies over time. This is essential for understanding dynamics in less developed markets like Romania. The impulse response graphs are crucial for understanding the dynamic interactions and stability of the system modeled by the VAR, providing insights into how economic or financial variables react to changes over time within the context of your specific dataset. This analysis sheds light on the transmission of shocks within the Romanian market, where low liquidity and structural constraints can amplify or dampen responses, offering practical insights for investors and policymakers.

4. RESULTS

4.1. Stationarity

In Table 1, we can see that both indices show growth but BET shows higher volatility and stronger growth potential. The S&P Index shows a mean value of around 397. The skewness is near zero, indicating that the distribution is symmetric. The kurtosis is less than 3, suggesting a distribution that is light tailed. The BET Index has symmetric distribution (skewness close to 0) and light tails (kurtosis less than 3), like the S&P Index. In the case of the PCR, there is a positive skew indicating a longer tail on the right side of the distribution. The kurtosis is close to 3, suggesting a near-normal distribution with slightly lighter tails. These characteristics underscore the distinct dynamics of the BET market, where higher volatility and structural constraints, such as low liquidity, influence its performance.

S&P Returns and BET Returns have both positive skewness and high kurtosis, indicating significant asymmetry and heavy tails in the distribution. For the variables SP, BET, PCR, the ADF test statistics (Table 2) are all above the critical values at 1%, 5%, and 10% significance levels, and the p-values are greater than 0.05, indicating that these variables are non-stationary at the levels. To make them stationary, we simply calculate simple returns for each variable, generating the following variables: SPr, BETr and PCRr. The ADF test statistics for these variables are well below the critical values at 1%, 5%, and 10% significance levels, and the p-values are 0.000, indicating that these variables are stationary at the levels.

The S&P 500 has experienced growth over the entire period of analysis, with some fluctuations (Figure 0-1). The overall upward trend indicates a positive market environment during this specific timeframe. The returns hover around zero without a discernible trend over time, indicating that daily performance varies without a consistent pattern of gains or losses. Similarly, the returns of the BET index (Fig.0-1 and Figure 0-2) fluctuate around zero, resembling the S&P 500, which suggests variability in performance. A significant spike could be an outlier, a data recording error, or a market reaction driven by an extraordinary event. The PCR index shows high volatility and no long-term trend. This pattern implies that it is influenced by market conditions that frequently change its valuation. The high variability in deviations, with values oscillating around zero, indicates that while there is substantial short-term fluctuation in the PCR index (Figure 0-3), there isn't a consistent deviation from the mean overtime. All three charts (Fig.0-1, 0-2 and 0-3) provide insights into the market dynamics and investor sentiment from 2016 to 2019. Both the S&P and BET indices show upward trends, indicating overall positive market performance during this period of reference. However, the returns on these indices are volatile, reflecting the inherent risks and market corrections during

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the period. The PCR provides an additional layer of insights into investor sentiment, showing that market participants were reacting strongly to various events during this period, leading to fluctuations in the ratio and corresponding returns. In Table 2., the ADF test results confirm that the PCR is stationary at its level, while the S&P 500 and BET indices required transformation into returns to achieve stationarity. This aligns with the expectations for time series data and ensures the robustness of the subsequent analyses.

Table 1. Descriptive Statistics for S&P 500, BET Index, and Put-Call Ratio (PCR) Variables, Including Stationary Transformations (SPr, BETr, PCRr), for the Period 06.07.2016–04.10.2019.

Variables	Obs	Mean	Std. Dev.	Min	Max	p1	p99	Skew.	Kurt.
SP	608	396.934	229.449	1	791	9	783	-.006	1.785
BET	608	399.082	229.449	1	797	10	789	.005	1.815
PCR	608	73.676	34.002	1	162	5	155	.348	2.687
SPr	608	2.022	22.67	-83.529	277.778	-40	72.222	7.306	84.062
BETr	608	.929	14.327	-83.333	200	-33.929	39.326	4.409	69.309
PCRr	608	34.226	178.821	-95.833	3000	-80.435	486.957	10.609	150.157

Table 2. Results of Augmented Dickey-Fuller (ADF) Test for Stationarity of S&P 500, BET Index, Put-Call Ratio (PCR), and Their Stationary Series (SPr, BETr, PCRr) for the Period 06.07.2016–04.10.2019.

ADF test/Variable	SP	BET	PCR	SPr	BETr	PCRr
Test-statistic	-1.067	-1.043	-12.073	-22.110	-29.719	-19.855
p-value	0.7280	0.7374	0.000	0.000	0.000	0.000
Critical values						
1%	-3.445	-3.445	-3.445	-3.445	-3.445	-3.445
5%	-2.873	-2.873	-2.873	-2.873	-2.873	-2.873
10%	-2.570	0.3609	-2.570	-2.570	-2.570	-2.570

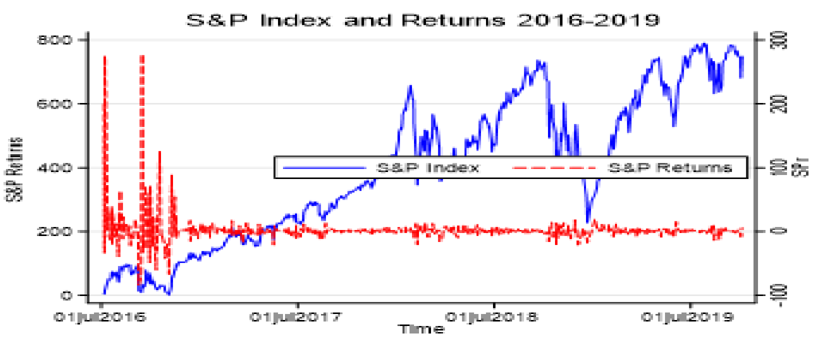

Figure 0-1 S&P 500 Index and Its Stationary Transformation (SPr) for the Period 2016–2019

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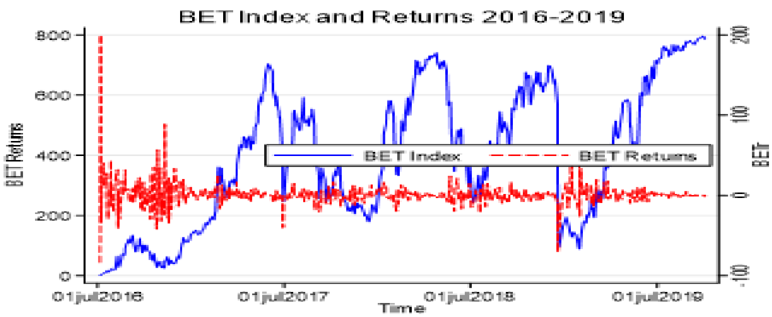


Figure 0-2 Bucharest BET Index and Its Stationary Transformation (BETr) for the Period 2016–2019

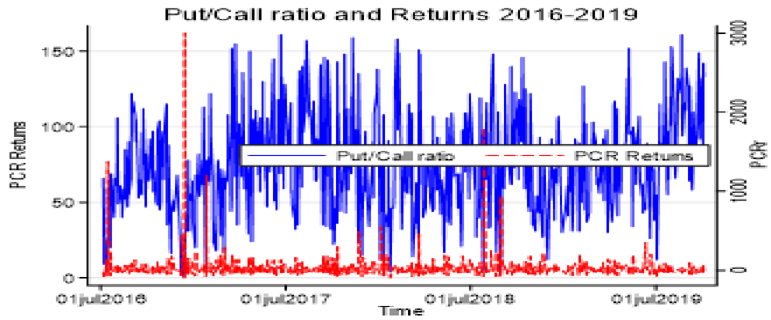


Figure 0-3 Put-Call Ratio (PCR) and Its Stationary Transformation (PCRr) for the Period 2016–2019

4.2. Lag-order selection

An essential component of econometric modeling, especially in the context of time series analysis, is the determination of lag length in autoregressive processes. The dependability of forecast outcomes, the robustness of inference, and the precision of model estimate are all strongly impacted by the lag duration; therefore, it must be determined correctly. In the literature, the significance of lag length optimal selection is emphasized by Lutkepohl (1993), who shows how an exaggerated lag order can raise mean-square forecast errors in Vector Autoregressive (VAR) models.

On the other hand, autocorrelated errors frequently arise from underestimating the lag time, which can skew the coefficient estimates and jeopardize the reliability of statistical inference. These results emphasize how difficult it is to specify lag orders without causing either overfitting or underfitting. These theoretical insights are supported by the current analysis's findings as well. Given that significant lag effects are mostly seen in the first two periods, the selected lag length of two (2) specifically seems to be well-suited to capture the underlying dynamics among the variables under investigation. This decision strikes a compromise between simplicity and complexity, guaranteeing that the model accurately captures the relationships between the variables without adding extraneous parameters. This conclusion is supported, and the suitability of the two-lag specification is validated by the lag order selection criteria, which are shown in Table 3. Table 3 summarizes the values of these criteria for lags ranging from 0 to 2. As shown in the table, AIC: Lag 2 has the lowest value (29.9784), HQIC: Lag 2 also has the lowest value (30.0899), SBIC: Lag 2 has the lowest value (30.256), although it is closely comparable to lag 1, FPE: Lag 2 achieves the smallest value (2.1e+09). The model adheres to the principle of selecting the lag where the values of the information criteria are minimized. Based on these results, lag 2 was chosen as the optimal lag for the VAR model. The chosen lag time of two effectively represents the short-term dynamics among SPr, BETr, and PCRr, ensuring both model robustness and improved interpretation. These findings are consistent with the broad literature (e.g. Lutkepohl, 1993), and they reinforce the crucial role that lag order specification plays in econometric analysis.

Table 3. Lag-Order Selection Criteria for Vector Autoregressive (VAR) Model of S&P 500, BET Index, and Put-Call Ratio (SPr, BETr, PCRr).]

Sample: 08jul2016 thru 04oct2019

Number of obs = 273

1)	Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
2)	0	-4137.08				3.0e+09	30.3302	30.3462	30.3699
3)	1	-4087.13	99.891	9	0.000	2.2e+09	30.0303	30.094	30.1889*
4)	2	-4071.05	32.165*	9	0.000	2.1e+09*	29.9784*	30.0899*	30.256

** optimal lag*

Endogenous: SPr BETr PCRr

Exogenous: _cons

4.3. VAR model

The complex relationships between SPr, BETr, and PCRr are explored here by the regression analysis, which reveals the interdependence between these. The findings show that the lagged values of BETr and SPr's historical values have the most powerful impact. A corrective or stabilizing process, in which abnormalities in SPr are partially rectified in later periods, may be indicated by the negative coefficient on the first lag of SPr (-0.218, significant at the 1% level). This might be a result of market pressures pushing SPr back towards a mean or equilibrium level. On the other hand, the presence of a delayed positive feedback loop is suggested by the positive coefficient on the second lag of SPr (0.225, significant at the 1% level), which may indicate persistence or momentum in SPr's dynamics following an initial adjustment. The findings show that BETr has a considerable interaction with SPr's lagged values as well as with its own lagged values. A corrective mechanism or mean-reverting behavior in BETr is suggested by the initial lag of BETr (-0.248, significant at the 1% level), which exhibits a negative impact on itself. A pattern like this could point out a short-term overreaction followed by several changes. Furthermore, the positive coefficients of both the first (0.108, significant at the 1% level) and second lag (0.174, significant at the 1% level) demonstrate that SPr has a large and long-lasting favorable impact on BETr. This suggests that historical changes in SPr have a long-term effect on BETr, maybe due to spillover effects or interrelated market dynamics.

With its own historical values and the lagged values of SPr and BETr mainly falling out of statistical significance, PCRr, on the other hand, seems to be isolated from the system. This lack of significance implies that either PCRr has a weak and indirect association with the other variables, or it may be impacted by external factors not included in this model. As an illustration of the low autocorrelation in PCRr, the coefficients for lagged PCRr in its own equation (-0.0914 and 0.0300) are negligible.

This result suggests that more research on the factors influencing PCRr is necessary, either by including more variables into the analysis, or by considering different econometric strategies. Therefore, the vector autoregressive (VAR) model highlights the complex connections between SPr and BETr, which are both under the influence of contemporaneous and lagged effects. Potential feedback loops, mean-reverting behaviors, and market interdependencies are all reflected by these dynamics. However, the PCRr limited participation to the system could be explained by the fact that it might function as an exogenous variable, or it might be influenced by other mechanisms, which calls again for more research.

Tabel 4. Vector Autoregressive (VAR) Model Results for Stationary Variables: S&P 500 Returns (SPr), BET Index Returns (BETr), and Put-Call Ratio Returns (PCRr).]

	(1) SPr
SPr	
L.SPr	-0.218** (0.0683)
L2.SPr	0.225** (0.0845)
L.BETr	0.512*** (0.104)
L2.BETr	0.0279 (0.120)

L.PCRr	-0.00220 (0.00681)
L2.PCRr	0.000714 (0.00751)
Constant	1.178 (1.492)
BETr	
L.SPr	0.108*** (0.0300)
L2.SPr	0.174*** (0.0371)
L.BETr	-0.248*** (0.0455)
L2.BETr	0.0742 (0.0528)
L.PCRr	-0.00185 (0.00300)
L2. PCRr	0.00669* (0.00330)
Constant	-0.435 (0.656)
PCRr	
L.SPr	0.395 (0.502)
L2. SPr	-0.378 (0.620)
L.BETr	0.914 (0.760)
L2. BETr	0.982 (0.882)
L.PCRr	-0.0914 (0.0500)
L2. PCRr	0.0300 (0.0551)
Constant	44.55*** (10.96)
Observations	273

4.4. Matrix of correlations

The relationships between the variables SPr, BETr, and PCRr can be also analyzed by the correlation matrix. The correlations are all near zero, indicating that there are little to no linear relationships between these variables. None of the pairs of variables are strongly correlated, meaning that they are likely to move independently. A negative slight correlation, as seen between SPr and BETr, and between SPr and PCRr, indicates that when one variable increases, the other tends to decrease. A positive correlation, as seen between BETr and PCRr, suggests that the relationship is very weak as one variable increase and the other tends to increase as well. This weak correlation reduces the possibility of multicollinearity, which is an important condition in all regression models, i.e. stating whether the explanatory variables are likely to vary significantly.

Table 5. Correlation Matrix for Stationary Variables: S&P 500 Returns (SPr), BET Index Returns (BETr), and Put-Call Ratio Returns (PCRr).

Variables	(1)	(2)	(3)
(1) SPr	1.000		
(2) BETr	-0.106	1.000	
(3) PCRr	-0.073	0.022	1.000

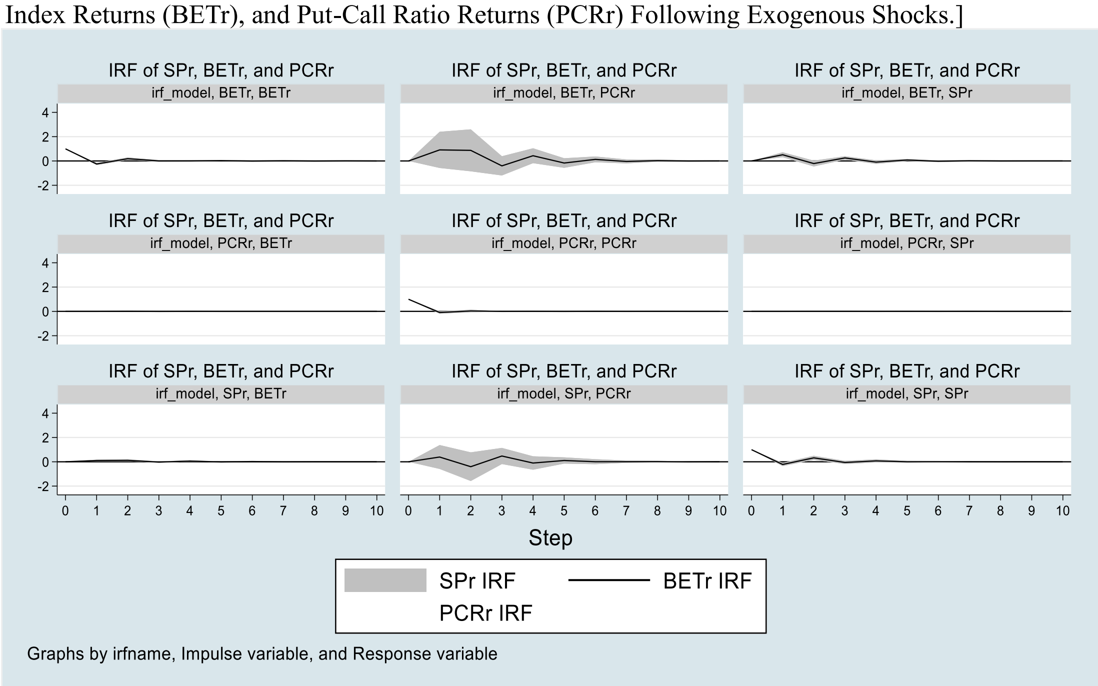
4.5. Impulse-response function

In Figure 0.6 we present the impulse-response function (IRF) charts (Figure 0.6) which show the response of variables to exogenous shocks or innovations in other variables. The direction, amplitude, and duration of these interactions are revealed by the IRFs, which provide crucial insights into the interdependencies among SPr, BETr, and PCRr by tracking the impact of a one-unit shock in one variable on the others.

Short-term oscillations near zero define SPr’s reaction to a shock in PCRr. Before stabilizing close to zero, SPr first shows a positive reaction that is swiftly followed by a modest negative response. According to this pattern, shocks in PCRr may cause temporary volatility in SPr, but they do not have long-lasting impactsThis pattern suggests that PCRr-induced shocks cause temporary volatility in SPr, but do not have lasting effects, consistent with Romania's market dynamics, where investor sentiment indicators may be muted due to structural constraints like low market depth. A brief positive response is followed by a modest negative reaction, indicating a low and transient effect of PCRr on BETr. The idea that PCRr’s impact on BETr is restricted in both magnitude and duration is further supported by the oscillation around zero, which implies that BETr is comparatively insensitive to shocks caused by PCRr. This highlights the limited influence of sentiment indicators like PCR in Romania's underdeveloped capital market, further constrained by the absence of derivative trading mechanisms supported by the Central Counterparty (CCP).

The PCRr response to a shock in SPr is negative. This significant initial negative impact may reflect how changes in stock performance (SPr) affect investor behavior or market sentiment, as measured by PCRr. The slow drop in significance, however, suggests that the effect is transient and that PCRr will eventually return to its baseline. This steep reaction underlines BET's susceptibility to shocks in SPr, which may reflect its lower resilience to systemic risks compared to developed markets like the S&P 500. A sharply positive response that progressively wanes over time is BETr's quick and steep response to a sudden shift in SPr. This implies that an instantaneous rise in BETr is linked to positive shocks in SPr, which are a sign of better stock performance. Even if the impact would be initially significant, it cannot be sustainable over time, as evidenced by the return to zero over time. This behavior illustrates the market's propensity to return to equilibrium, a key feature of BET's emerging market dynamics, where external shocks are absorbed relatively quickly but do not leave lasting structural impacts.

Figures 0-4. Impulse-Response Functions Depicting the Dynamic Interactions Between S&P 500 Returns (SPr), BET Index Returns (BETr), and Put-Call Ratio Returns (PCRr) Following Exogenous Shocks.]



4.6. Granger Causality test

The test results show that SPr and BETr have a bidirectional Granger-causal relationship (Table 0-8). There is significant evidence that BETr Granger-causes SPr, as indicated by the chi-square statistic for BETr predicting SPr of 26.142 (p-value < 0.01) and that SPr Granger-causes BETr of 34.272 (p-value < 0.01), respectively.

A dynamic link between stock performance (SPr) and (BETr) is suggested by this bidirectional causality. The interdependence of variables and market performance is highlighted by the fact that changes in one variable provide valuable insights into future changes in the other. PCRr does not show a substantial Granger-causal effect on SPr or BETr, despite its conceptual significance as a sentiment indicator. The chi-squared statistic, for example, is 4.808 (p-value = 0.090) for BETr and 0.121 (p-value = 0.941) for PCRr predicting SPr. There is no predictive association between the two outcomes since the correlation is not statistically significant. This lack of significance implies that either PCRr's influence is mediated by other unobserved factors or that it functions independently of the dynamics reflected by SPr and BETr in this model.These results underscore the limited role of sentiment indicators like PCRr in predicting market performance in Romania, reinforcing the need for infrastructure like the CCP to enhance market depth and indicator relevance.

As shown in Table 0-8, the chi-squared statistic of 26,461 (p-value < 0.01) is obtained for the SPr equation from the joint test of BETr and PCRr, indicating that these variables together help predict SPr. On the other hand, a chi-squared statistic of 2.735 (p-value = 0.603) for PCRr (in its own equation), confirms its weak predictive role in this system. The joint significance of considering both variables in the models of market dynamics is shown by the bidirectional Granger causality between SPr and BETr. This finding emphasizes the interconnectedness of stock performance and risk metrics, reflecting the mutual feedback loops that characterize emerging markets like BET. Although PCRr may be used as a general market sentiment indicator, its direct impact on stock performance (SPr) or risk (BETr) is minimal in the context analyzed here, according to its limited Granger-causal role. This independence is consistent with earlier correlation matrix results showing poor connections between PCRr and SPr and BETr. When analyzing the relationship between SPr and BETr, the null hypothesis that there is no Granger causation is strongly refuted by the significance thresholds for the Granger causality tests ($p < 0.05$, 0.01). To properly assess the real role played by PCR in international stock markets, new modeling approaches may be necessary, such as in nonlinear methods or the incorporation of additional explanatory variables.

Granger Causality Wald tests

Equation	Excluded	chi2	df	Prob>Chi2
SPr	BETr	26.142	2	0.000
SPr	PCRr	0.121	2	0.941
SPr	ALL	26.461	4	0.000
BETr	SPr	34.272	2	0.000
BETr	PCRr	4.808	2	0.090
BETr	ALL	37.768	4	0.000
PCRr	SPr	1.007	2	0.604
PCRr	BETr	2.067	2	0.356
PCRr	ALL	2.735	4	0.603

Table 6. Granger Causality Test Results Highlighting Predictive Relationships Among S&P 500 Returns (SPr), BET Index Returns (BETr), and Put-Call Ratio Returns (PCRr).]

5. DISCUSSION

The Romanian market is defined by several structural limitations that significantly impact the predictive utility of sentiment indicators like the Put-Call Ratio (PCR). These include low trading volumes, a limited number of listed companies, and the absence of a developed derivatives market. Such conditions constrain the PCR's effectiveness as a sentiment indicator, as its relevance relies heavily on the presence of active derivatives trading and higher market liquidity. The findings of this study highlight the importance of tailoring sentiment indicators to specific market conditions. In the case of Romania, the structural and behavioral characteristics of the BET index underline the need for caution in interpreting PCR as a reliable tool for market sentiment analysis. The findings of this study, which show a lack of significant connections or causality between the Put-Call Ratio (PCR) and both the S&P 500 and BET indices, can be attributed to several factors.

While methodological limitations, such as the reliance on linear models like VAR, may have influenced the results, we believe that the unique structural and behavioral characteristics of the Romanian market play a critical role. These include low liquidity, the absence of derivatives trading, and the concentrated composition of the BET index. To address these limitations, future studies should consider exploring alternative econometric approaches and incorporating a broader range of market-specific variables to capture the complex dynamics at play. The study's conclusions add to the increasing amount of research examining the connection between stock market indexes and the put-call ratio (PCR), especially in developing markets such as the Bucharest Stock Exchange (BSE). Despite being generally accepted as a sentiment indicator in established markets, our findings show that the PCR has little use in forecasting or elucidating the BET index (BETr).

These results are in line with other research that emphasizes how difficult it is to apply global sentiment indices to developing markets that have distinct structural features. According to our research, PCR has no discernible predictive ability for either the BET index returns (BETr) or the S&P 500 returns (SPr). This is consistent with the findings of Jena and Dash (2014), who investigated how well the PCR predicted market returns. According to their research, PCR is a more accurate predictor in markets with more sophisticated derivatives trading and over longer time horizons. PCR's predictive ability, however, declines in less liquid markets, which is indicative of structural constraints in those settings. The PCR's function as a contrarian sentiment indicator in mature markets was also highlighted by Whaley (Whaley Robert, 2000). High PCR levels may indicate a market reversal because they are frequently perceived as being overly pessimistic. However, the limited use of derivatives and options trading on the Bucharest Stock Exchange is reflected in the weak predictive association between the PCRr and BETr that we found in our study. In the Romanian context, these market features make it more difficult for the PCR to precisely gauge investor sentiment and forecast market movements. A select group of blue-chip companies, mostly from established industries like utilities, energy, and finance, control much of the BET index. Speculative behavior, which propels PCR in more volatile markets, might have less impact on these industries. The lack of robust derivatives trading in Romania also hinders the PCR's ability to effectively capture investor sentiment. As highlighted by Houlihan and Creamer (2019), sentiment indicators in markets without extensive derivative instruments tend to underperform, as they lack the trading depth needed to produce meaningful signals. Due to regional political and economic influences, emerging markets frequently display distinctive investment behavior. According to Bohl (Martin Bohl & B, 2011), sentiment indicators like the PCR may be less effective in emerging markets where retail investors dominate trading activity and are more likely to base decisions on fundamental or macroeconomic considerations rather than derivative market sentiment. The results align with broader literature on emerging markets, which emphasizes the need for localized sentiment measures tailored to specific market structures and investor compositions. While the VAR model provides valuable insights, its assumptions of linearity and stationarity may limit its applicability in some contexts. While the VAR model offers a flexible and interpretable approach for analyzing short-term dynamics, its linearity imposes constraints on the depth of insights it can provide. Non-linear relationships, such as those captured by Markov-switching or regime-change models, may uncover additional complexities in the interactions between the PCR and market indices.

Future research should explore these advanced econometric approaches to better understand the intricate dynamics present in both developed and frontier markets. Jordà (2005) proposes local projections as an alternative method for estimating impulse responses, which relaxes these assumptions and could be considered in future research (Jorda`, 2005).Employing advanced econometric techniques, such as regime-switching models or machine learning algorithms, could uncover hidden relationships that are not captured by linear models. In the Romanian context, the absence of a Central Counterparty (CCP) and the resulting lack of advanced derivatives markets amplify these limitations. The development of a CCP would not only enhance market liquidity but also facilitate more sophisticated trading strategies, potentially increasing the relevance of sentiment indicators like the PCR. As emphasized by Amazouz (Amazouz, 2022), improving financial infrastructure in emerging markets can significantly enhance the applicability of traditional sentiment tools. Future research could benefit from employing advanced econometric techniques, such as re-game-switching models or machine learning algorithms, to uncover hidden relationships that may not be captured by linear models. Machine learning approaches have shown promise in analyzing sentiment indicators in complex and evolving market environments (Blau & Brough, 2015). These methods could help identify non-linear dynamics and offer deeper insights into the interplay between sentiment and market performance.

6.CONCLUSIONS

The results of this paper are expected to shed some light on the relationship and bicausalities between the PCRr, BETr, and SPr. The dynamics of these variables and their interactions have been addressed by an econometric framework that includes correlation analysis, impulse-response functions (IRFs), and Granger causality tests. The PCRr and SPr are found to be linked by a negative connection, suggesting that increases in PCR are correlated with the decrease of stock index performances. As a sentiment indicator, the PCR is frequently viewed as a contrarian signal in equity markets, which is consistent with earlier research (Whaley Robert, 2000).

However, the absence of a significant correlation between PCR and BET offers important insights within the unique context of the Romanian market. This reflects structural limitations, such as the lack of developed derivatives markets and the concentrated structure of the BET index. These findings emphasize the limited utility of sentiment indicators like PCR in emerging markets, where structural constraints play a critical role in shaping their relevance. The impulse-response study, however, shows that shocks to SPr have a substantial negative effect on PCR, which will eventually end up decreasing. This aligns with findings that market sentiment indicators are less effective in environments with low market liquidity and limited access to derivative instruments (Amazouz, 2022). This emphasizes the transient character of these processes in the sense that although there are short-term interactions, the relationship is not persistent.

The correlation analysis and Granger causality tests repeatedly show here that there is no substantial predictive association between the put-call ratio and the returns of the BET index or the S&P 500. These findings raise concerns about the accuracy of using PCR as a prediction tool for market players, particularly in the context of the Bucharest Stock Exchange, where the PCR appears to not be an accurate and significant predictor of market movements. The interdependence of regional and international financial markets is highlighted by the bidirectional Granger causality between BETr and SPr. This conclusion underscores the necessity of incorporating cross-market dynamics when analyzing indexes and devising investment strategies. The effects of shocks are most noticeable in the short term after the shock, but they tend to level out over time, according to the impulse-response functions. The system's resilience and propensity to return to equilibrium are reflected by this pattern.

Market players and portfolio managers should be prudent when using only the PCR indicator due to its poor forecasting ability. Predictive accuracy may be improved by including more indicators, such as macroeconomic factors or volatility indices (like the VIX). PCR and SPr are in a moderately inverse relationship, which could reflect stock market behavioral tendencies like overreaction or herd mentality. Strategies to take advantage of market inefficiencies could be influenced by these observations. The absence of meaningful correlations between PCR and the BET index suggests that the Romanian and American markets may differ in terms of investor behavior or market structure. These discrepancies could be thoroughly examined in future research. For both strategic investment and econometric research, this empirical analysis provides a basis for well-informed financial and economic decision-making.

According to our results, PCR is not very useful as a forecasting tool for market players, especially those who trade on the Bucharest Stock Exchange. To provide more reliable insights into the market dynamics, future studies should examine how PCR interacts with other volatility and sentimental indices. The absence of meaningful correlations between the PCR and the BET index suggests that the Romanian and US markets may differ in terms of investor behavior or market structure. These discrepancies could be thoroughly examined in future research. Expanding the dataset to include more recent data could provide additional insights into the evolving dynamics between the PCR and market indices, particularly considering significant events such as the COVID-19 pandemic.

Future research should consider extending the analysis period to capture these broader trends and assess the robustness of the findings under varying market conditions. When analyzing the predictive dynamics of sentiment indicators in developing European markets, Badea et al. pointed out that structural variations in these markets, like a lack of depth in options trading, can make indicators like the PCR less relevant (Leonardo Badea; Daniel Stefan Armeanu; Iulian Panait and Stefan Cristian Gherghina, 2019).These results highlight once again the necessity of placing the PCR forecasting accuracy in the context of the unique features of the Romanian market and the BET index. The dominance of sector-specific blue-chip companies in the Bucharest Stock Exchange and the underdevelopment of derivatives may be the reasons behind the PCR poorer predictive. These findings raise questions about the broader utility of the PCR in emerging markets and its role as a standalone sentiment indicator. Recent research suggests that integrating macroeconomic variables, such as GDP growth and volatility indices (e.g., the VIX), could enhance predictive accuracy, particularly in markets undergoing rapid evolution like Romania (Blau & Brough, 2015); (Tsukahara & Tsuchimura, 2021). Policymakers should prioritize the development of financial infrastructure, such as the Central Counterparty (CCP), to improve market liquidity and enable the effective use of sentiment indicators.

Future research should explore how the introduction of derivative instruments in Romania might influence the relationship between sentiment indicators and market performance. Comparative studies between emerging and developed markets could provide further insights into the structural and behavioral factors influencing PCR's effectiveness. Expanding methodological frameworks to include non-linear models, alternative sentiment indicators, and region-specific variables could yield more nuanced findings. While the study provides valuable insights into the relationship between the Put-Call Ratio (PCR) and market indices, it is not without limitations. The analysis is constrained by the lack of a developed derivatives market in Romania, the assumption of linear relationships in the VAR model, and the limited temporal scope. Future research could address these gaps by incorporating data from Romania's emerging derivatives markets once operational, exploring nonlinear models, and integrating sentiment analysis tools rooted in behavioral finance. Additionally, comparative analyses between emerging and mature markets could enhance the understanding of PCR dynamics across different market structures. These extensions would further contribute to the development of robust investment strategies and market risk management frameworks. While this study focused on the relationship between the PCR and market indices, future research could benefit from incorporating additional variables that may influence these dynamics. Macroeconomic factors such as GDP growth, inflation, and interest rates could provide context for understanding broader market trends. Additionally, market-specific variables like liquidity levels and alternative investor sentiment indicators could further enhance the analysis. These additions would allow for a more nuanced understanding of the interplay between the PCR and market indices, particularly in various market environments.

In conclusion, this study highlights the importance of contextualizing sentiment indicators like PCR within the structural realities of different markets. While the PCR demonstrates some utility in developed markets like the U.S., its role in emerging markets remains constrained by structural and behavioral factors. Addressing these gaps through targeted policy interventions and further empirical research is essential for improving market efficiency in Romania.

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