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SENTIMENT ANALYSIS OF COMMENTS ON BORSA ISTANBUL TOURISM STOCKS: A PYTHON-BASED APPROACH

1. Aykan Burak Bolat[1]

ABSTRACT

The speed and content of information flow in financial markets play a critical role in shaping investor behavior and stock price formation. In recent years, the increasing feasibility of analyzing user generated content through sentiment analysis techniques has paved the way for alternative approaches to measuring market sentiment. In this context, the present study analyzes the emotional tone of user comments shared on the Investing.com regarding the stocks of companies listed under the Borsa Istanbul Tourism Index. The study investigates the potential relationship between these sentiment orientations and stock price movements. Within the scope of the Python-based application developed for this research, comments were analyzed using models compatible with the Turkish language, and each comment was labeled as either positive or negative. The resulting sentiment labels were then matched with the respective stock's closing price on the date the comment was posted. This allowed for a statistical examination of the relationship between sentiment direction and price movement. The findings indicate that the impact of comments on stock prices varies across different companies. Moreover, the results highlight the applicability of the Python in financial data analysis.

Keywords: Borsa Istanbul, Python, Sentiment Analysis, User Comments, NLP

BORSA İSTANBUL TURİZM HİSSELERİ ÜZERİNE YORUMLARIN DUYGU ANALİZİ: PYTHON TABANLI BİR YAKLAŞIM

ÖZET

Finansal piyasalarda bilgi akışının hızı ve içeriği, finansal oyuncunun davranışları ile pay senedi fiyatlaması üzerinde belirleyici bir rol oynamaktadır. Son yıllarda, özellikle kullanıcılar tarafından oluşturulan içeriklerin duygu analizi yöntemleriyle analiz edilebilir hale gelmesi, piyasa duyarlılığının ölçümünde alternatif yaklaşımların önünü açmıştır. Bu bağlamda, çalışmada Borsa İstanbul Turizm Endeksi altında işlem gören şirketlerin pay senetlerine ilişkin olarak Investing.com web platformunda paylaşılan kullanıcı yorumlarının duygusal tonları analiz edilmiş ve bu yönelimlerin fiyat hareketleriyle arasında oluşabilecek ilişkiler araştırılmıştır. Python programlama dili kullanılarak geliştirilen uygulama kapsamında, yorumlar Türkçe diline uyumlu modeller ile analiz edilmiş ve her bir yorum pozitif ve negatif olarak etiketlenmiştir. Analiz sürecinde ortaya çıkan duygu etiketleri, yorumların yapıldığı günün pay senedi kapanış fiyatlarıyla eşleştirilmiş; böylece fiyat yönü ile duygu yönü arasında istatistiksel ilişki tespit edilmiştir. Bulgular, yorumların fiyatlar üzerindeki etkisinin şirketten şirkete farklılık gösterdiğini ortaya koymaktadır. Sonuçlar ise Python programlama dilinin finans alanında kullanılabilirliğini de ortaya koymuştur.

Anahtar Kelimeler: Borsa İstanbul, Python, Duygu Analizi, Kullanıcı Yorumları, NLP

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[1] PhD Candidate, Akdeniz University, Department of Business Administration, bolat.aykan@gmail.com, ORCID: 0000-0002-0259-9614

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INTRODUCTION

It is prioritized in the academic literature that financial markets are those of rapid information-driven decision-making with highly dynamic, multidimensional, diverse actors. Price formation in such markets, therefore, cannot rely entirely upon historical data but would greatly be spurred by investor psychology, shared sentiment, and socially driven content. More recently, improvements in text mining and NLP have allowed for the automated analysis of user-generated content that is indicative of the potential of this type of data to reflect investor behavior (Bollen, et al., 2011).

Whereas the Efficient Market Hypothesis assumes, as postulated by Fama (1970), that all information is immediately reflected in the price of an asset, behavioral finance puts forward the view that investors are not consistently rational. According to this school, decision-making processes are significantly influenced by biases, emotional states, and social influences, as stated by Kahneman & Tversky (1979). In this respect, the content analysis of comments left by investors, and particularly those directly reflecting perceptions and emotions, is a growing subject of interest in the academic literature, especially with regard to its possible implications for stock prices.

Comments shared by users on online financial platforms are not only sources of information that drive investment decisions but also indicators of overall market sentiment. Various studies based on the content of social media and the web indicate that the emotional tone of those comments may be related to short-run price movements (Bollen et al., 2011). However, there are some analytical obstacles to processing and classifying Turkish texts because of the specific linguistic structure of the language. (Çakıcı et al., 2024) state that with the increasing availability of open-source tools and collaborative contributions from the developer community, feasible solutions to these challenges have been emerging.

In the last few years, NLP applications developed in Python, especially BERT-based models fine-tuned for the Turkish language, showed very good accuracy in financial text sentiment analysis. Among these, FinBERT, which was developed by Araci (2019), has been efficiently used to classify the positivity and negativity of sentiments in finance-related content, thus becoming helpful for user comment analysis.

The paper aims to empirically investigate the emotional orientation of user comments regarding companies listed under the Borsa Istanbul Tourism Index, shared on the Investing.com platform, and their possible relation to the relevant daily stock closing prices. In parallel, the work intends to showcase how financial and NLP-driven analysis can be performed using Python-based tools. The system developed in Python allows for an investigation into sentiment signals and their relationship with stock price direction using text mining methodologies.

Market-specifically, tourism in Turkey is very sensitive to changes in foreign exchange rates, geopolitical climate, or sudden economic shocks. Thus, investigating the impact of investor sentiment through user comments on stock pricing within the Tourism Index contributes findings not only from the sector-specific perspective but also adds value from a behavioral finance point of view. In addition, the tourism sector is closely associated with public perception and consumer experiences, which results in a relatively high volume of user-generated comments on social media platforms and financial forums. This characteristic increases the availability of textual data and helps mitigate potential limitations arising from small sample sizes in sentiment analysis studies. Furthermore, the Borsa Istanbul Tourism Index groups together companies operating within the same sector, allowing sector-based analysis and facilitating the interpretation of results at the industry level. For these reasons, the tourism sector was selected as the focus of analysis in this study.

1. CONCEPTUAL FRAMEWORK

Decision-making processes in financial markets cannot be fully explained solely by purely rational conceptions of expectations. In particular, theories of behavioral finance have been able to show that the flow of information, perceptual biases, and social interactions are some of the structural factors that influence investment behavior. While traditional financial models tend to explain price movements in terms of either technical or fundamental analysis, text data that capture investors' emotional and perceptual tendencies offer other methods of interpretation beyond these conventional frameworks.

In recent years, with the increasing interaction among users on financial web platforms, it has become progressively possible to directly observe investor sentiment through comments and discussions. These comments generated by users often reflect intangible factors such as expectations, perceptions of risk, and levels of market confidence, which constitute a source of data valuable for sentiment analysis. Advances in NLP and techniques of sentiment analysis have allowed the systematic classification and quantification of such textual content, turning qualitative investor sentiment into analyzable numerical data. Therefore, assessing investor psychology via text and its possible statistical relationship with the movements of stock prices has become an easier and more feasible task.

The Python-based sentiment analysis models utilized in the current study can, therefore, classify user comments in terms of positive or negative polarity scores, acting as proxies for investor sentiment. These models not only provide categorical sentiment labels but also generate sentiment scores, making the analysis even more deep and interpretable. By matching the resulting sentiment scores with the movements of the stock closing price on the same day, the study empirically tests the potential relationship between emotional score and price direction, offering insights into how market sentiment and financial performance interact.

2. LITERATURE REVIEW

The increase in the volume of information about financial markets, coupled with the acceleration with which this information becomes available, has made the way investors process this information a significant factor in the process of price formation. According to traditional theories of finance, the process of price formation is primarily determined by past market data and fundamental economic factors (Fama, 1970). By contrast, behavioral finance stretches this paradigm, asserting that investment choices are influenced to a great extent by feelings, cognitive biases, and social influences (Kahneman & Tversky, 1979). This theoretical shift has recently encouraged a surge of research into how user-generated content on online platforms can be used to understand investor psychology better.

Gupta et al. (2025) identified strong correlations between online user content and movements in stock prices, suggesting that such data can be used as a fundamental component in market analysis.

Li and Hu (2024) also noted that hybrid models using comment content and the intensity of user participation can give considerable accuracy in short-term market forecasting.

In the context of the Turkish market, there is still a significant literature gap regarding the linkage of the Borsa Istanbul Tourism Index with macroeconomic variables. Demirkale & Can (2021) tested the influence of exchange rates, interest rates, and oil prices on the BIST Tourism Index in a VAR model framework and found evidence that the index is very responsive to exchange rate changes and shares a negative association with interest rates. Gülay et al. (2023) also investigated the associations between Tourism Index and main macroeconomic indicators using both ARIMA and artificial neural network models and derived statistically significant results for different modeling strategies. However, studies that directly consider the emotional tone of investors' comments and the stock price relationship are scarce, especially those based on Turkish-language data and domestic indices. The present study might therefore offer an original and valuable contribution to the existing literature.

In their 2025 study, Davidovic & McCleary (2025) aimed to evaluate the impact of investor sentiment on market indicators by extracting sentiment scores from news headlines. As a financial indicator, they utilized the returns of major companies listed on the U.S. stock market and conducted their analysis using NLP-based techniques. The findings of the study suggest that sentiment scores derived from news content can serve as useful indicators in understanding the short-term direction of stock prices.

Tokcaer (2021) states that sentiment analysis research has traditionally been dominated by studies conducted in English. Nevertheless, recent years have witnessed a growing body of work focusing on sentiment analysis in the Turkish language. In this context, the study reviews the analytical approaches adopted in Turkish sentiment analysis research and provides a compilation of the datasets and data sources used in these studies.

In the study conducted by Kemaloğlu et al. (2021), the aim was to develop a system capable of measuring the sentiment tones of texts shared on social media in Turkish. In this context, an analysis system was developed by applying natural language processing and machine learning methods. Accordingly, a sentiment classification model was established using Logistic Regression, Random Forest, and LSTM algorithms. As a result of the study, it was determined that the highest accuracy was achieved with the LSTM model.

Huang et al. (2023) aimed to determine the performance of the FinBERT language model in comparison with other sentiment analysis methods. As data, sentiment tones derived from financial texts, labeled words in analysts' reports, conference call transcripts, and texts obtained from financial documents were used. The findings of the study indicate that the FinBERT model demonstrates higher performance compared to other machine learning methods.

3. METHODOLOGY

In this study, NLP techniques, methods for sentiment detection, and basic statistical analysis tools were applied, using the Python programming language, to investigate the potential influence of user comments that had been posted on Investing.com on stock prices. The research process was based on three-layered datasets.

In the first step, user comments published to the Investing.com platform were manually gathered. In the second step, daily closing prices of companies listed under the Borsa Istanbul Tourism Index were gathered. Finally, in the third step, sentiment scores derived from the comments were matched with the corresponding price movement directions, allowing an evaluation of the potential relationship between those two variables.

The total dataset, after compilation, consists of 5,541 rows in an .xlsx file format. In the sentiment analysis phase, a single average polarity score for each company was determined on a per-day basis. All dates where either price or comment data was missing were excluded from the analysis. Data used for this study ranges from September 19, 2025, to October 20, 2025.

User comments are direct representatives of investor sentiment since they reflect emotional states and real perceptions among the market participants. Consequently, the emotional tone embedded in comment texts was compared against stock price movements on that very day. By doing so, the study can test for the statistical existence of a relationship between sentiment orientation and price direction.

3.1 DATA COLLECTION PROCESS

Investor comments regarding companies included in the Borsa Istanbul Tourism Index were gathered from the relevant stock pages of the Investing.com web platform. These comments are publicly available and include the content voluntarily shared by users. It was initially planned to extract such data automatically by developing a Python script for web scraping. However, this approach could not reach the desired degree of efficiency due to the security measures taken by the platform. For that reason, all comments were gathered manually and the date of each comment was preserved; they are prepared as a .csv file. The .csv file has been converted to .xlsx format before conducting the analysis.

Each stock's data were organized across the 30-day span, from September 19, 2025, to October 20, 2025, including date, firm name, and comment content. Other financial data providers, whose security protocols and API access rates are more in line with modern standards, could not be used as alternative data gathering platforms. Therefore, this whole process of data collection had to be performed completely manually, taking extreme care that the comments be company-specific and of good enough quality.

Stock price data was collected, corresponding to the comments gathered, in the same date range and initially stored in .csv format by manual compilation. From these, daily closing prices were extracted and organized into Excel spreadsheets in date-row format for each company. This structure allowed for efficient comparison of comment timing with the corresponding changes in stock prices.

The resulting text dataset contained only the comment content and date, with no disclosure of user identities. For sentiment analysis, the model savasy/bert-base-turkish-sentiment-cased, which is specifically trained for the Turkish language and provided on the Hugging Face platform, was utilized. This model classifies text into three primary sentiment categories: positive, negative, and neutral, assigning a probability score for each class. Then the sentiment-labeled data were combined with the respective stock closing prices on the same date, allowing the statistical relationship of the emotional tone of each comment with the same-day price movement to be analyzed by regression.

3.2 SENTIMENT ANALYSIS PROCESS

The applied sentiment analysis approach aimed to identify and classify the emotional tone embedded in user comments. Accordingly, the procedure was performed in the Python programming language, while the analyses were carried out in the Spyder development environment, version 3.13.1. The "savasy/bert-base-turkish-sentiment-cased" pre-trained model was used for sentiment detection; this model has been fine-tuned for the Turkish language and financial commentary. Available at Hugging Face, this model classified comments into three categories: positive, negative, and neutral. Each category receives a probability score within a range of 0–1. While scores closer to 0 indicate lower likelihood, values closer to 1 suggest stronger association with the respective sentiment category.

Previous studies have tested sentiment models based on BERT, and they have demonstrated strong performance in analyzing financial texts. Some examples of such studies are Araci (2019) and Halder et al. (2022). These findings support the applicability of the chosen model for comment-based financial sentiment analysis.

The comments had been prepared before the sentiment analysis in .xlsx format, retaining the date attached to each entry. During sentiment analysis, each of these comments was given a sentiment classification and a probability score for that classification for every row in the dataset. The structure of the data generated allows for seamless alignment with stock price movement data on the same dates. A major benefit of the script implemented is its integration with a BERT model optimized for Turkish, supporting full automation of sentiment classification. The results of this procedure sentiment labels, i.e., "positive," "negative," or "neutral," and their probability scores can be used as such in further statistical analyses. This will lay a very robust basis for investigating the possible dependencies between the emotional tone of messages and stock price behavior.

3.3 PRICE DATA AND DIRECTION CALCULATION

For this research, the period for which stock price data was utilized covers September 19, 2025, through October 20, 2025. This period was chosen in order to maintain the consistency between sentiment data and market activities since the collection of comments also happened during this period. The price data were gathered from the Investing.com platform in a manual fashion and prepared in .xlsx format, based on the closing prices every day for each company.

Due to the weekend and public holiday market closures in Turkey, no price data were available for those days. However, since users continued to post comments during non-trading days, an approach was adopted to maintain continuity in the analysis. More precisely, the closing price from the most recent trading day was assigned to comments posted on weekends. This approach relies on the Last Observation Carried Forward (LOCF) technique, which is widely adopted in financial time series analysis for handling missing observations by carrying forward the most recent valid value.

This method was first proposed by Tetlock (2007) in the context of investor sentiment analysis and its contemporaneous impact on stock returns for those situations in which content creation does not stop even when markets are closed. It follows that the same logic has been applied for this research work, aiming to maintain the time correspondence between sentiment data and the fluctuation of stock prices with no artificial gaps.

The approach used in this research was inspired by Tetlock's (2007) analysis of financial media pessimism's effect on the SMB (Small Minus Big) factor returns, and the regression model he employed is introduced below:

$$\mathrm{SMBt} = \alpha 4 + \beta 4 \cdot \mathrm{L5(Dowt)} + \gamma 4 \cdot \mathrm{L5(BdNwst)} + \delta 4 \cdot \mathrm{L5(Vlmt)} + \pi 4 \cdot \mathrm{L5(SMBt)} + \lambda 4 \cdot \mathrm{Exogt} - 1 + \varepsilon 4\mathrm{t} \quad \textbf{(1)}$$

- $SMBt: the\ factor' sreturn\ on\ the\ relevant\ day$
- $L5(Dowt): DJ\ index\ 5 - day\ lagged\ return$
- $L5(BdNwst): The\ last\ 5\ delays\ of\ pessimism$
- $L5(Vlmt): 5 - day\ lag\ in\ NYSE\ trading\ volume$
- $L5(SMBt): SMB\ factor's\ past\ 5 - day\ return$
- $Exogt - 1: Pessimism\ value\ of\ the\ previous\ day$
- $\varepsilon: Error\ Term$

The motivation behind this model was to investigate how pessimistic media content relates to SMB returns. This framework inspired the method used here in analyzing the relationship between user-generated sentiment scores and individual stock price movements.

The process of analysis for this study was organized in three major steps:

- Collection and classification of comments by users, where in each comment, a sentiment score was assigned based on emotional tone.
- Calculation of the company's daily average sentiment polarity and normalization of the data.
- Performing a regression analysis that tests the relation between the average daily sentiment and changes in the stock closing price.

The core regression model underlying this particular analysis can be stated mathematically as:

$$Price\ Difference_{i,t} = \partial + \beta\ x\ Polarite_{i,t} + \varepsilon_{i,t} \quad \textbf{(2)}$$

Where:

- $\text{Price Difference}_{it}$: Percentage change in the share price of company i on day t
- ∂: stability coefficient
- β: coefficient showing the effect of average polarity on price change
- $\text{Polarite}_{i,t}$: Average polarity value of company i′s comments on day t. coefficient is defined between 0 and 1.
- $\varepsilon_{i,t}$: Error term

This regression model is used to test whether there is a statistically significant relationship between real time user sentiment and corresponding movements in stock prices.

3.4 STATISTICAL ANALYSIS

In order to test the relationship between the sentiment orientation embedded in user comments on Investing.com and corresponding stock price changes, an Ordinary Least Squares (OLS) linear regression analysis was performed. The model was developed within a Python environment, making use of its statsmodels.api library. Some key details of this analysis process are summarized below:

- This dataset includes the average daily sentiment polarity scores obtained from company-specific user comments, matched with the percentage change in closing stock prices on the same day.
- In the regression setup, average polarity was defined as the independent variable, while stock price change was used as the dependent variable.
- A constant term was added to the regression with sm.add_constant(), and the model was estimated using sm.OLS(y, X).fit().
- Model results were retrieved with the model.summary() function, which provided core performance metrics that included the R-squared (R^2) value, the regression coefficient (β), t-statistics, and p-values.
- A regression plot of sentiment versus price movement was created using seaborn.regplot() to display the linear relationship between the variables.
- To gain a better insight from the model, the R^2 value, statistical significance of the independent variable, and the overall explanatory power of the model were evaluated together.

Based on this analysis, the key findings from the model are as follows:

- The magnitude and statistical significance of the effect of average sentiment polarity on stock price change — specifically, the β coefficient and its p-value
- The overall explanatory power of the model, as expressed through the R-squared (R^2) value
- The linear trend observed graphically in the regression plot
- The interpretive implications of these results at the firm or sector level

4. FINDINGS

The completed regression analyses tested the relationship between daily average sentiment polarity scores—extracted from user comments on the Investing.com platform—and stock price changes on a firm-specific basis. As presented in Table 1, the R-squared (R^2) values, p-values, and beta coefficients were used to evaluate both the explanatory power and statistical significance of the regression model for each company.

Table 1. Descriptive Statistics of Variables

Firm	R^2	p-value	Beta	n
AVTUR	0,01	0,6509	-0,0828	23
AYCES	0,001	0,8887	0,3335	29
DOCO	0,079	0,1636	-12,179	26
ETILR	0,008	0,6713	0,0206	25
MAALT	0,016	0,4965	-93,732	31
MARTI	0,068	0,2084	0,0333	25
MERIT	0,055	0,2613	0,3424	25
PKENT	0,071	0,1965	37,238	25
TABGD	0,029	0,4523	-0,6792	22
TEKTU	0,004	0,7514	0,1765	30
ULAS	0,007	0,6771	0,2079	26
BIGCH	0,228	0,0525	-13,975	17
BYDNR	0,208	0,1587	-0,2116	11

Firm-level results clearly indicate that the influence of investor sentiment on price movements does not follow a uniform pattern across all companies. The model demonstrated relatively high explanatory power for BIGCH and BYDNR, whereas it was notably low for AYCES and TEKTU. In certain companies particularly PKENT, MERIT, and DOCO the results approached statistical significance.

These findings suggest that investor sentiment may have an impact on stock prices; however, this relationship appears to vary depending on firm-specific dynamics and the volume of available data. In other words, while sentiment can be a relevant factor in price formation, its strength and direction may differ based on the structural characteristics of individual companies and the density of comment data during the observation period.

CONCLUSION

The analyses conducted in this study using the Python programming language demonstrate that both sentiment classification and statistical testing can be effectively applied to financial data. Sentiment scores derived from user comments related to companies listed under the Borsa Istanbul Tourism Index were compared with contemporaneous stock price movements. The results suggest that while there may be a modest relationship in certain firms, in others, such a link was either weak or statistically insignificant. When the obtained results are evaluated in general, it can be stated that the data based on user comments in the study were collected manually due to technical limitations in the data collection process. For this reason, the fact that the data consisting of user comments were obtained within a limited time period constitutes a data limitation of the study. Considering the table that presents the analysis results, it is observed that the explanatory power of the model is weak for many of the firms analyzed. At this point, the conclusion that can be drawn is that the sentiment tone scores derived from investors' comments have a limited ability to explain the changes in the stock returns examined in the analysis. In terms of statistical significance, it has been determined that the p-values obtained for many firms are in the form of p-value > 0.10. This result indicates that a strong relationship between investor sentiment and daily return movements could not be identified. However, for the BIGCH firm, the p-value is 0.0525, which distinguishes it from the other firms in terms of statistical significance; nevertheless, since the value is at a marginal level, this finding should be interpreted with caution. When the statistical results are evaluated overall, it has been revealed that the results for the firms included in the analysis do not produce strong and statistically significant outcomes. This finding signals that investor sentiment is not a strong explanatory factor on its own in explaining stock price movements.

Beyond the specific results, the primary objective of this research was to showcase the applicability of Python in financial data analysis, particularly in integrating sentiment-based models with statistical evaluation. This objective has been largely achieved. As a recommendation for future research, the use of open APIs or publicly accessible data pools may enable larger sample sizes. Expanding the dataset would enhance the reliability and explanatory power of the model.

Additionally, the BERT-based sentiment analysis model employed in this study produced satisfactory results. However, future comparative studies involving alternative models could offer valuable insights into how model selection influences analysis outcomes.

Ultimately, this research highlights Python not only as a programming language but also as a powerful analytical tool capable of supporting scientific inquiry in business and finance. Future studies incorporating larger-scale, real-time data from web-based platforms may contribute to the development of sentiment-driven financial decision models and help open new avenues in the literature.

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APPENDICES-1

Figure 1. Avtur

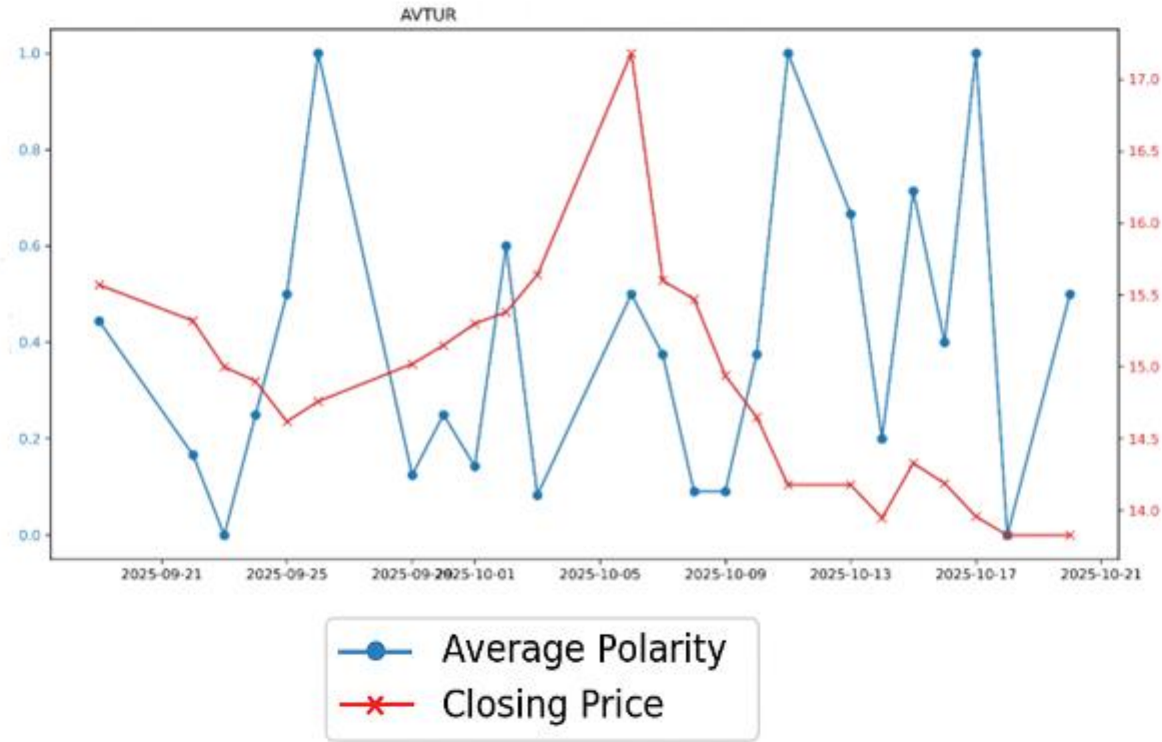

Figure 2. Ayces

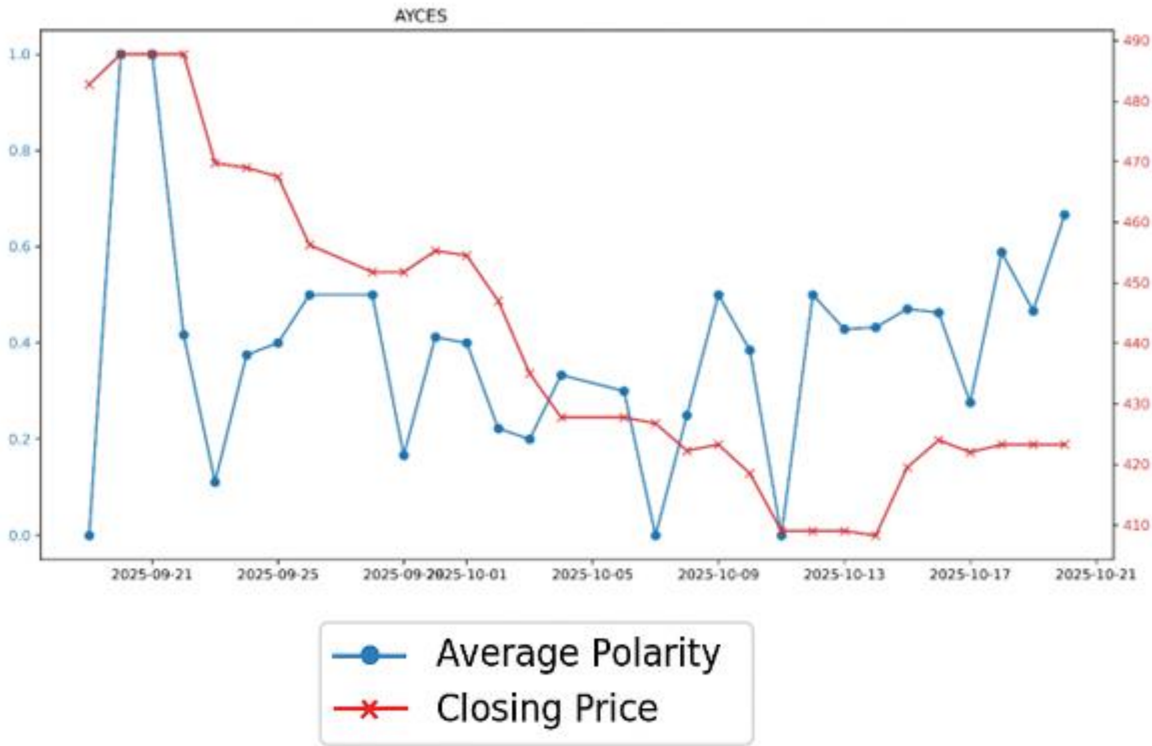

Figure 3. Bigch

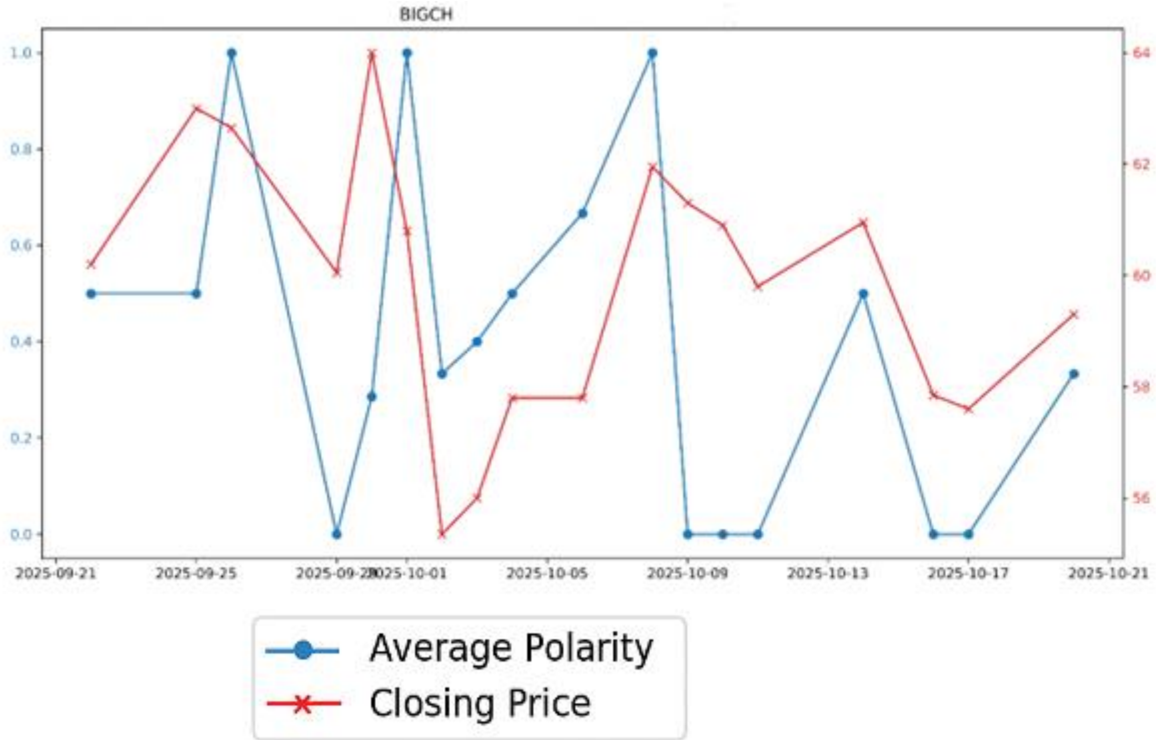

Figure 4. Bydnr

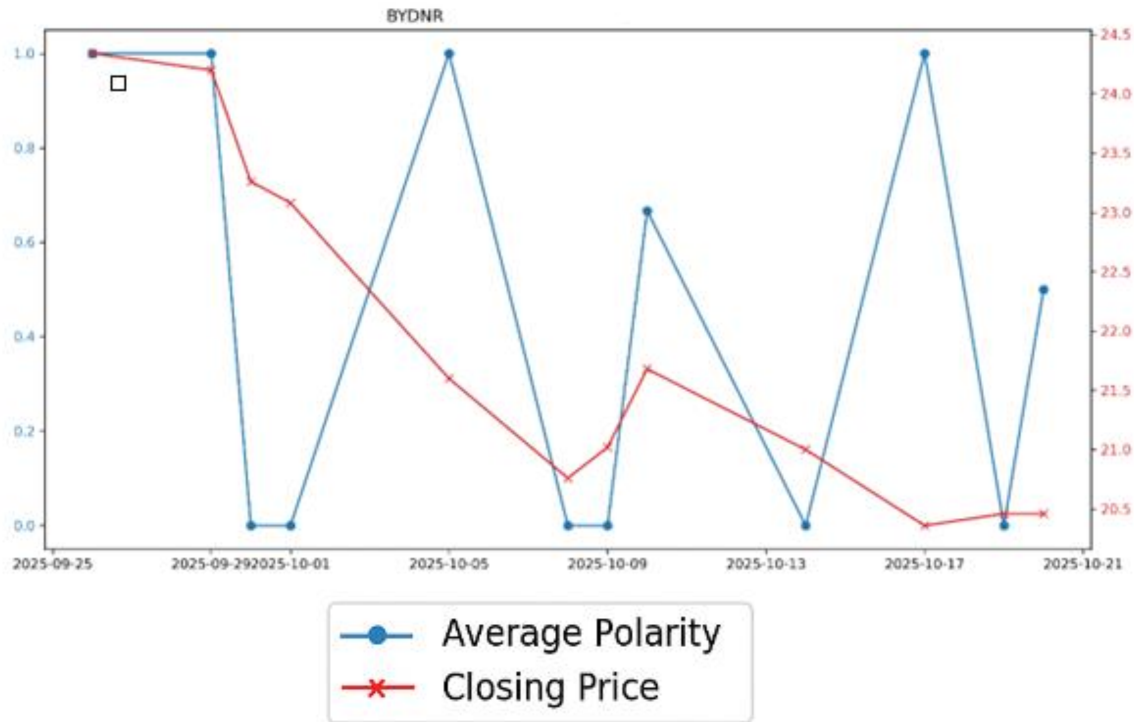

Figure 5. Doco

Figure 6. Etilr

Figure 7. Maalt

Figure 8. Martı

Figure 9. Merit

Figure 10. Pkent

Figure 11. Tabgd

Figure 12. Tektu