

Research on the Relationship between Stock Price and Financial Indicators using Ordinary Least Squares Model

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Abstract. Understanding the association between stock price and financial indicators is important. After summarizing the directions of previous research, collecting data from Yahoo Finance and the basic information of Inner Mongolia Yili Industrial Group Co., Ltd. in the investor relations module of its official website and exploring the correlation between explanatory variables, this paper uses OLS Model to give an insight into the correlation between stock price and financial indicators. This paper not only confirms independence between each explanatory variable as well as the robustness of the model, but also proves the parsimony of the OLS model and the fitness between the model and the data. Based on the results of this study, it can be inferred that ITO and net asset growth rate are primary determinants of stock prices, while Equity Ratio and the net asset value per share do not make a remarkable effect. In conclusion, studying the relationship between stock price and financial indicators, the paper gains insights into financial markets and can help stakeholders make more informed decisions in the increasingly complex world of finance.

Keywords: Stock price, financial indicators, OLS model.

1. Introduction

Stock price and financial indicators play important roles in understanding the dynamics of financial markets. Over the years, lots of studies have been conducted to explore the relationship between stock prices and various financial metrics, aiming to provide insights into market behavior and investment decision-making.

Many scholars studied the relationship between stock prices and social platform activities, especially Twitter. Dubey et al. investigated the feasibility of predicting stock market movements by leveraging data from Yahoo Finance and sentiment analysis of Twitter posts. The research methodology collected historical stock market data, made sentiment analysis of tweets related to financial topics and employed predictive modeling techniques [1]. Teti et al. delved into the correlation between Twitter activity and stock prices. The study entailed analyzing Twitter data, including tweet volume, sentiment, and content related to technology firms, alongside corresponding stock price movements [2]. Corea investigated the feasibility of using Twitter as a proxy for investors' sentiment, with a focus on the technology sector. The research analyzed Twitter data, sentiment analysis algorithms, and stock price movements within the technology industry. By examining correlations between Twitter sentiment and subsequent market behavior, the research aimed to assess the reliability and predictive power of Twitter as an indicator of investor sentiment [3]. Ruan et al. explored the utilization of the Twitter trust network for stock market analysis [4]. Wei et al. analyzed large-scale Twitter data to identify significant volume spikes. By investigating the information content embedded in Twitter volume spikes, the research contributed to the understanding of options market behavior [5].

Lots of researchers were devoted to studying the influencing factors of stock prices and predict stock price. Sanapala et al. explored the application of linear regression techniques in optimizing trading strategies based on stock prices. The study involved constructing and back-testing trading models using historical stock price data and regression analysis to identify potential predictors of price movements [6]. Li et al. focused on stock price prediction using Constrained P-Spline Regression Generalized Additive Models (CPP-GAM). The research applied CPP-GAM to historical stock price data, incorporating constraints to enhance predictive accuracy. By integrating advanced

statistical methods, the study provided a robust model for forecasting stock prices [7]. Checkley et al. delved into the predictive power of market sentiment in forecasting stock market behavior. The study analyzed sentiment data from diverse sources to capture the collective wisdom (or hasty judgments) of market participants [8]. Banerjee employed the Ordinary Least Squares (OLS) regression approach with a focus on structural breaks to forecast Apple Inc. stock prices. The research modeled the relationship between Apple Inc. stock prices and the broader market index while accounting for structural shifts in the data. By employing a robust statistical methodology, the study improved the accuracy of stock price forecasts [9].

Some scholars have also conducted research on new issues that have recently emerged in the stock market. Sung and Ki investigated the profitability of heeding security analyst recommendations [10]. Basse scrutinized the significance of adhering to green finance principles for stock valuation, employing a unique approach of testing for (co-)explosiveness [11]. Wang et al. explored the influence of digital finance on stock price crash risk, with a focus on the Chinese market. Empirical evidence from China shed light on the relationship between digital finance and the occurrence of stock price crashes [12].

In light of the diverse perspectives and methodologies employed in previous research, this research conducts a study of the correlation between financial indicators and stock price. By using OLS model, this paper seeks to identify key factors influencing a company's stock prices.

2. Methods

2.1. Data Source

The data utilized in this study is obtained from Yahoo Finance, a popular financial information platform which provides a wide range of financial data and tools. The stock prices data is collected from the historical stock price database of Yahoo Finance. This dataset includes daily, weekly, or monthly closing prices, trading volumes, and other relevant metrics. The stock prices data covers a specified time period, allowing for a detailed analysis of stock performance over different market conditions. Financial indicators data is sourced from the basic information of Inner Mongolia Yili Industrial Group Co., Ltd. in the investor relations module of its official website. These financial indicators provide a comprehensive snapshot of financial health and performance. The company's basic information which includes financial statements of the company spans multiple fiscal periods, enabling a longitudinal analysis to identify trends and patterns.

2.2. Variable Description

The data used in this paper involves 100 samples, one dependent variable: The stock price and 4 explanatory variables: Equity Ratio, Inventory Turnover (ITO), Growth rate of net assets, Net asset value per share. These four explanatory variables are important financial indicators.

Equity Ratio measures the proportion of a company's assets that are financed by shareholders' equity. A high equity ratio suggests the company has a strong financial position. Net asset growth rate measures the growth in a corporation's net assets over a specific period. A corporation with a higher net asset growth rate is expanding its assets and potentially increasing its value. ITO shows how efficiently a firm is managing its inventory. A higher ITO means that the firm is selling its inventory more frequently, managing its inventory efficiently and generating revenue. The net asset value per share measures the value of a company's assets per share of its common stock. A company with a higher net asset value per share has a higher value of assets per share along with a stronger financial position and potentially higher intrinsic value.

In summary, these financial indicators reflect a corporation's financial health and performance, which can guide investors in predicting potential stock price movements. All of these variables are represented in Table 1 in which also indicates important statistics such as the mean, variance, standard deviation.

Table 1. Different types of variables

Variable	Symbol	Min	Max	Mean	Variance	SD
The stock prices	y	1	5	3.480	1.767	1.329
Equity Ratio	x1	0.015	0.125	0.050	0	0.021
ITO	x2	1	3	1.900	0.717	0.847
Growth rate of net assets	x3	-2.092	1.685	0	1.010	1.005
Net asset value per share	x4	1	3	1.740	0.215	0.463

2.3. Method Introduction

The method used in this paper is the Ordinary Least Squares (OLS). It serves as a cornerstone in understanding the relationships between variables, particularly in the field of economics. Through its application, this article will uncover insights into various economic phenomena, assess the significance of explanatory variables, and make predictions with a certain degree of confidence. The linear fitting equation in OLS Model can be written as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k + \varepsilon \quad (1)$$

In the formula above, y represents the dependent variable, the outcome, or the variable we are trying to predict or explain and x_1, x_2 are the independent variables, each contributing to the linear relationship with y . The last term of this formula represents the error term or the residual, capturing the unobserved factors that affect y but are not accounted for by the independent variables in the model.

3. Results and Discussion

3.1. Descriptive Analysis

After calculating important statistics of each explanatory variable, this paper conducts descriptive analysis of the data.

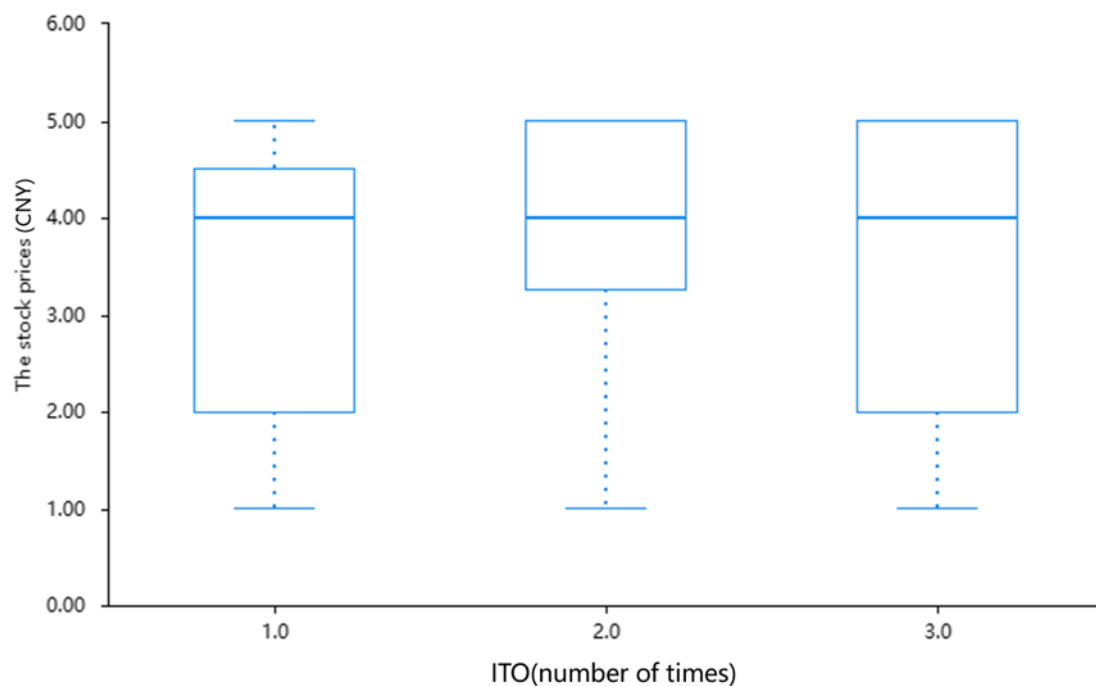


Fig. 1 Box-plot reflecting the distribution of the stock prices under different values of ITO

The box-plot in Figure 1 indicates the distribution of the stock prices under different values of ITO. It is obvious that the median of the stock prices is not affected by ITO. No matter what value ITO takes, most of the stock prices are distributed between 2.00 CNY and 5.00 CNY.

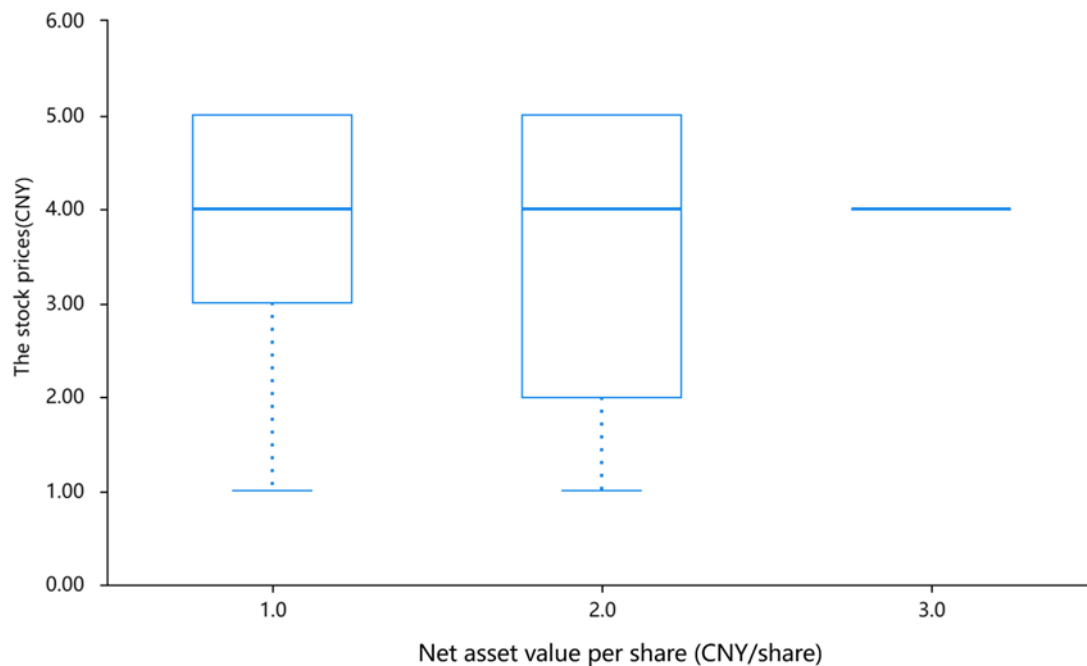


Fig. 2 The distribution of the stock prices under different values of the net asset value per share

It can be drawn from Figure 2 that the stock prices remain 4.00 CNY. When the value of the net asset value per share changes from 1.0 CNY/share to 2.0 CNY/share, the distribution of the stock prices is generally stable.

3.2. Collinearity Diagnosis

Before establishing the OLS regression model, a collinearity test is conducted on the explanatory variables. Through the research result displayed in Table 2, it is obvious that all variables exhibit low Variance inflation factor (VIF) values in this analysis, ranging from 1.001 to 1.081, well below the commonly accepted threshold of 10. These values indicate that multicollinearity is not a significant concern among the predictor variables. Additionally, the tolerance values range from 0.925 to 0.999, indicating that each predictor variable provides unique information not redundant with other variables in the model. These results suggest that the four explanatory variables do not suffer from significant collinearity issues. Consequently, the coefficients estimated in regression models involving these variables are likely to be stable and reliable. The analysis above proves the independence of these variables when interpreting the results of regression analyses, enhancing the robustness of the findings and the validity of conclusions drawn from the model.

Table 2. The outcome of the collinearity diagnosis

	VIF	Tolerance
Equity Ratio	1.058	0.945
ITO	1.029	0.972
Growth rate of net assets	1.001	0.999
Net asset value per share	1.081	0.925

3.3. OLS Regression Model

After the above preparation work, the paper started to establish the OLS regression model.

Table 3. OLS regression analysis results

	Coefficient	SE	t	p	95% CI
Constant	3.495	0.177	19.789	0.000**	3.149 ~ 3.841
Equity Ratio	-2.087	1.865	-1.119	0.263	-5.743 ~ 1.569
ITO	0.128	0.038	3.332	0.001**	0.053 ~ 0.203
Growth rate of net assets	1.281	0.031	40.69	0.000**	1.220 ~ 1.343
Net asset value per share	-0.089	0.071	-1.245	0.213	-0.228 ~ 0.051
R ²			0.944		
Adjust R ²			0.942		
F			F (4,95) = 468.679, p=0.000		
D-W value			2.237		
Dependent variable: Stock Price					
* p<0.05 ** p<0.01					

Through the outcome of the OLS model presented in Table 3, the model equation can be expressed as:

$$y = 3.495 - 2.087x_1 + 0.128x_2 + 1.281x_3 - 0.089x_4 \quad (2)$$

Based on the results of the OLS regression analysis, the correlation between the dependent variable and the four explanatory variables can be interpreted as follows:

It is indicated in Table 3 that the coefficient for ITO is 0.128, and it is statistically significant ($p = 0.001$). This suggests that there is a positive and significant linear relationship between ITO and stock price. As ITO increases by one unit, stock price is expected to increase by 0.128 units, holding other variables constant. The coefficient for the equity ratio is -2.087, but it is not statistically significant ($p = 0.263$). This implies that there is no significant linear relationship between Equity Ratio and stock price. The confidence interval (-5.743 to 1.569) includes zero, indicating that the true coefficient could be zero. The coefficient for net asset growth rate is 1.281, and it is highly statistically significant ($p = 0.000$). This means a strong positive linear relationship between net asset growth rate and stock price. As net asset growth rate increases by one unit, stock price is expected to increase by 1.281 units, holding other variables constant. The coefficient for net asset value per share is -0.089, but it is not statistically significant ($p = 0.213$). This suggests that there is no significant linear relationship between the net asset value per share and stock price. The confidence interval (-0.228 to 0.051) includes zero, indicating that the true coefficient could be zero. The D-W value of 2.237 implies that there is no significant autocorrelation present in the residuals, which strengthens the reliability of the regression results.

Overall, the adjusted R² value of 0.942 suggests that approximately 94.2% of the variability in stock price can be explained by the four explanatory variables included in the model. The F-test with a high F-statistic (468.679) and a significant p-value ($p = 0.000$) confirms the overall significance of the regression model. Therefore, based on these results, ITO and net asset growth rate appear to be important determinants of stock prices, while Equity Ratio and the net asset value per share may not have a significant impact.

3.4. Information Criterion Indicators

After establishing the OLS model, information criterion indicators are reckoned, including Log likelihood, AIC value and BIC value.

Table 4. The result of the information criterion indicators

Log likelihood	AIC value	BIC value
-25.465	0.609	0.74

It can be noticed from Table 4 that the information criterion indicators provide essential insights into the model's goodness-of-fit and complexity. The log likelihood value of -25.465 represents the logarithm of the likelihood function at the maximum likelihood estimate. Lower the log likelihood values indicate poorer fit or higher data uncertainty. In this research, the Akaike Information Criterion (AIC) value of 0.609 and Bayesian Information Criterion (BIC) value of 0.740 suggest relatively low levels of model complexity compared to the fit achieved. These indicators collectively imply that the model provides a reasonable fit to the data while maintaining parsimony.

4. Conclusion

Overall, the result of the collinearity diagnosis indicates that there is good independence between each explanatory variable and the OLS model in this research has good robustness. From the outcome of the information criterion indicators, it can be inferred that the OLS model in this paper corresponds to the data to a large extent while maintaining parsimony. Based on the research above, ITO and net asset growth ratio are main determinants of stock prices, while Equity Ratio and the net asset value per share do not show a significant influence. It is fairly to say that the application of OLS regression analysis in studying the relationship between stock prices and financial indicators holds significant practical implications across various domains, including investment decision-making, financial performance evaluation, risk management, and policy formulation. Therefore, stakeholders can make informed decisions, optimize resource allocation, and drive sustainable value creation in the financial markets. However, one thing that cannot be ignored is the data used in this research is from financial indicators and stock price of Inner Mongolia Yili Industrial Group Co., Ltd. Although it can represent some manufacturing enterprises, it is difficult to apply to other types of enterprises. Further research could be implemented in future, in which different types of companies such as production-oriented enterprises and service enterprises in different countries are considered.

References

- [1] Simren Dubey, Nisarg Patil, Pallavi Thakur, Harshil Kanakia. Stock Market Prediction Using Yahoo finance and Twitter Polarity. 2022 IEEE 3rd Global Conference for Advancement in Technology (GCAT), 2022.
- [2] Emanuele Teti, Maurizio Dallochio, Alberto Aniasi. The relationship between twitter and stock prices. Evidence from the US technology industry. Technological Forecasting & Social Change, 2019.
- [3] Francesco Corea. Can Twitter Proxy the Investors' Sentiment? The Case for the Technology Sector. Big Data Research, 2016.
- [4] Yefeng Ruan, Arjan Durrezi, Lina Alfantoukh. Using Twitter trust network for stock market analysis. Knowledge-Based Systems, 2018.
- [5] Wei Wei, Yuexin Mao, Bing Wang. Twitter volume spikes and stock options pricing. Computer Communications, 2016.
- [6] Srinuvasarao Sanapala, et al. Optimising Trading Strategies using Linear Regression on Stock Prices. 2023 International Conference on Research Methodologies in Knowledge Management, Artificial Intelligence and Telecommunication Engineering (RMKMATE), 2023.
- [7] Yong Li, Mingrui Bai, Jianguo Liu. Stock Price Prediction Based on CPP-GAM. Journal of Physics: Conference Series, 2020.
- [8] Checkleya M S, D. Añón Higónb, Alles H. The hasty wisdom of the mob: How market sentiment predicts stock market behavior. Expert Systems With Applications, 2017.
- [9] Trishit Banerjee. Forecasting Apple Inc. Stock Prices Using S&P500—An OLS Regression Approach with Structural Break. 2020 IEEE International Conference for Convergence in Engineering, 2020.
- [10] Sung Jun Park, Ki Young Park. Can investors profit from security analyst recommendations: New evidence on the value of consensus recommendations. Finance Research Letters, 2019.

- [11] Tobias Basse, Majdi Karmani, Hatem Rjiba, Christoph Wegener. Does adhering to the principles of green finance matter for stock valuation? Evidence from testing for (co-)explosiveness. *Energy Economics*, 2023.
- [12] Wenjing Wang, Moting Wang, Yizhi Dong. The impact of digital finance on stock price crash risk: evidence from China. *Kybernetes Emerald Publishing Limited*, 2023.