IMPACT OF FUNDAMENTAL AND TECHNICAL FACTORS ON FIRM VALUE MODERATED BY INVESTOR SENTIMENT AND NETIZEN SENTIMENT

Hana Tamara Putri [1*], Tona Aurora Lubis [2] and Rike Setiawati [3]

[1, 2, 3] Economics Doctoral Study Program, Faculty of Economics and Business, Jambi University, Indonesia.

*Corresponding Author Email: hanatamaputri88@gmail.com, ORCID ID: [1]0009-0009-0335-7535

DOI: 10.5281/zenodo.11083309

Abstract

The analysis of company value is important in formulating intelligent, data-based investment decisions to reduce risk and generate more profits. Therefore, this quantitative research aimed to analyze the impact of fundamental and technical factors affected by investor and netizen sentiment on Twitter social media. Primary and secondary data collected online were assisted and processed using Python Programming and SmartPLS software, respectively. The results showed that fundamental and technical factors had a positive and significant influence on company value, while investor and netizen sentiment strengthened the factors. In this context, adding variations in indicators to proxy the Netizen Sentiment Variable could serve as input for future research. The assessment of corporate valuation holds paramount importance in formulating judicious investment strategies grounded in data analytics, thereby mitigating risks and enhancing profit margins.

Keywords: Fama French Model, Tracking Error, Consumer Confidence Index, Investor Sentiment, Twitter Sentimen.

1. INTRODUCTION

Company value is an essential component in financial analysis, providing insight into performance and serving as a benchmark for assessing the success of a strategy. The variable is influenced by Fundamental and Technical Factors, and investors must conduct the analyses to obtain profits (Sharma et al., 2021). Fundamental analysis is a method of exploring the intrinsic value of a company's shares by analyzing accounting data and financial history (Nti et al., 2020). Long-term investors use this analysis to obtain benefits such as dividend income and growth in stock prices. However, short-term investors adopt technical analysis to gain profits from the difference between prices when buying and selling shares (Husnan, 2014).

A method for calculating fundamental factors used the Multi-Asset Pricing Model developed by several experts, namely the Fama French Three Model (Fama, 2014). This model was added by Carhart to become the Carhart Four Factor (Carhart, 1997) and refined by Fama French to Fama French Five Model (Fama, 2014). The research used 5 fundamental variables from the Fama French Five Factors, namely Market Risk, Size, Value, Profitability, and Investment.

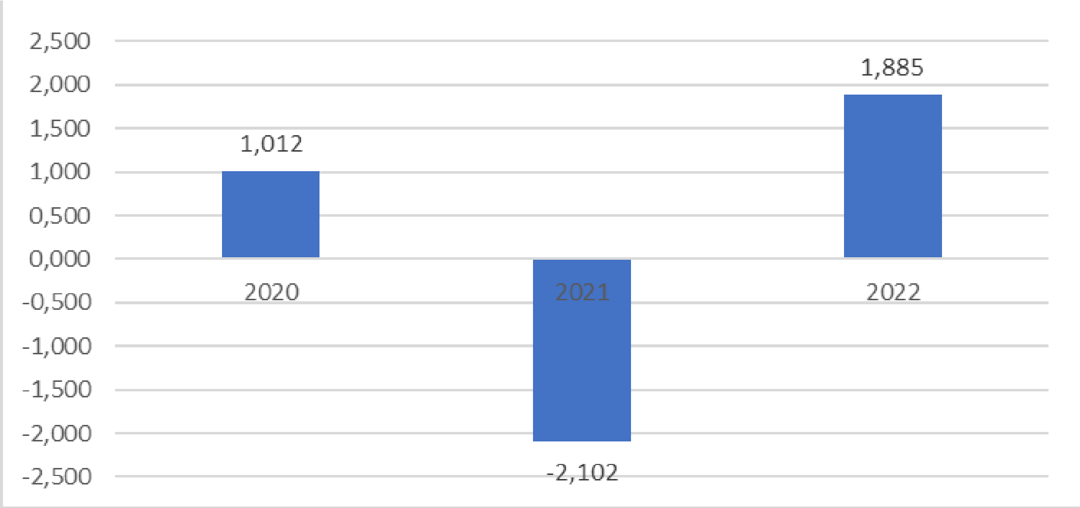

Figure 1: Market Risk Data for 2020-2022 (Sources: Indonesian Stock Exchange)

Technical Analysis is a method for analyzing the performance of stocks and other financial instruments using historical price and trading volume data through patterns and trends to predict future price movements (Gadella, 1994). This assists investors and traders in understanding market behavior by showing the reaction of stock prices to various economic, political, and social factors (Neely, 2001; Han et al., 2021; Lo et al., 2000). Technical factor calculations can be proxied using the Total Volume Activity (TVA) indicator (Carhart, 1997) and Tracking Error (Blume et al., 1994). The Errors can also be seen as an indicator of funds management with the level of risk-borne (Wicaksono, 2021). Company value is a measure of the success of management in convincing shareholders of past operations and prospects, which is measured by Stock Return, Tobins Q, PER, and PBV (Hidayat, 2019). These four variables provide different perspectives on company performance, growth potential, and market perception.

Research on behavioral issues has received considerable attention relating to the role of investor sentiment in asset valuation models. Meanwhile, sentiment from investors arises due to the tendency to speculate (Baker, 2007). Investor sentiment has a positive effect on stock returns and can be used as an indicator to predict stock returns (Brown, 2005; Pandey, 2019; Yu, 2021). On the contrary, Lemmon and Portniaguina (2006) found that there was a relationship between investor sentiment and stock returns only for small companies. The prediction of stock returns in large companies was insignificant as confirmed by Tabassum et al. (2021), where investor sentiment had no impact on the decisions to buy shares.

In the current digital era, social media has become a primary source of information and sentiment in the financial markets. Social media is quickly becoming a tool for disseminating information. According to data collected by Goodstats, there will be 14.8 million active Twitter users in 2023. This information influences Investor sentiment and the desire to buy or sell shares (Nurdhiana, 2017). Even though several analyses showed positive effects of Fundamental Factors on Company Value (Wu et al., 2020; Ali, 2016; Pandey, 2019). Wijaya et al. (2017) reported a contrary result. Technical factors had a positive effect on company value based on research by (Marmoito 2021; Ghoul, 2020; Cremers, 2009; Blume et al., 1994). However, there was also a negative influence between technical factors on company value, as proven by (Brennan et al., 1998).

Investor sentiment can moderate a company's fundamental and technical factors because financial markets do not behave rationally or are based on analysis. Psychological and emotional factors as well as market sentiment can significantly impact stock prices and market performance (Nurdhiana, 2017). In addition, investor sentiment has a positive effect on company value (Firdaus, 2021; Neal, Wheatley, 1998; Jansen, 2003). According to (Istiqomah et al., 2021; Mala, 2022), Twitter's social media sentiment did not influence stock prices. This research showed that sentiment analysis of statements uploaded on Twitter had an insignificant correlation with Company Value. Based on the Research Gap, previous results were expected to combine all fundamental, technical, investor, and netizen sentiment variables.

2. RESEARCH METHOD

2.1. Data Analysis Method, Population and Sample

According to Trochim (2007), quantitative research methods were scientific ways to understand phenomena through collecting, analyzing, interpreting, and presenting data in numbers. The data adopted were financial, market and sentiment data processed using *Structural Equation Modeling-Partial Least Square* (SEM-PLS). The primary data were obtained from netizen comments (tweets) on Twitter social media using keywords such as IHSG, IDX, Stocks, Indonesian Capital Market Netizen Sentiment, Investor Sentiment, Stock Prices, and Stock Returns through a coding process from the Python application. Meanwhile, secondary data were Annual Financial Report data in the form of Share Price, Number of Shares outstanding, Return On Equity, Share Return, Net Profit, Total Assets, Total Debt, Total Equity, Market Capital, Market to Book Value Tobins Q, PER, PBV as well as IHSG data, State Bond Yield, Consumer Confidence Index (Consumer Confidence Index) and Promp Manufacturing Index.

The population observed 142 issuers registered in the IDX IC (IDX Industrial Classification) Sector, namely Basic Material, Consumer Cyclical, and Consumer Non-Cyclical, as the most significant sectors forming the Promp Manufacturing Index in 2022. Furthermore, the sample was selected purposively using specific consideration criteria (Sugiyono, 2020) to obtain 93 issuers

Table 1: Operational Research Variables

Variables	Indicator	Formulas
1. Fundamental Factors	*Market Factors*X1	$Rmt - Rft = (\text{Market Return} - \text{Risk Free Rate})x\ 100$
	*Size Factor*X2	$SMB = \frac{(SMBB/M) + SMBOP + SMBinv)}{3}\ x\ 100$
	*Value Factor*X3	$HML = \frac{(SH - SL) + (BH - BL)}{2} x\ 100$
	Profitability Factor X4	$RMW = \frac{(SR-SW)+(BR-BW)}{2} x\ 100$
	Investment Factor X5	$CMA = \frac{(SC - SA) + (BC - BA)}{2}\ x\ 100$
2. Technical Factors	Tracking Error (X6)	$(Return\ Difference - Average\ Return\ Difference)x\ 100$
	Total Volume Activity (X7)	$\text{TVA} = \frac{\text{Total Traded Shares}}{\text{Total Outstanding Shares}}\ \text{x}\ 100$

ISSN 1462 2815

1. Investor Sentiment	*Consumer Confidence Index*(Z1)	$Consumer\ Confidence\ Indeks = (\text{Balance Score Consumer Index} - \text{Net Balance}) + 100$
	Prompt Manufacturing Index(Z2)	Prompt Manufacturing Index = (Balance Score Manufacturing Index – Net Balance) + 50
4. Netizen Sentiment	Netizen Sentiment (Z3)	h(x)= wx+ b≤ –1 negative h(x)= wx+ b = *0 neutral* h(x)= wx+ b≤+1 positive
5. Firm Value	*Return*Shares (Y1)	$\frac{Close\ Price\ it\ -\ \text{Close Price it} - 1}{\text{Close Price it} - 1}$
	Tobin's Q (Y2)	$= \frac{\text{Debt Total} + (\text{Total Outstanding Shares x Closing Pr}}{Assets\ Total}$
	Price to Earnings Ratio(Y3)	$PER = Closing\ Price: Earning\ per\ Share$
	Price to Book Value(Y4)	$PBV = Closing\ Price : Book\ Value\ of\ Shares$

2.2. Hypothesis

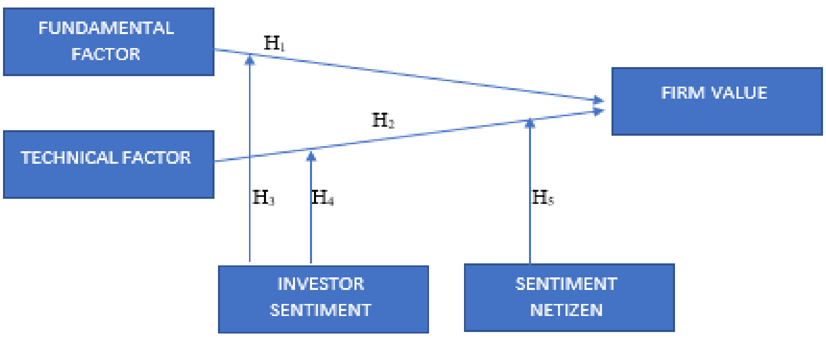

Figure 2: Hypothesis

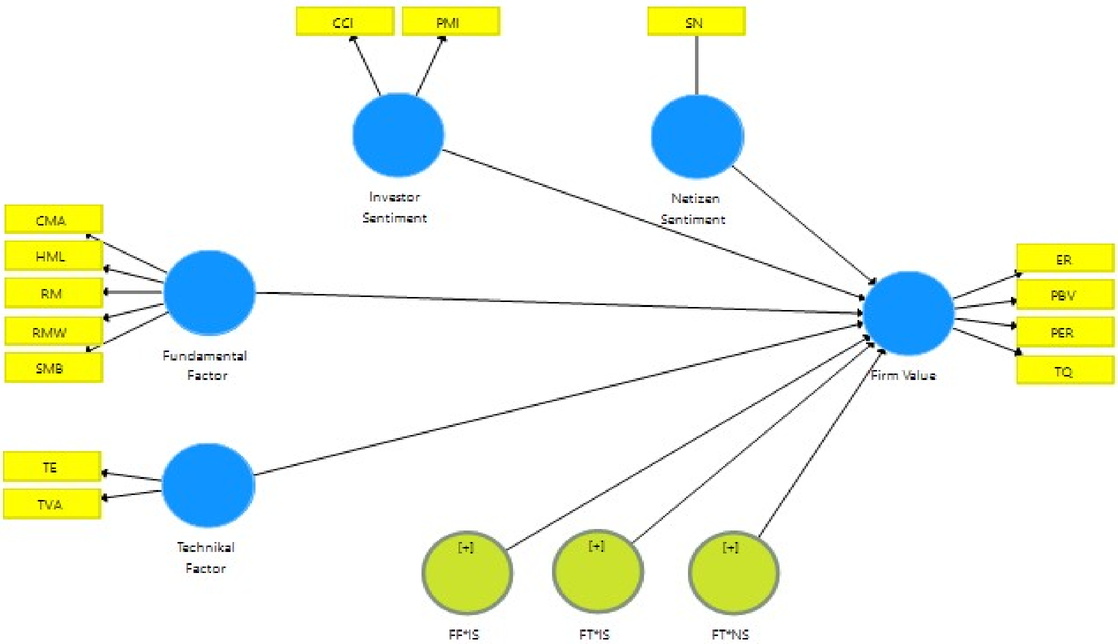

Figure 3: Research Models

3. DISCUSSION

3.1. Convergent Validity

The picture shows the results of the outer loading for all proxies, which are declared valid.

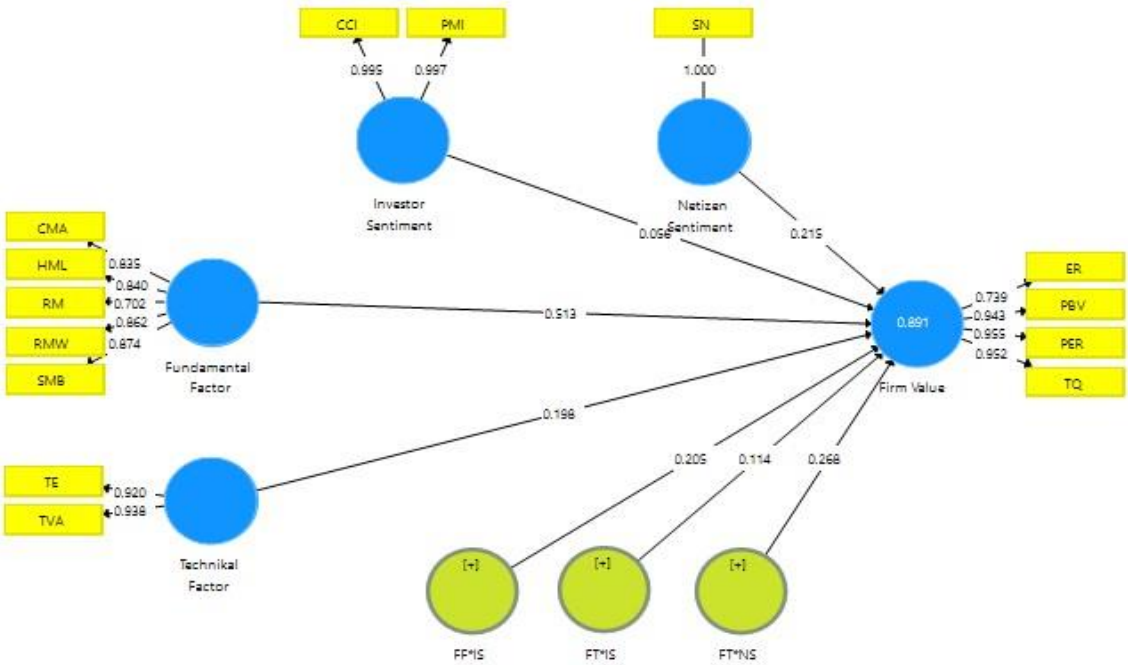

Figure 4: Convergent Validity. Source: Smart PLS, 2024.

Table 1: Outer Loading Value

	X1	X2	Y	Z1	Z2	modX1Z1	modX2Z1	modX2Z2
RM	0.702							
SMB	0.874							
HTML	0.840							
RMW	0.862							
CMAs	0.835							
TE		0.920						
TVA		0.938						
CCI				0.995				
PMI				0.997				
S.N.					1,000			
E.R.			0.739					
TQ			0.952					
PBV			0.943					
PER			0.955					
X1 * Z1						1,017		
X2 * Z1							1,016	
X2 * Z2								1,057

Source: Data Processing Results, 2024.

The outer loading value of the indicators meets the criteria of being above 0.7, hence the results obtained are significant.

Table 2: Construct Reliability and Validity

	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
X1	0.883	0.914	0.681
X2	0.842	0.927	0.863
Y	0.920	0.945	0.814
Z1	0.992	0.996	0.992
Z2	1,000	1,000	1,000
modX1Z1	1,000	1,000	1,000
modX2Z1	1,000	1,000	1,000
modX2Z2	1,000	1,000	1,000

Source: Data Processing Results, 2023.

Based on Table 2, the variables have shown data accuracy and reliability, where the Cronbach Alpha, Composite Reliability, and Average Variance Extracted (AVE) values are above 0.5 since the variables are said to be Reliable.

3.2. Discriminant Validity

Discriminant validity was used to explain that latent variables differ from others. The value could be seen based on the Fornell Larcker Criterion by comparing the minimum root (AVE) with the correlation built by the construct in question with other variables. This was said to be invalid when the condition of the construct described by the Minimum AVE value and having a Cross-Correlation with other constructs was greater, as shown below:

Table 3: Fornell Larckel Criterion Test Results

	X1	X2	Y	Z1	Z2	modX1Z1	modX2Z1	modX2Z2
X1	0.825							
X2	0.684	0.929						
Y	0.755	0.576	0.902					
Z1	0.350	0.174	0.318	0.996				
Z2	0.205	-0.045	0.293	0.328	1,000			
modX1Z1	-0.065	-0.046	0.432	-0.057	-0.042	1,000		
modX2Z1	-0.046	-0.018	0.386	0.050	-0.058	0.709	1,000	
modX2Z2	0.222	0.138	0.614	-0.056	-0.076	0.693	0.562	1,000

Source: Data Processing Results, 2023.

Table 3 presents the data from the Fornell Larcker Criterion test results showing that the variable value was more significant than others, such as X1_X1 of 0.825 > X1_X2 of 0.684. Therefore, the results were said to meet the requirements for Discriminant Validity. Apart from the Fornell Larckel Test, other tests could also be carried out using the Cross Loading Test. The value of each construct was evaluated to ensure that the correlation with the measurement items was more significant than others. In this context, the expected cross-loading value was more significant than 0.7 (Ghozali, 2015).

Table 4: Cross Loading Factor Test Results

	X1	X2	Y	Z1	Z2
Z1	0.318	0.132	0.283	0.995	0.396
X5	0.835	0.537	0.600	0.341	0.292
Y1	0.680	0.605	0.739	0.341	-0.082
X3	0.840	0.537	0.758	0.321	0.367
Y4	0.706	0.474	0.943	0.244	0.359
Y3	0.681	0.504	0.955	0.285	0.372
Z2	0.373	0.207	0.345	0.997	0.271
X1	0.702	0.548	0.374	0.096	-0.438
X4	0.862	0.519	0.534	0.426	0.349
X2	0.874	0.684	0.724	0.222	0.048
Z3	0.205	-0.045	0.293	0.328	1,000
X6	0.515	0.920	0.500	0.114	-0.038
Y2	0.656	0.501	0.952	0.284	0.372
X7	0.743	0.938	0.566	0.204	-0.045

Source: Data Processing Results, 2023.

The indicator for the Fundamental Factor Variable with the highest and lowest Cross Loading values was the Size Factor (SMB) and Risk Market (R.M.) with a value of 0.874 and 0.702, respectively. The Technical Variable and Company Value indicators with the highest cross-loading values were the Total Volume Activity (TVA) and Price to price-to-earning ratio (PER) of 0.938 and 0.955, respectively. The indicators had a cross-loading value above 0.7, hence the constructs had good discriminant validity and the indicators in the model contributed to more than a latent variable or construct.

3.3. Composite Reliability

Composite Reliability tests the value between each construct's indicators in forming the model. The test ensured that the indicators or items used to measure a construct provided consistent and reliable results. The recommended Composite Reliability value was more significant than 0.7, and the recommended Cronbach Alpha value was above 0.6, as shown in Table 5:

Table 5: Composite Reliability Test Results

	Cronbach's Alpha	Composite Reliability	Test results
X1	0.883	0.914	Reliable
X2	0.842	0.927	Reliable
Y	0.920	0.945	Reliable
Z1	0.992	0.996	Reliable
Z2	1,000	1,000	Reliable
modX1Z1	1,000	1,000	Reliable
modX2Z1	1,000	1,000	Reliable
modX2Z2	1,000	1,000	Reliable

Source: Data Processing Results, 2023.

The Composite Reliability values of Variable X1 (Fundamental Factors), Variable Y (Company Value), Variable Z1 (Investor Sentiment), and Variable Z2 (Netizen Sentiment) were 0.883, 0.920, 0.992, and 1.000, respectively. The constructs had a Cronbach Alpha value above 0.6, hence the reliability test requirements were met and the indicators had a consistent relationship in measuring the model.

ISSN 1462 2815

3.4. Coefficient of Determination (R^2)

R-squared measures the extent to which the independent variables in the model can explain variability in the dependent variable. This construct has a value between 0 and 1, where the higher the value, the better the model explains variations in the dependent variable.

Table 6: R Square Results

	R Square	R Square Adjusted
Y	0.891	0.888

Source: Data Processing Results, 2023.

The R-squared value of 0.891 shows that the contribution of Fundamental Factor Variables and Technical Factors in influencing Company Value is 0.891 or 89.1%, while variables outside this research influence 10.9%.

3.5. Q Square Value (Q^2)

Q-squared measures a model's predictive ability against new (out-of-sample) data. A positive value shows that the model has good predictive ability. Meanwhile, a higher value reports the level of generalization conducted to obtain new data. Based on the results of data processing in the PLS application, the Q Square calculation is obtained as follows:

Table 7: Q Square Results

	Q^2 (=1-SSE/SSO)
Y	0.716

Source: Data Processing Results, 2023

The results of the calculation are more significant than 0, namely 0.716 or 71.6%. Therefore, the model has a relevant predictive value to obtain the information contained in the research data of 71.671.6%.

3.6. Results and Discussion

3.6.1. The Influence of Fundamental Factors on Company Value

Fundamental factors influencing company value can be seen from various aspects. The indicators used are Market Risk, proxied by the Composite Stock Price Index, and Risk-Free Rate, showing that shares with higher exposure to market risk can produce higher returns with increased performance. An increase in the IHSG reports economic growth to promote investment. Therefore, the influence of Market Risk and Company Value is positive due to the direct relationship between the variables.

The second indicator is small minus big (SMB), which is excess return with a smaller market capitalization minus more considerable value. The portfolio will outperform the market in the long term with smaller companies.

The third indicator is High Minus Low (HML), namely the difference between companies with high and low book values. HML substantially impacts returns because a portfolio that includes more businesses with high book values outperforms fewer companies with low book values. Therefore, HML is directly proportional to the value factor of a company.

The fourth indicator is Robust Minus Weak (RMW), which proxies profitability. According to (Gumilar et al., 2019), a high profitability value is an attraction for investors. The profitability of a company is directly proportional to the number of shareholders interested in buying shares.

The fifth indicator is Conservative Minus Aggregate (CMA), where investment factors provide insight into the relationship between a company's policy and stock returns. Aggressive investment and high stock returns can influence investors' perceptions of the company's strategy. Companies with aggressive investments have higher market valuations due to significant growth and profit opportunities in the future.

3.6.2. The Influence of Technical Factors on Company Value

Technical factors can influence company value to analyze patterns, movement trends, and stock trading volume. Tracking error measures the deviation of return on an investment portfolio from the reference used as a benchmark. A lower tracking error is considered better because the portfolio is moving in line with the benchmark's performance. Meanwhile, Total Volume Activity reflects the high liquidity of a company's stock market. Shares with high liquidity are more accessible to trade, increasing investor interest to easily access shares and company value. High trading activity provides a positive indication to investors that a company's shares are in demand and are actively traded. This creates a positive perception, as well as increases investor confidence and shareholder value. The market assessment of a company's performance and growth potential is reflected by an increase in share prices and high trading activity. Technical factors have a positive and significant effect on company value, in line with (Marmoiton 2021; Ghoul, Saint-jean 2020; Cremers, Petajisto 2009; Blume et al. 1994; Surono et al. 2020).

3.6.3. The influence of fundamental factors on company value is moderated by investor sentiment

Sentiment can moderate the decision of investors, who may be more inclined to stay away from a stock when the fundamental factors are vital. Conversely, positive sentiment can strengthen investment choices even with reduced fundamental factors. News and external events can trigger changes in investor sentiment by moderating the influence of fundamental factors. Sentiment creates herding behavior, where investors follow the majority's flow without considering fundamental factors in depth, as supported by (Pandey, 2019; Brown, 2005; Baker, 2007; Ferrer et al., 2016; Lemmon, 2006; Yu, 2021).

3.6.4. The influence of technical factors on company value is moderated by investor sentiment.

Sentiment can influence investor preferences for technical or fundamental analysis. In the context of dominant sentiment, technical analysis may become more relevant than fundamental, which is more related to factors in financial statements. Meanwhile, changeable or unstable sentiment leads to higher price volatility, which can make technical analysis less reliable, specifically when the volatility is triggered by emotional factors or unrelated news. External events that influence investor sentiment disrupt existing technical patterns. Even though a stock may show a particular trend or pattern based on technical analysis, bad or good news causes sudden changes in price behavior, as reported by (Fisher, 2000; Afshar, 2007; Wendy, 2019; Julia, 2019; Fariska et al., 2020).

3.6.5. The influence of technical factors on company value is moderated by netizen sentiment

Netizens' positive or negative feelings on social media influence investment choices. Investors may purchase shares when many netizens express positive beliefs about a stock. Favorable netizen sentiment can make investors more optimistic about buying shares, resulting in increased prices and significant movements in stock trading. Sentiment analysis of Twitter social media positively influences the stock market, as supported by (Kirlic et al., 2018; Duz, Tas, 2021; Kolasani, 2020; Bollen et al., 2011b; Corea 2016; Singh et al., 2022).

CONCLUSIONS

In conclusion, Fundamental and Technical Factors were reported to have a significant influence on Company Value. Meanwhile, Investor and Netizen Sentiment as a Moderating Variable Strengthened the Influence of the Factors. This research found a gap in examining the tracking error variable, which was different from the theory of negatively influencing company value. Therefore, future analyses should add the Active Share variable to the Technical Factors.

Acknowledgements

The author would like to express his deepest gratitude to Batanghari University for its support and for allowing the author to study in the doctoral program at Jambi University. I also express my appreciation to Dr. Tona Aurora Lubis, SE, MM and Dr. Rike Setiawati, SE, MM, as Promoter and Co-Promoter for their valuable contributions to the experimental setup and data analysis. Special thanks go to the Examining Team from the Jambi University Economics Doctoral Study Program for their in-depth comments and suggestions during this research. Finally, we would like to thank the anonymous reviewers for their constructive feedback, which greatly improved the quality of this manuscript.

Funding

Funding for this research was provided personally by Hana Tamara Putri

Author contributions

First Author: Conceptualization, Data Curation, Methodology, Writing - Original Draft, Editing

Second Author: Supervision, Methodology, Review & Promoter

Third Author: Supervision, Review & Co-Promoter

Disclosure statement

Authors are required to include a statement at the end of their article to declare whether or not they have any competing financial, professional, or personal interests from other parties.

References

1) Ali, A., & Boadu, S. (2016). *Analyse the bid-ask spread and its implications for portfolio returns.* Supervised by Thomas Leirvik.

2) Baker, M., & Wurgler, J. (2007) Investor sentiment in the stock market. *Journal of Economic Perspectives, 21*(2), 129–151. https://doi.org/10.1257/jep.21.2.129

3) Blume, L., Easley, D., & O'Hara, M. (1994) Market Statistics and Technical Analysis: The Role of Volume. *The Journal of Finance, 49*(1), 153–181. https://doi.org/10.1111/j.1540-6261.1994.tb04424.x

4) Brown, G. W., & Cliff ,M. T. (2005). Investor sentiment and asset valuation. *Journal of Business, 78*(2), 405–440. https://doi.org/10.1086/427633

5) Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance, 52*(1), 57–82. https://doi.org/10.1111/j.1540-6261.1997.tb03808.x

6) Cremers, K. J. M., & Petajisto A. (2009). How Active Is Your Fund Manager? A New Measure That Predicts Performance. *Review of Financial Studies*, *22*(9), 3329–3365. https://doi.org/10.1093/rfs/hhp057

7) Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds*. *Review of Finance, 21*(4), 1355–1401. https://doi.org/10.1093/rof/rfx003

8) Fama, E. F., & French, K. R. (2014). A five-factor asset pricing model. *Journal of Financial Economics, 116*(1), 1–22. https://doi.org/10.1016/j.jfineco.2014.10.010

9) Firdaus, A. P. (2021) Analysis of the Influence of Investor Sentiment on Stock Returns. *Khazanah Intelektual, 5*(20). https://doi.org/10.37250/newkiki.v5i2.121

10) Gadella. J. W. (1994) Avoiding Expensive Mistakes in Capital Investment. *Long Range Planning*, 103–110.

11) Ghoul, S. E., Saint-Jean, C. (2020) Fund Performance and Social Responsibility: New Evidence using Social Active Share and Social Tracking Error. *Journal of Banking and Finance*, 1–44.

12) Han, Y., Liu, Y., Zhou, G., & Zhu, Y. (2021). Technical Analysis in the Stock Market: A Review. *SSRN Electronic Journal, 2013*. https://doi.org/10.2139/ssrn.3850494

13) Hidayat, M. (2019). Factors That Influence Price To Book Value. *Journal of Business and Accounting*, *20*(2), 101–106. https://doi.org/10.34208/jba.v20i2.414

14) Husnan, S. E. (2014). *Financial Management* (7 ed.). YKPN STM.

15) Istiqomah, I., Wardhani, D. K., Supratiwi, W., Ratnawati, T. (2021). Investor Sentiment Towards JII Stock Returns at the Beginning of COVID-19. *Accounting E-Journal, 31*(5), 1277. https://doi.org/10.24843/eja.2021.v31.i05.p15

16) Jansen, W. J., Nahuis, N. J. (2003). The stock market and consumer confidence: European evidence. *Economic Letters, 79*(1), 89–98. https://doi.org/10.1016/S0165-1765(02)00292-6

17) Lo, A. W., Mamaysky, H., Wang, J. (2000). Foundations of technical analysis: Computational algorithms, statistical inference, and empirical implementation. *Journal of Finance*, *55*(4), 1705–1770. https://doi.org/10.1111/0022-1082.00265

18) Mala, R. F. (2022). The role of investor overconfidence sentiment in moderating the influence of firm size, firm value and price-earnings ratio on stock returns, Thesis. Maulana Malik Ibrahim State Islamic University, Malang http://etheses.uin-malang.ac.id/id/eprint/39116

19) Marmoiton, A. (2021). An approximate formula for linking active share and tracking Errors. *SSRN Electronic Journal*, https://doi.org/10.2139/ssrn.3771144

20) Neal, R., & Wheatley, S. M. (1998). Do Measures of Investor Sentiment Predict Returns? *Journal of Financial and Quantitative Analysis*, *33*(4), 523–547.

21) Neely, C. J., & Weller, P. A. (2001). Technical analysis and central bank intervention. J*ournal of International Money and Finance,* 20(7), 949–970. https://doi.org/10.1016/S0261-5606(01)00033-X

22) Nti, I. K., Adekoya, A. F., & Weyori, B. A. (2020). A systematic review of fundamental and technical analysis of stock market predictions. *Artificial Intelligence Review, 53*(4), 3007–3057. https://doi.org/10.1007/s10462-019-09754-z

23) Nurdhiana, E., & Norita, N. (2017). Analysis of Optimal Portfolio Formation Using the Capital Asset Pricing Model and Portfolio Performance Assessment Based on the Sharpe Ratio, Treynor Method. *eProceedings of Management, 4*(1), 95–102. https://openlibrarypublications.telkomuniversity.ac.id/index.php/management/article/view/3891

24) Pandey, P., Sehgal, S. (2019). Investor sentiment and its role in asset pricing: An empirical study for India. *IIMB Management Review, 31*(2), 127–144. https://doi.org/10.1016/j.iimb.2019.03.009

25) Sharma, L., Patil, P., Choudhari, S., Sangle, D., & Reddy, V. P. K. (2021). Fundamental and Technical Analysis of Stock for Beginners. *International Journal of Innovative Science and Research Technology, 6*(5), 1334–1339. https://ijisrt.com/fundamental-technical-analysis-of-stock-for-beginners

26) Surono, Y., Siregar, A. I., & Adisetiawan, R. (2016). Perspective of the Asset Pricing Model and its Development in the Indonesian Capital Market. *Eksis: Scientific Journal of Economics and Business, 11*(1), 25. https://doi.org/10.33087/eksis.v11i1.194

27) Wicaksono, D. (2021). *Starting from ETFs* (M. Yulian (Ed.)). PT Elex Media Komputindo.

28) Wu, L., Shao, Z., Yang, C., Ding, T., & Zhang, W. (2020). The impact of CSR and financial distress on financial performance from Chinese listed companies of the manufacturing industry. *Sustainability (Switzerland),* 12(17). https://doi.org/10.3390/SU12176799

29) Yu, S. (2021). The impact of investor sentiment on the U.S. stock market based on the Fama-French 3-factor model. *E3S Web of Conferences, 275*, 0–3. https://doi.org/10.1051/e3sconf/202127501055)