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Instagram Endorsement and Stock Return

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Abstract: Investors obtain information from various sources, including social media, which can make them act irrationally by imitating the decisions of others. This study aims to investigate the impact of influencers endorsements on abnormal stock returns. This event study used 291 Instagram posts by social media influencers. Using Generalized Least Square (GLS), this study demonstrates that endorsement positively affects stock abnormal returns. The endorsement effect appears prior to the post and stops following the endorsement. Endorse was successful in creating a favorable sentiment, so that other investors are interested in making similar decisions to generate abnormal returns. This study shows the short-term effect of endorsements. Therefore, investors need to be aware and make rational decisions.

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INTRODUCTION

An efficient market is a market that can reflect all information (Fama, 1970; Swamy & Dharani, 2019) in the form of facts and issues that can make stock prices fluctuate (Nurheriyani, 2014). In an efficient market, prices depend on the rationality that investors have towards information in the form of good news and bad news (Septyanto, 2013; Ah Mand & Nature, 2021). However, investors are not fully rational due to heuristic behavior and bias (Tuyon and Ahmad, 2016) and emotional decision making (Han, Li and Li, 2020; Singh, Babshetti & Shivaprasad, 2021). This results in market anomalies in which the occurances are irrational and contrary to the efficient market (Latif et al., 2011; Haggard, Jones & Witte, 2015).

When anomalies occur, events can be used to obtain abnormal returns (Werastuti, 2012), which is the difference between the actual return and the expected return (Hartono, 2009). Herding, or following the actions of other investors, is one of the behaviors that causes abnormal returns because investors buy or sell certain stocks at the same time, causing stock prices to rise or fall (Tan et al., 2008; Guilmi, et al., 2014). Herding behavior can be created through the role of print media such as newspapers (Graham, 1999) and social media (Sibande et al., 2021). In addition to herding, investor sentiment through social media can also affect stock prices (Born, et al,, 2017; Fenn, 2019; Ajjoub, Walker and Zhao, 2021).

Sentiment and the act of herding through social media indicates that investors base their investment decisions on information from digital sources, one of which is social media (Manson, 2019). Social media users are dominated by millennials and generation Z (Annur, 2020). At least 60 percent of investors on the Indonesia Stock Exchange are millennials and generation Z (KSEI, 2021a). However, Indonesia's financial literacy index is only 38.03% (Financial Services Authority, 2021) creating investors with lack of financial literacy abilities. Investors often base their decisions on social media influencers and disregard the information they have (Tan et al., 2008). Influencers are individuals with the ability and effectiveness to spread messages about new products, initiate and popularize trends, and boost product sales (Jin, et al., 2019). Influencers can disseminate and manipulate information to their followers, and investors continue to follow them despite being aware of the potentional for manipulation (Wang & Wang, 2018).

This study focuses on the influence of herding behaviour through social media on abnormal returns, adding to the previous studies which focused on the effect of market sentiment through social media on abnormal returns (Born, et al., 2017; Fenn, 2019; Ajjoub, Walker & Zhao, 2021). Additionally, this study incorporates social media due to the large number of investors who use it to make investment decisions (Manson, 2019). While prior studies mostly largely employ Twitter, this study focuses on Instagram. Therefore, this study contributes to the behavioral finance literature by examining herding behavior through social media and its impact on abnormal returns. Hence, the purpose of this study is to determine the effect of influencer stock endorsements via Instagram on stock abnormal returns.

LITERATURE REVIEW AND HYPOTHESES

Under efficient market conditions, investors have limited access to market-wide information, resulting in delays in their reactions to relevant information (Hirshleifer et al., 2004; Peng & Xiong, 2006). Investor decision making is also influenced by emotions (Peters & Slovic, 2000; Lo & Repin, 2001) which can lead to market anomalies (Archana, et al., 2014). Market anomalies can occur once and then disappear, or they can also occur continuously (Latif et al., 2011). The existence of market anomalies raises a behavioral finance perspective (Tuyon & Ahmad, 2016) which is an approach explaining the what, why, and how of financial and investment performance through human perspective and behavior (Ricciardi & Simon, 2000). Behavioral finance provides an understanding that humans make decisions by combining rational elements in the form of cognitive and irrational logic in the form of heuristics and affective bias (Tuyon & Ahmad, 2016). Behavioral finance is caused by overconfident behavior (Ritter, 2003; Ahmad & Shah, 2022), insufficient information, and environmental differences (Angel, 2013; Carrillo & Brocas, 2000). Behavioral finance is considered more effective and relevant than the efficient market hypothesis for analyzing variations in investor behavior under dynamic market conditions because it is able to consider various possibilities in the market rather than focusing on a single perspective—investor rationality (Soufian, Forbes & Hudson, 2013).

Herding behavior is one of the 17 behavioral biases in making investment decisions identifid by behavioral finance (Zahera & Bansal, 2018). Herding behavior is the tendency of investors to follow the actions of other investors (Tan et al., 2008; Balcilar, Demirer & Hammoudeh, 2013; Guilmi, He & Li, 2014) although their information suggests different things (Banerjee, 1992; Wang & Wang, 2018). Herding, which occurs when a group of investors trades in the same direction over time, is easily observable (Hachicha et al., 2023; Nofsinger & Sias, 1999). Herding occurs because there is either too little or too much information on the market; consequently, investors are confused and unable to make informed decisions (Hachicha et al., 2023; Nofsinger & Sias, 1999). The most common approach for dealing with herding conditions is to imitate what other investors are doing (Ahsan & Sarkar, 2013). Herding also occurs when investors use emotions and feel they find certainty by following other investors' decisions (Ahsan & Sarkar, 2013).

Herding behavior is driven by irrational motives that result in abnormal returns (Kumar & Persaud, 2002; Wanidwaranan & Padungsaksawasdi, 2020) and mispricing for investors (Hwang & Salmon, 2004; Vo & Phan, 2019). Herding is not only done by individual investors, but also by investment managers as an effort to maintain their reputations (Graham, 1999; Liu et al., 2023; Swank & Visser, 2008). Several

previous studies have shown a positive effect of herding during the COVID-19 period (Arias & Mendez, 2021) and herding in the capital market (Dang & Lin, 2016; Galariotis, Krokida & Spyrou, 2016). There are also studies that demonstrate how sentiment through the media influences the capital market (Tetlock, 2007; Bhattacharya et al., 2009; Dougal et al., 2012). However, this study makes use of social media,s so it will focus on previous studies that has established a connection between social media and the capital market (Born, et al., 2017; Fenn, 2019; Ajjoub, Walker & Zhao, 2021).

Born et al (2017) analyzed the effect of Donald Trump's tweets and showed that negative and positive sentiments caused abnormal returns, even when the lacked new information. Accordingly, Ajjoub et al. (2021) showed that positive sentiment affected the abnormal return of media companies, while negative sentiment only affected abnormal return of non-media companies. Because abnormal returns are also driven by information in the news, Donald Trump's negative tweets that have been reported by other parties have a growing impact on the abnormal returns of non-media companies. However, Fenn (2019) found that Donald Trump's tweet had no effect on the company's abnormal return, but did impact trading volume. This is because the capital market is dominated by institutional investors who focus on fundamental news, whereas trading volume is affected because it is related to investor sentiment. In addition, a number of previous studies have also shown the existence of herding behavior in various media (Graham, 1999; Gurdgiev & O'Loughlin, 2020; Sibande et al., 2021).

Graham (1999) analyzed herding behavior through newspapers and found that herding occurs when the media that informs has a solid reputation and provides consistent information. Gurdgiev and O'Loughlin (2020) also observed that cryptocurrency price fluctuations were influenced by herding factors from *bitcointalk*.org forum. The research showed that asset investor sentiment could create herding behavior in a bearish market. In addition, investor sentiment on the financial market could be gauged using the happiness index on Twitter (Sibande et al., 2021).This study shows that positive sentiment through social media has a positive effect on herding behavior. Indeed, social media is widely used in various aspects of human life, including as a channel for users to share information and their personal feelings (Sul, et al., 2016). In fact, 88 percent of investors make investment decisions based on information from digital sources, including social media (Manson, 2019).

Previous studies on herding and market sentiment had been carried out through newspapers (Graham, 1999) and Twitter media (Born, Myers & Clark, 2017; Ajjoub, Walker & Zhao, 2021; Sibande et al., 2021). However, there is no research on herding behavior through Instagram. This study employs the social media platform Instagram which has two billion monthly active users, far exceeding other social media platforms such as Twitter, which has 206 million monthly active users (Riyanto, 2021). Based on this, the hypothesis for this study is as follows:

H1: Endorse posts have a positive effect on stock abnormal returns

METHODS

This event study measures the impact of an event on the stock return of a company (Agrawal & Kamakura, 1995; Binder, 1998). The purpose of the event study is to identify changes in stock prices that can lead to abnormal returns after an event occurs in the market. This study focuses on the Instagram posts of Raffi Ahmad, Ari Lasso, Ustadz Yusuf Mansur, and Belvin Tannadi because they have published stock endorse posts and have over one million followers (Jannah, 2021). A large number of followers influences the rate at which these influencers spread information (Sul, et al., 2016). This event study measures the impact of an event on the stock return of a company (Agrawal & Kamakura, 1995; Binder, 1998). The purpose of the event study is to identify changes in stock prices that can lead to abnormal returns after an event occurs in the market. We drew sample for this study purposively by using several criteria. First, this study focuses on the Instagram posts of Raffi Ahmad, Ari Lasso, Ustadz Yusuf Mansur, and Belvin Tannadi because they have published stock endorse posts and have over one million followers (Jannah, 2021). A large number of followers influences the rate at which these influencers spread information (Sul, et al., 2016). Second, this study used Instagram posting data throughout 2021 due to an increase in the number of

investors in the capital market by 92.7% (KSEI, 2021b). The year of 2021 was selected because in that year, the Indonesia Stock Exchange (IDX) highlighted stock endorsement activities by calling a number issuers and influencers (Fuad, 2021) regarding policies that prohibit the promotion of an issuer to the public (Law No. 8 of 1995 article 5 paragraph 3). Third, posts with negative and neutral sentiments were excluded. Similarly, several same-day posts on certain stocks were also excluded. Table 1 conclude the number of stock endorse posts made by research objects.

Table 1. Criteria and number of posts

Criteria	N
The total number of posts	744
Posts with negative and neutral sentiments	(200)
Post with stock code and same day	(253)
Number of posts used	291

Source: processed data.

Data in this study was retrieved manually using the Instagram application because the posts were not only text but also videos and photos. In addition, there are also many unique vocabularies, and hence, human analysis is preferable to algorithmic analysis (Ajjoub, et al., 2021). The researcher then maps the sentiments into positive, negative, and neutral (Ajjoub, et al., 2021). Examples of positive sentiments such as "company X's shares will soar today, with a potential 8% return". Negative sentiments include "I sold X shares after the price reached Rp.1300" while neutral sentiments such as "JCI conditions have started to improve after experiencing a correction over the past 2 weeks".

To ensure objectivity of research, a coding process is necessary. Therefore, a codebook is developed which contains information related to the data coding process. One of the researcher and one independent coder coded 20 percent of the posting data based on the codebook (Maiorescu, 2017). After completing the coding, the researchers conducted a reliability test using Kappa Cohen's. The intercoder reliability must be greater than 0.80 for the coder and independent coder to be considered to have an almost perfect agreement (Burla et al., 2008). In this study, Cohen's Kappa results were 0.81. This was then continued by coding all data. Because the research focuses on stock endorsement activities, researchers only use posts with positive sentiment.

The next step is to calculate the stock abnormal return with an estimated observation period of 100 trading days (Qian, Suryani and Xing, 2020) as well as a window period of 5 days before and 5 days after the event (Al-Shattarat, Atmeh and Al-Shattarat, 2013). The window period was determined not to be too long to reduce the possibility that other factors could influence the results of the study (Kusnandar & Bintari, 2020; Tanoyo, 2020). To minimize the effect of the event, the estimation period used is t-11 to t-110 (Al-Shattarat, Atmeh and Al-Shattarat, 2013). The posting date is labeled as the event date, and posts uploaded on a holiday are considered as the event date on the next business day (Ajjoub, et al., 2021).

In calculating abnormal returns, it is necessary to calculate stock returns first with the following equation:

$$R_{i,t} = ln \frac{Pi,t}{Pi,t-1} \qquad eq.\ 1$$

$R_{i,t}$ is the natural logarithm of *returns* stock i in period t. $P_{i,t}$ is the price of stock i in period t and $P_{i,t-1}$ is the price of stock i in period t-1. In addition, calculations for market returns are also needed:

$$RM_t = ln \frac{PI,t}{PI,t-1} \qquad eq.\ 2$$

RM_t is the natural logarithm of the market return in the t-period, PI,t is the Jakarta Composite Index (JCI) value in the t-period, and PI,t-1 is the JCI value in the t-1 period. After doing the calculations in equations 1 and 2, the expected return is calculated using the market model (Henderson, 1990) because it can reflect returns and certain market conditions (Minenna, 2003; Indariyah, 2016). The researcher carried

out a regression to obtain alpha and beta values, but the classical assumption tests (in the form of normality, heteroscedasticity, and autocorrelation tests) were carried out first to fulfill the prerequisites for the regression test (Hair et al., 2019). The research data does not meet the classical assumption test of normality, heteroscedasticity and autocorrelation, and hence it will be estimated using the GARCH test because OLS cannot provide the best estimate (Helanda & Suryani, 2020).

Calculation of alpha and beta values is formulated by the equation:

$$R_{i,t} = \alpha + \beta_i RM_t + \varepsilon_{it} \qquad eq.\ 3$$

α is the intercept for the security, ßi is the slope coefficient which is the beta of security i, and ε is the error. In equation 3, variable Y which had a zero value above 50% was removed (n=36) (Hair et al., 2019). Data that could not be be estimated because it has a constant or flat pattern (n=71) were also removed. This resulted in the total event data used of 184. After finding the value of α and β, the researcher calculates the expected return in the window period through the equation:

$$E(R_{i,t}) = \alpha + \beta_i RM_t \qquad eq.\ 4$$

The next step is to calculate *abnormal returns* on the window period with the equation:$(AR_{i,t})$

$$AR_{i,t} = R_{i,t} - E(R_{i,t}) \qquad eq.\ 5$$

After calculating the abnormal return, the control variables in the form of size and spread are added to the regression model to control for company size and liquidity (Gu & Kurov, 2020). In addition, industry and Rm are also added (Ajjoub, et al., 2021). Industries that have a high risk have a greater possibility of getting higher profits. The corporate action (CA) variable is also added as a control variable to control corporate action. The equation used to calculate the effect of endorsement on abnormal returns is formulated as follows:

$$Y = a + b_1 X_1 + b_1 C_1 + b_2 C_2 + b_3 C_3 + b_4 C_4 + b_5 C_5 + e \qquad eq.\ 6$$

A detailed description of the variables, definitions, and data sources used in the research can be seen in Table 2.

Table 2. Variable operational definitions

Variable	Definition	Source
Dependent Variable		
Y-AR	*Abnormal returns* which is obtained from reducing the actual return with the expected return in the window period.	Researcher calculations
Independent Variable		
X - Endorsement	Share endorse post	*Instagram*
Control Variables		
C1 - CA	A dummy variable that uses 1 as the day of the corporate action and 0 otherwise.	*Eikon Refinitive Database*
C2 - Spreads	The natural logarithm for measuring spread is measured using the ask-bid for company i at time t.	*Eikon Refinitive Database*
C3 - Size	The natural logarithm is measured as market capitalization.	*Eikon Refinitive Database*
C4 - Rm	The natural logarithm is measured as the market return.	*Eikon Refinitive Database*
C5 - Industry	Variables using numbers 1-11 are used to classify industry types.	*www.idx.co.id*

Source: processed data.

Prior the ordinary least squares (OLS) regression to test equation 6, the classical assumption tests were carried out first. The significance value of both the heteroscedasticity test and the normality test was less than 0.05, indicating that the data experienced heteroscedasticity and was not normal. The data exhibited autocorrelation with a p-value of less than 0.05 as determined by the Wooldridge test. Pairwise correlation test showed no multicollinearity between independent and dependent variables. Therefore, this study uses the GLS (Generalized Least Square) method because the research data did not meet the classical assumption tests. The GLS model is a regression model that can overcome autocorrelation and heteroscedasticity violations (Froot, 1989) and more efficient than the OLS test.

RESULTS AND DISCUSSION

Table 3 shows the number of endorsed posts by industry type. The industry with the most endorsements is the financial sector. The financial industry is the most frequently endorsed because it is one of the industries with the highest number if issuers, 105 (IDX, 2022). Financial sector stocks are also liquid because they are in high demand by many investors (Mahardika, 2022). This is consistent with the calculation of the average abnormal return generated by this industry which is positive, indicating the sicess of the endorsement.

Table 3. Industry type and number of endorsements

Industry Code	Industry Type	N *endorse*	AR mean at t_0
1	Financials	52	0.041
2	Consumer Cyclicals	38	0.044
3	Basic Materials	32	0.105
4	Energy	25	0.059
5	Infrastructures	13	0.064
6	Properties & Real estate	8	0.041
7	Consumer non cyclicals	7	0.111
8	Industrials	5	0.004
9	Transportation & Logistics	2	0.102
10	Healthcare	1	-0.074
11	Technology	1	-0.072
	Total	184	

Source: processed data.

Healthcare and technology sectors received the fewest endorsements among industries. With 24 and 31 issuers, respectively, these two industries have the fewest issuers compared to other industries, which explains the lack of endorsement posts (IDX, 2022). In addition, the inability of endorsements to create abnormal returns in these two industries is a contributing factor to the lack of endorsements. In the healthcare industry, the endorsed company is PT Kalbe Farma Tbk (KLBF), which has a market capitalization greater than the average variable size value. The share price of KLBF at the time of the endorsement was Rp1,565. High prices make it difficult to purchase large quantities of stocks, preventing abnormal returns from occurring. This is consistent with the findings of this study, which indicate that endorsements are frequently made on low-priced stocks, as 84.2 percent of endorsed posts have a price below $500 per share (Suryahadi, 2021). The number of positive sentiments in this sector has prevented endorsement sentiment from generating abnormal returns.

Table 4 Panels A and B show that the abnormal return variable has a positive average value in the event window. This indicates that stock endorse posts have succeeded in giving positive sentiment to these stocks, resulting in abnormal returns. Positive sentiment is a result of influencers recommending the purchase of specific stocks, so that investors who follow this recommendation will buy the same shares.

This can result in an increase in stock prices and create abnormal returns. The abnormal return generated by Panel B ($\mu = 0.058$) is higher than the other panels ($\mu = 0.009$ for Panel A, $\mu = 0.014$ for Panel C, and $\mu = -.0.006$ for Panel D). This demonstrates that endorsements are highly effective in creating abnormal returns on posting days. This is supported by the results of the Wilcoxon Signed Rank test ($Z= 7.236$, $p<0.05$) which indicates that the abnormal return on the day of posting is higher than during other time periods. In addition, based on the total data, 71.2% of them have a positive abnormal return on the day of posting. The standard deviation values of abnormal returns in Panels A and B are higher than the standard deviation Rm in Panels A and B, suggesting that endorsed stocks experience high volatility during the event window and endorse day.

Table 4. Descriptive statistics

Variable	*N*	*Means*	*std. Dev.*	*Min*	*Max*
Panel A: Overall Event Window Period (t-5 to t+5)					
Abnormal	2024	0.009	0.074	-0.108	0.307
Rom	2024	0.000	0.009	-0.021	0.034
Spreads	2024	-0.028	0.092	-0.652	0.115
size	2024	14,443	1699	10,524	18,549
Panel B: Period of Endorsement (t-0)					
Abnormal	184	0.058	0.103	-0.104	0.306
Rom	184	0.001	0.009	-0.021	0.021
Spreads	184	-0.045	0.118	-0.652	0.115
size	184	14,491	1,686	10,687	18.315
Panel C: Period Before Endorsement (t-5 to t-1)					
Abnormal	920	0.014	0.071	-0.108	0.307
Rom	920	0.001	0.008	-0.021	0.034
Spreads	920	-0.025	0.092	-0.652	0.042
size	920	14,388	1,729	10,524	18,311
Panel D: Period After Endorsement (t+1 to t+5)					
Abnormal	920	-0.006	0.064	-0.103	0.307
Rom	920	0.000	0.009	-0.021	0.034
Spreads	920	-0.027	0.084	-0.652	0.115
Size	920	14,489	1,673	10,645	18,549

Source: processed data.

One example of a company experiencing a positive abnormal return on the endorsement date is PT Bumi Citra Permai Tbk (BCIP). This company was endorsed by Belvin Tannadi on 11 November 2021. BCIP received a return of 34.7% or experienced auto rejection (ARA), a condition when the share price has reached a maximum point and is not permitted to increase again within one trading day (Wijayanti, 2022). On that date, BCIP's share price increased from IDR 69 to IDR 93 per share. This significant increase also impacted BCIP's abnormal return of 30.6%. In the t-5 to t-1 period (see Table 4 Panel C), the average value of the abnormal return variable is also positive. However, from t+1 to t+5 (see Table 4 Panel D), there are negative abnormal returns. Statistical test using the Wilcoxon Signed Rank ($Z=5.528$, $p<0.05$) also shows that the abnormal return generated before the endorsement is greater than the period after.

In general, influencers can generally increase sales after endorsement (Jin, Muqaddam and Ryu, 2019). However, in this context, positive results appeared before the endorsement and decreased after the endorsement. This increase in share price can be used by a party to sell previously acquired shares, as it provides momentum for an increase in share price at the endorse event dates. This pattern must be considered by investors because an endorsement that is considered as a momentum to buy a share can actually be used by another party to sell the shares it owns. These results are in line with Haroon and Rizvi

(2020) research which states that an changes in stock prices due to a sentiment typically returns to its original price.

Table 5 shows the results of the GLS regression of all variables used in the study. The endorse variable has a positive effect on abnormal return, indicating that the endorsement has been successful in boosting a company's stock return beyond the expected return. Abnormal returns exist because of positive sentiment in the form of invitations to buy a stock through endorsement posts so that other investors are interested in making a similar decision (Tian et al., 2021). Investors will follow influencers' actions even when the information they have is different (Banerjee, 1992).

Endorse also generates positive abnormal returns despite the fact that the information provided is unrelated to company fundamentals, such as an invitation to buy a certain stock without reason. This occurs because investors act irrationally by making decisions using emotions (Singh, Babshetti & Shivaprasad, 2021). This irrational behavior can be exploited by influencers to manipulate information for their own benefit (Wang & Wang, 2018).

Table 5. GLS regression results of abnormal returns

Variables	Coef.	St. Err.	t-value	p-values
endorse	0.050	0.005	9,370	0,000***
Spreads	-0.219	0.017	-13,080	0,000***
Rom	0.687	0.172	3,990	0,000***
size	-0.004	0.001	-4,970	0,000***
Industry	-0.002	0.001	-2,950	0.003***
ca	0.017	0.016	1.020	0.308
Constant	0.070	0.013	5,300	0,000***

Source: processed data. Note: ***significant at $p<0.01$

This irrational behavior of investors is caused by herding behavior, or following other investors' decisions (Balcilar, Demirer & Hammoudeh, 2013). Herding occurs due to a lack of trustworthy information (Ahsan and Sarkar, 2013), and hence, investors tend to follow the actions of influencers who believed to have access to more complete and comprehensive information (Balcilar, Demirer and Hammoudeh, 2013). Investors take this action because they feel assured by following the influencer's actions (Galariotis, Krokida & Spyrou, 2016).

Herding behavior is particularly dangerous for investors with limited information/knowledge (Balcilar, Demirer and Hammoudeh, 2013). When investors engage in herding behavior that results in mispricing, the stock price may deviate from its fundamental value, causing investors to incur losse (Dang & Lin, 2016). Investors will incur losses when stock prices that deviate from their fundamental value due to sentiment return to their original price (Haroon & Rizvi, 2020; Tetlock, 2007). In addition, investors in developing country capital markets are more susceptible to herding, especially if the information presented specifically mentions a company by name (Dang & Lin, 2016). This is because there are few experienced market players in developing countries with limited access to information (Dang & Lin, 2016). Investors have different methods of gathering and analyzing information. Some investors who find it difficult and costly to collect and analyze information themselves tend to imitate the actions of other investors (Chiang & Zheng, 2010).

The results of this study are consistent with previous studies which indicate that positive sentiment through social media influences the abnormal return of a stock (Born, et al., 2017; Ajjoub, et al., 2021). These results also confirm that positive recommendations and reviews by influencers via social media can attract someone to make a buying decision (Tian et al., 2021) especially in developing country capital markets (Dang & Lin, 2016). The abnormal return that only occurs on endorsement days is also comprable to the effect resulting from the positive sentiment of Donald Trump's tweets (Born, et al., 2017). Therefore, the existence of abnormal returns caused by endorse posts provide support for the hypothesis (H1) in this study that stock endorse posts have a positive effect on abnormal returns.

This study also examines the impact of control variables such as spreads, market returns, industry, size, and corporate action. Table 5 shows that spreads have a negative effect on abnormal returns. This means that the more liquid a company is, the greater its impact on abnormal returns. This finding indicates that the high demand for a stock increases the likelihood of abnormal returns. In addition, the market return variable (Rm) also has a positive influence on abnormal returns. These findings are consistent with previous research indicating that index variables have a positive influence on abnormal returns (Ajjoub, et al., 2021).

Firm size has a negative effect on abnormal returns. This implies that the larger the size of the company, the possibility of an abnormal return occurs because of the endorsement is getting smaller. Abnormal returns for companies with large market capitalization occur when institutional investors buy the stock for fundamental reasons. However, only individual investors are affected by endorsement sentiment (Fenn, 2019). This is consistent with previous research that sentiment is more influential in small companies compared to those with large market capitalization (Gu & Kurov, 2020).

Table 5 shows the type of industry that has an effect on abnormal returns; therefore, a separate regression is performed to determine which types of industry have an influence on abnormal returns. Based on the 11 existing industry types, endorsement has no effect on the properties & real estate, healthcare, technology, and industrials industries. Due to activity restrictions and decreased property sales, the properties and real estate industry is the sector most impacted by COVID-19 in 2021 (Utami, 2021). Consequently, the positive effect of endorsement is offset by investors' concerns regarding the uncertainty of this sector. The healthcare and technology industries did not respond positively due to the lack of endorsement posts and other factors as explained in the descriptive statistics section, while industrial sector was unaffected because it was not a particularly attractive invesment sector (Purwanti, 2022).

The last control variable used is the corporate action (CA) which shows no effect on abnormal returns. This result is consistent with previous research, that corporate action has no effect on abnormal returns (Tanoyo, 2020). This is due to the fact that positive news about corporate actions is rarely unexpected, as there is frequently a leak of information prior to the official announcement (Sprenger et al., 2014). The numerous factors that contribute to abnormal returns indicate that stock prices are influenced not only by the changes in company fundamentals, but also by existing sentiment.

CONCLUSION

This study aims to determine the impact of stock endorsements by influencers via Instagram on stock abnormal returns. The results of this study indicate that endorsements can generate positive abnormal returns for a stock. However, the effect of this event is only temporary, as the average abnormal return generated is negative in the period after the endorsement. The occurrence of abnormal returns due to endorse posts is the result of herding behavior, i.e., an investor’s tendency to imitate the actions of other investors who are perceived to have more information. This allows investors who own endorsed shares to profit by selling their holdings at the endorsed time. However, investors who do not already own these shares are able to buy them after the endorsement moment, when the stock price drops. Therefore, to avoid incurring losses, investors are expected to exercise greater caution when making investment decisions, particularly if they observe conditions that promote herding behavior. Herding behavior can result in losses for investors because the effect is temporary and can be used by certain parties to gain profits.

In this study the data used did not meet the assumptions of normality, experienced heteroscedasticity, and autocorrelation, failing the classical assumption test. Therefore, researchers predict the expected return using the GARCH model, but there are some data that cannot be estimated. Future research is suggested to predict the models using T-GARCH and E-GARCH as they have a higher success rate than GARCH.

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