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Can Use Simple Messages Information to Make a  
Remuneration Profit? –Evidence from Taiwan Stocks



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## Can Use Simple Messages Information to Make a Remuneration Profit? –Evidence from Taiwan Stocks

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### Abstract

**Purpose:** The goal of this research is to use the correlation analysis method (CAM) to find out the investors can invest with simple messages.

**Results:** This research's empirical results indicate the following: (1) Based on our empirical results obtained from using the correlation analysis method (CAM) method, the highest price, lowest price, and closing price can affect the opening price, and there is a significant and positive relationship. Moreover, the stock trading volume is an insignificant positive correlation, and the rate of price spread is an insignificant negative correlation. (2) This research assumes no external interference and government protection. And that stock investors do not have any technical analysis and other conditions. Whether the company can make a profit can reflect the value of bonds and stocks through public information. Therefore, investors can invest based on simple information. The grey relational analysis (GRA) research shows that that both the highest price and the lowest price displays were significant. The closing price was strong. In contrast, the study found that the stock trading volume and price spread displays are weak, and the analysis results showed almost no effect.

**Unique contribution to theory, policy and practice:** Therefore, if you play day trader it is feasible to use the high and low stock prices to make a remuneration profit.

**Keywords:** *Correlation analysis method, Grey relational analysis, Day trader, Taiwan Stocks*

**JEL Classification:** G1, G10, G11.

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## 1. Introduction

Taiwan's economy is stable and shows an upward trend, with its economic indicators having changed from yellow to red in February 2021. The country's red-light status (monitoring indicator: bombing) for seven consecutive months since the start of 2021 indicates an excellent economic status.

In August 2021, Taiwan's manufacturing purchasing managers index (PMI) decreased from 68.5 to 62.1, with the number of new orders on the rise and fall lines for 14 consecutive months, reaching a high of 62.3%. Consequently, the overall economic recovery in 2021 is expected to remain unchanged and at this stage, liquidity is not a concern since the market is experiencing a growth trend.

Taiwan's current industrial trends and supply-demand structure are differentiated, and the country's foundry capacity is still facing shortages. The long-term development of technology applications continues to support the long-term direction of the electronics industry and Taiwan stocks, and corporate profits remain at a record high, which will promote the stability of the stock market and growing up. Therefore, the weighted index of Taiwan stocks grew from 12026 points to 17021 points in 2020, which is a growth level of approximately 5,000 points (42%; TWSE, 2020).

According to the TWSE, securities digital accounts have continued to grow substantially. According to the latest statistics obtained from the TWSE, this market opened 584,000 new accounts in the first August of this year. The number of account openings reached 11,819,500, accounting for more than 50% of the total population. The data shows that, prior to the COVID-19 pandemic, most account openings were 31 to 50 years old. After the epidemic, the age of individuals that open securities account must become younger, i.e., 21-40 years old.

Additionally, owing to the pandemic, in 2021, investment behavior shifted toward digital accounts, which has driven the growth of digital account opening multiples. Since the end of 2019, it has launched simultaneous report opening in both Taiwan and US markets, simplifying the past Taiwanese stocks and re-entrusted account opening procedures. The annual growth rate of account openings increased sharply to 240.4%, and the number of accounts opened in the first September of this year has also nearly doubled compared with the same period last year. Therefore, digital funds accounted for 83%, showing explosive growth. Digital account opening operations can be completed with mobile phones, no need to go to the counter, the convenience of online investment and financial management, and the activeness of the Taiwan and US stock markets to attract investor attention.

However, young people tend to possess no knowledge of stock price trends or

industry trends, and do not typically undertake various stock market technical analyses. They only use simple securities information such as stock price, transaction price, trading volume, etc., and play the stock day with this simple information. Therefore, this article studies whether these simple stock market data tools are helpful for novices in the stock market.

The rest of the paper is organized as follows. Section 2 reviews, scholarly studies that are relevant to our work. Section 3 explains the methodologies used correlation analysis method (CAM) method and traditional grey relational analysis (GRA). Section 4 shows the study results with investigations, and Section 5 summarizes the entire paper.

## 2. Literature Reviews

To mobilize the stock market's trading volume, the government issued investor stocks. Additionally, owing to the low trading of Taiwan stocks and the hope for active trading, the tax was cut. The Ministry of Finance (2017) stated that the average daily tax revenue derived from stock exchanges was about 451 million yuan, higher than the 56 million yuan in the first year of the tax reduction. Drive market transaction volume and enhance market liquidity.

Furthermore, we know that a stock market is a place for trading stocks (equity) and other financial instruments of public listed companies, where the price of shares is termed "share" or "stock price" (Wanjawa & Muchemi, 2014). The company's stock price level reflects the company's value, and the company's profit figures are the most important variable that affects the trend of stock prices (Conroy & Harris, 1999). Therefore, investors can potentially obtain potential profits based on the value of the stock price.

However, to obtain potential profits from the value of stock prices, it is necessary to analyze the trend of stock value. However, investments in the stock markets are often guided by some form of prediction (Wanjawa & Muchemi, 2014; Ghaznavi et al., 2016). According to Dunne (2015) points out that are three main approaches for stock market prediction, namely: fundamental analysis, technical analysis (charting), and technology (Machine learning) methods. However most, scholars do categorize these three into 2, thus technical analysis and fundamental analysis (Nassirtoussi et al., 2014; Dunne, 2015; Gyan, 2015; Sankar et al., 2015; Ahmadi et al., 2018; Seong & Nam, 2021).

Although the fundamental analysts approach concerned with the company operating conditions (for example, when the company was established, what business is the main business, how much registered capital, what is the current sales income, etc.) that underlies the stock itself instead of the actual stock price (Anbalagan & Maheswari,



2014; Ghaznavi et al., 2016; Agarwal et al., 2017). However, the fundamental analyst's data are usually unstructured, which poses a difficult challenge. Thus, occasionally been proven used fundamental analysis be a good predictor of stock price movement in the works of Zhang et al. (2014), Checkley et al. (2017), Tsai & Wang (2017), Coyne et al. (2017), and Nti et al. (2019).

Second, Technical analysis refers to the study of information in the past market, mainly using charts to observe and predict future price trends and determine how investment strategies should be implemented more appropriately. Research the past data of the need to predict the future direction. These past data are the charts of price and volume trends, which is the basis of technical analysis. Like trading volume and stock prices, many technical analysis indicators are developed based on these two. therefore, in the technical analysis, the analyst predicts the future price of stocks by studying the trends in the past and present stock price (Anbalagan & Maheswari, 2014; Agarwal et al., 2017; Ahmadi et al., 2018). The following studies (Akinwale Adio et al., 2009; Guresen et al., 2011; Wang et al., 2012; Rather et al., 2015; Thanh et al., 2018; Umoru & Nwokoye, 2018; Zhou et al., 2018) predicted future stock price movements based on technical analysis. Globally, billions of dollars are traded on the stock market daily to earn profits (Dunne, 2015). Thus, making stock-market predictions is an attractive research area for researchers, investors, and financial analysts, despite the difficulties involve (Ticknor, 2013; Agarwal et al., 2017; Tsai & Wang, 2017; Lin, 2018; Zhou et al. 2018; Seong & Nam, 2021).

Young individuals in Taiwan typically prefer not to conduct technical and fundamental analysis; however, they are usually eager to earn profits. Subsequently, they seek to participate in day-trading. Day-trading refers to when investors buy and then sell or sell and then buy on the same day, buying and selling the same number of stocks in the same tranche. Subsequently, they complete the sell-off on the same day to earn the spread. Thus, they utilize simple information to take advantage of trading opportunities (Barber et al., 2014). Therefore, day-trading is a phenomenon of earning and losing money, even when there is a severe breach of contract. While day-trading can lead to personal credit bankruptcy, it also can generate profits as high as tens of millions.

Additionally, several studies utilized the correlation analysis method (CAM) to measure the strength of the linear relationship between two variables and determine the extent of their association. In other words, CAM helps to calculate the level of change in one variable caused by the change in another variable (He et al., 2015). Moreover, Deng (1982) stated that the grey relational analysis (GRA) methodology involves first

translating the performance of all alternatives into a comparability sequence, and an alternative will be the best choice.

According to the literature review, few studies analyzed whether simple stock price information can be used to conduct a stock price analysis. Hence, this study utilized CAM to examine the relationships among these simple stock prices. Next, the GRA methodology was used to determine which simple information will affect the stock price; this serves as a reference for investors who cannot use the analysis technology.

### 3. Study Model

There are two purposes of this research, one is to use the CAM to measure the strength of the linear relationship between all the variables, followed by we apply to use the GRA methodology to determine which simple information will affect the stock price. due to, the GRA methodology can be widely be used in many decision-making problems (Deng, 2000).

#### 3.1 Correlation Analysis Method

CAM analysis is a statistical method used to measure the strength of the linear relationship between all variables and compute their association. In other words, correlation analysis calculates the level of change in one variable due to the difference in the other. A high correlation points to a strong relationship between the two variables, while a low correlation means that the variables are weakly related. Hence, Correlation between all variables can be either a positive correlation, a negative correlation, or no correlation.

Hence, the stronger the association of the two variables, the closer the Pearson correlation coefficient,  $r$ , will be to either +1 or -1 depending on whether the relationship is positive or negative, respectively. Achieving a value of +1 or -1 means that all your data points are included on the best fit line – there are no data points that show any variation away from this line. Values for  $r$  between +1 and -1 (for example,  $r = 0.8$  or  $-0.4$ ) indicate variation around the line of best fit. The closer the value of  $r$  to 0, the greater the variation around the best fit line, which will be defined as Equation (1) for  $n$  is a sample size and  $x_i, y_i$  are the individual sample points indexed with  $i$

$$r_{xy} = \frac{n \sum x_i y_i - \sum x_i \sum y_i}{\sqrt{n \sum x_i^2 - (\sum x_i)^2} \sqrt{n \sum y_i^2 - (\sum y_i)^2}} \quad (1)$$

### 3.2 GRA Method

The GRA methodology comprised the following steps: First, the performance of all alternatives was translated into a comparability sequence. This step is known as grey relational generating (Deng, 1982). Deng (1989) stated that grey relational analysis is designed to allow investigators to examine system information that is unclear or incomplete; subsequently, energy system modeling is used to analyze the degree of association among sequences of discrete data. Thus, based on these sequences, a reference sequence (ideal target sequence) was defined. Next, the grey relational coefficient for all comparability sequences as well as the reference sequence was calculated. Finally, based on the grey relational coefficient, the grey relational grade between the reference sequence and every comparability sequence is calculated (Hsiang & Kuo, 2018). If a comparability sequence translated from an alternative has the highest grey relational grade between the reference sequence and itself, that alternative will be the best choice. The details of the GRA are summarized as follows:

#### 3.2.1 Grey Relational Generating

The GRA methodology suggested by the Deng (1989) of this article includes three stages:

Stage 1. List the factors that will affect the system. The related, influencing factors do not necessarily have to be listed, but the factors must have an impact on the system.

Stage 2. GRA methodology is called grey relational generating, which is translating the performance of all alternatives into a compatibility sequence in a process analogous to normalization, this step GRA methodology is called grey relational generating, which is translating the performance of all alternatives into a compatibility sequence in a process analogous to normalization (Mehregan, et al., 2012).

Stage 3. In a MADM problem that includes  $m$  alternatives and  $n$  attributes,  $y_{ij}$  denotes the performance value of attribute  $j$  of alternative  $i$ . in this stage  $y_{ij}$  is translated into comparability sequence  $x_{ij}$ . The normalization can be done from three different approaches as follows (Kirubakaran & Ilangkumaran, 2016) :

$$x_{ij} = \frac{y_{ij} - \text{Min}\{y_{ij}, i=1,2,\dots,m\}}{\text{Max}\{y_{ij}, i=1,2,\dots,m\} - \text{Min}\{y_{ij}, i=1,2,\dots,m\}} \quad \text{for } i = 1,2, \dots, m \quad j = 1,2, \dots, n \quad (2)$$

$$x_{ij} = \frac{\text{Min}\{y_{ij}, i=1,2,\dots,m\} - y_{ij}}{\text{Max}\{y_{ij}, i=1,2,\dots,m\} - \text{Min}\{y_{ij}, i=1,2,\dots,m\}} \quad \text{for } i =$$

$$1, 2, \dots, m \quad j = 1, 2, \dots, n \quad (3)$$

$$x_{ij} = 1 - \frac{|y_{ij} - y_j^*|}{\text{Max}\{\text{Max}\{y_{ij}, i=1, 2, \dots, m\} - y_{ij}^*, y_{ij}^* - \text{Min}\{y_{ij}, i=1, 2, \dots, m\}\}} \quad \text{for } i = 1, 2, \dots, m \quad j = 1, 2, \dots, n \quad (4)$$

Eq. (2) Is used for the larger-the-better attributes, Eq. (3) Is used for the smaller-the-better attributes, and Eq. (4) Is used for the-closer-to-the-desired-value- $y_j^*$ -the-better.

### 3.2.2 Reference Sequence Definition

In this stage an ideal reference sequence  $x_0$  as  $x_0 = (x_{01}, x_{02}, \dots, x_{0j}, \dots, x_{0n}) = (1, 1, \dots, 1, \dots, 1)$  is defined. Inasmuch all performance values gained from Eq. (2), (3) or Eq. (4) are scaled into  $[0, 1]$ , The nearer  $x_{ij}$  to 1 means the better performance of alternative  $i$  in attribute  $j$ . To put it another way, the aims to find the alternative whose comparability sequence is the closest to the reference sequence.

### 3.2.3 Grey Relational Coefficient Calculation

A grey relational coefficient is calculated to express the relationship between the ideal and actual normalized results and can be expressed as follows (Deng, 1982):

$$\gamma(x_{0j}, x_{ij}) = \frac{\Delta_{\text{Min}} + \zeta \Delta_{\text{Max}}}{\Delta_{ij} + \zeta \Delta_{\text{Max}}} \quad (5)$$

for  $i = 1, 2, \dots, m$  ;  $j = 1, 2, \dots, n$

In Eq. (5),  $\gamma(x_{0j}, x_{ij})$  is the grey relational coefficient between  $x_{ij}$  and  $x_{0j}$ , and

$$\Delta_{ij} = |x_{0j} - x_{ij}|,$$

$$\Delta_{\text{min}} = \text{Min}\{\Delta_{ij}, i = 1, 2, \dots, m \quad ; \quad j = 1, 2, \dots, n \},$$

$$\Delta_{\text{max}} = \text{Max}\{\Delta_{ij}, i = 1, 2, \dots, m \quad ; \quad j = 1, 2, \dots, n \},$$



$\zeta$  is the distinguishing coefficient;  $\zeta \in [0,1]$

### 3.2.4 Grey relational Grade Calculation

The grey relational grade can be calculated using Eq. (6).

$$\Gamma = (x_0, x_i) = \sum_{j=1}^n w_j \gamma(x_{0j}, x_{ij}) \quad , \quad \sum_{j=1}^n w_j = 1 \quad , \quad i = 1, 2, \dots, m$$

(6)

Where  $w_j$  represents the normalized weighting value of attribute  $j$ . In addition,  $\sum_{j=1}^n w_j = 1$ . The grey relational grade indicates the degree of similarity between the comparability sequence and the reference sequence. As mentioned above, on each attribute, the reference sequence represents the best performance that could be achieved by any among the comparability sequences. Therefore, if a comparability sequence for an alternative gets the highest grey relational grade with the reference sequence, it means that a particular comparability sequence is more important than the other comparability sequences to the reference sequence, and it would be the best alternative to be chosen.

In this Eq. (6), the  $\Gamma$  shows the grey relational grade indicates the degree of similarity between the comparability sequence and the reference sequence. Hence, the "rule of thumb" for interpreting grey relational grade results is as follows: 0 to 0.20 is negligible, 0.21 to 0.35 is weak, 0.36 to 0.67 is moderate, 0.68 to 0.90 is strong, and 0.91 to 1.00 is considered very strong (Taylor, 1990; Shavelson, 1996), the rank of grey relational coefficient results in Table no. 1

**Table no.1-** The rank of GRA calculated

No	GAR value	Variable correlation degree
1	0.91-1.00	Very strong
2	0.68-0.90	Strong
3	0.36-0.67	Moderate
4	0.21-0.35	Weak
5	0-0.20	Negligible

Source: Authors' Compilation

## 4. Empirical Results and Analysis

The empirical analysis of this study is mainly composed of three parts: First, description of the study objects and variables. Secondly, to use the CAM to measure

the strength of the linear relationship between all the variables. Last, application of the GRA model to analyze the factors.

#### 4.1 Study Objects and Variables in this Study

This section comprises two main sub-sections. The first sub-section describes the study objects, while the second sub-section describes the study variables and discusses the data collection process.

##### 4.1.1 Study Objects

The research object was Evergreen Marine Corporation (LSE: Evergreen Marine Corp Taiwan Ltd Stock Price Quote; EGMD: 2603). Evergreen Shipping is a Taiwanese shipping company, which is one of the core businesses of the Evergreen Group. It is also the largest shipping company in Taiwan and the seventh largest shipping company in the world. The company, along with Yang-ming Shipping and Wan-hai-lines Shipping, is jointly referred to as “Taiwan Container Three Heroes.”

Evergreen Shipping’s stock price, which was about 10 yuan at the beginning of 2021, rose to about 121 yuan in November 2021(Figure 1). Its trading volume per day increased from 50,000 to 500,000, i.e., a ten-fold increase. Furthermore, the number of shareholders increased from 100,000 to 500,000 at the beginning of the year. The current shareholder structure stands at about 70% of the shares below 400 sheets, with a day trading ratio of about 60%. These shareholders do not buy stocks for the profit of the company but seek to make profits by trading based on the high and low prices of popular stocks.

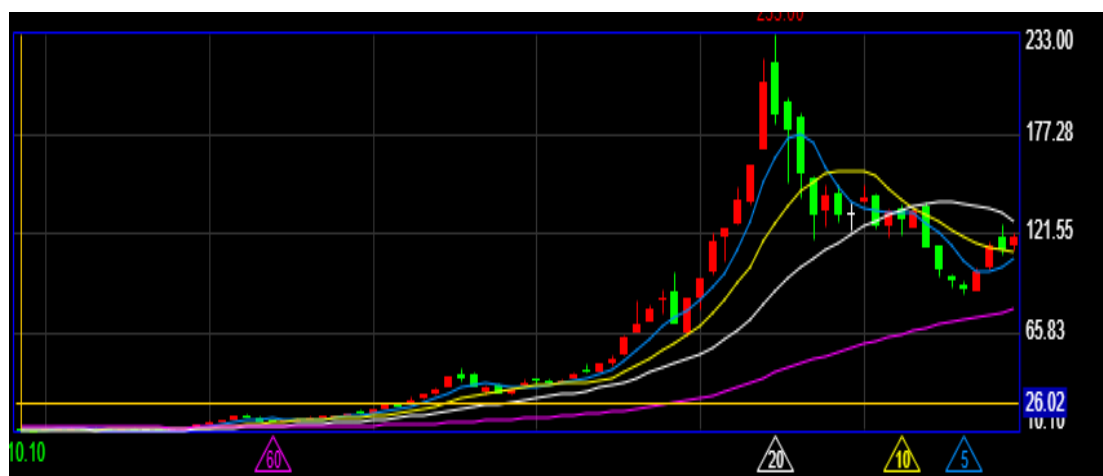


Figure 1: The stock price change of Evergreen Shipping in 2021.

Source: <https://www.money.net.com.tw/stock/list/2603>.

#### 4.1.2 Describes Variables and Data Collection Instructions

##### A. Describes Variables

The general free stock market analysis software has opening price, highest price, lowest price, stock trading volume, rate of price spread, and closing price. The variables are described in **Table no.2** as follows:

##### B. Data Collection Instructions

Due to the changes in Evergreen’s (EGMD:2603) share price, there will be changes starting in early 2021. Therefore, the study in this paper is based on weeks. Collect 10-month data for analysis.

#### 4.2 CAM Methodology Analysis

This research assumed the absence of factors, such as external interference and government protection, the stock investors’ lack of ability in conducting any technical analysis, and other conditions.

For the analysis based on CAM methodology, basic information on stock, including opening price, highest price, lowest price, stock trading volume, rate of price spread, and closing price. The research shows that the highest price, lowest price, and closing price can affect the opening price, and there is a significant and positive relationship. GRA Methodology Analysis

In CAM methodology analysis, the highest price, lowest price, stock trading volume, and closing price can all affect the opening price and this is a significant and positive relationship. Additionally, the GRA model to determine the order of influence and then puts it for investors' reference.

To determine which type of simple information will affect the stock price, the description is as follows. The description is as follows and listed in **Table no.3**

:

**Table no.2-** Six major indicator definitions for variables

NO	Indicators	Code	Definition
1	Opening price	$y_1$	Closing price of the previous day
2	Highest price	$x_1$	Highest stock price today
3	Lowest price	$x_2$	Lowest stock price today
4	Stock trading volume	$x_3$	Specific transaction quantity
5	Rate of price spread	$x_4$	On the stock rate of price spread
6	Closing price	$x_5$	Today's closing price

Source: This study.

**Table no.3-** Correlation test and analysis

	$y_1$	$x_1$	$x_2$	$x_3$	$x_4$	$x_5$
$y_1$	1					
$x_1$	0.921**	1				
$x_2$	0.911**	0.998	1			
$x_3$	0.254	0.075	0.125	1		
$x_4$	-0.107	-0.078	-0.069	-0.007	1	
$x_5$	0.995*	0.997*	0.998*	0.095	0.024	1

\*:0.05, \*\*:0.01.

Source: This study.

### 4.3 GRA Methodology Analysis

In CAM methodology analysis, the highest price, lowest price, stock trading volume, and closing price can affect the opening price, and there is a significant and positive relationship. Therefore, this research further uses the GRA model to determine the order of influence and then puts it for investors' reference.

Explaining to determine which simple information will affect the stock price, and the description is as follows and listed in Table no.4:

1. Highest price ( $x_1$ ): According to the empirical results shown in Table no. 4, the highest price ( $x_1$ ) very strong impacts the stock price because the high stock price reflects the stock value through the company's bullishness. The high stock price reflects the stock value through the company's bullishness. Therefore, it will affect whether investors invest in the company (buy this company stock) to obtain profits.

2. Lowest price ( $x_2$ ): As shown in Table no.4, the lowest price ( $x_2$ ) had a very significant impact on stock price since the stock value of companies fell when the lowest stock price. A low stock price indicates that a company has not made a profit under the company's normal operation or has not managed well, which affects investors' unwillingness to invest in the company and shows a lower stock price.

3. Stock trading volume ( $x_3$ ): The results shown in Table no.4 indicate that trading volume ( $x_3$ ), although an indicator for judging stock market trends, did not affect stock prices. Trading volume refers to the specific number of transactions completed within a certain period. Changes in trading volume reflects the situation of funds entering the market. Therefore, investors do not want to invest in the company based on the volume of transactions.

4. Rate of price spread ( $x_4$ ): According to the empirical results (Table no.4), the rate of the price spread ( $x_4$ ) is weak and does not have a significant impact on stock

prices. In other words, it is the maximum allowable drop in price of a stock, commodity, or index futures contract in a single trading session. Therefore, investors do not want to invest in the company based on the rate of the price spread.

5. Closing price ( $x_5$ ): The empirical results in Table no.4 show that closing price ( $x_5$ ) strongly impacts the stock price because the closing price refers to the last trading level of an asset before the market closes on any given day; usually, the closing price is determined by auction. The closing price is usually regarded as a key indicator for analyzing long-term changes in the price of a particular stock. Therefore, investors can invest in the company based on the closing price.

Table no.4- CAM methodology analysis

No	GAR value	Variable correlation degree
$x_1$	0.959	Very strong
$x_2$	0.939	Very strong
$x_3$	0.352	Weak
$x_4$	0.241	Weak
$x_5$	0.891	Strong

Source: This study.

#### 4.4 Order of Importance

The importance of affecting the stock price is explained as follows:

$$x_1 > x_2 > x_5 > x_3 > x_4$$

#### 5. Concluding Remarks

Based on our empirical results obtained from using the CAM method, the highest price, lowest price, and closing price can affect the opening price, and there is a significant and positive relationship. Moreover, the stock trading volume is an insignificant positive correlation, and the rate of price spread is an insignificant negative correlation.

The research findings showed that both the highest price and the lowest price displays as well as the closing price were very strong. In contrast, the stock trading volume and price spread displays were weak, and the analysis results showed almost no effect.

This research assumes no external interference and government protection, and stock investors do not have any technical analysis and other conditions. Whether the company can make a profit can reflect the value of bonds and stocks through public information. Therefore, investors can invest based on simple information.

The research showed that both the highest price and the lowest price displays were



significant. The closing price was strong. In contrast, the study found that the stock trading volume and price spread displays are weak, and the analysis results showed almost no effect. Therefore, if you play day trader it is feasible to use the high and low stock prices to make a remuneration profit. Lastly, the conclusions and recommendations presented here are based on the models constructed, sample data collected, and research methodologies employed in this study. Hence, it is necessary to consider the current situation and changes in the environment that are impacting the company in the Taiwan District, so any application of our findings can be further tailored to yield more accurate conclusions.

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