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PREDICTING THE DIRECTION OF THE LQ45 STOCK MARKET IN INDONESIA

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Abstract

To cope with the unpredictability of the stock market, investors should have a solid understanding of the ups and downs of bullish and bearish phases. This is especially true when looking at Indonesia's LQ45 index, which consists of 45 of the most liquid stocks in Indonesia. This study carefully predicts the future direction of movement of the LQ45 stock price index by first figuring out its bearish and bullish periods, and then finding important macroeconomic factors. In this study, techniques such as X13 ARIMA SEATS, Bry-Boschan, and Binomial Logistic Regression are used to find clear bullish and bearish phases in the LQ45 index time frame. These techniques also point out certain macroeconomic indicators, such as Motor Sales, Retail Sales, Oil Prices, BI Rate, 1-month Deposito Rate Working Capital Rate, Rupiah Exchange Rate, Inflation Narrow Money, Broad Money, US PMI Manufacture, and US Inflation, which have a great effect on these market conditions, as indicated by their p-values. Based on these insights, predictive models were created to show how the LQ45 index may change in the future. These models provide asset management companies with a solid basis for making smart investment decisions, with a tendency to be more aggressive when the market is up and more cautious when the market is down. This study is special because it combines the analysis of LQ45 index market trends with important macroeconomic factors in a way that has never been done before in the Indonesian market.

Keywords: LQ45 Index, Bearish, Bullish, Macroeconomic, Indonesian stock market, Predictive modeling.

Introduction

Attention and sentiment from investors have been evidenced to significantly impact stock market dynamics, according to various research. For instance, Andrei & Hasler (2013) revealed that there's a positive correlation between investor attention and stock market volatility, suggesting that when investor focus intensifies, market volatility tends to rise correspondingly. On the other hand, Li & Yu (2012) delved into the relationship between psychological benchmarks and the predictability of stock returns, discovering that attention and psychological factors can substantially influence stock prices. Moreover, Baker & Wurgler (2007) examined the connection between investor

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sentiment and stock market returns, underscoring the pivotal role of sentiment in influencing observed market movements.

Understanding investor attention and sentiment, as well as their impacts on market dynamics, is crucial in forecasting stock market behavior. These studies indicate that an analysis of these factors can provide invaluable insights regarding market operations. By taking into account investor attention, referring to the degree of focus and interest of investors in particular stocks or sectors, and investor sentiment, which reflects the overall attitudes and emotions of investors towards the market, analysts can make more accurate predictions regarding stock market behavior.

Every investor in the stock market is undoubtedly familiar with the terms Bullish and Bearish. Bullish refers to a condition where the stock market is experiencing a rise in stock prices, typically influenced by a country's economic condition or perhaps a globally improving economic scenario. Bearish represents a situation where the stock market is witnessing a decline in stock prices influenced by the economic growth of a nation or even a global downward trend. Periods of bearishness and bullishness have proven to be unpredictable, presenting challenges for investors in determining the right timing for buying or selling stocks.

When future market conditions are anticipated to be bullish, investors tend to increase the proportion of their investment portfolio allocated to stocks. Conversely, when future stock prices are projected to be bearish, investors are inclined to decrease the proportion of their investment portfolios allocated to stocks. For investors, it's vital to identify the current market condition (bullish or bearish) and its future projection to determine the appropriate investment strategy.

However, stock market conditions aren't easily ascertainable since they're influenced by various complex factors, both from the company's internal standpoint and external factors, such as global economic conditions, politics, and market sentiment. To tackle these uncertain stock market fluctuations, investors need to engage in thorough research, utilize technical and fundamental analysis, and consult financial experts to make more informed investment decisions. Furthermore, portfolio diversification and robust risk management are also essential in navigating the unpredictable nature of the market.

Such an approach is intriguing to apply in the Indonesian stock market, specifically by predicting and identifying bearish and bullish periods in the IHSG. This would enable stakeholders to discern when the stock market will experience bullish or bearish trends. This research will primarily focus on examining the directional movements of the stock market encompassed within the LQ45 stocks.

The LQ45 stock index consists of 45 companies with high liquidity levels that are significantly influenced by the economic situation in Indonesia. This index is one of the stock indices that exhibit a high reaction rate to economic indicator changes. Every three months, companies included in the LQ45 stock index are selected from firms traded on the Indonesia Stock Exchange (BEI) based on their market capitalization and significant liquidity.

In response to the urgent demands of investors, a multitude of professionals have undertaken the task of formulating diverse quantitative methodologies aimed at identifying and forecasting stock market conditions. In his study, Chen (2009) utilized parametric and non-parametric approaches to identify periods of bearishness in the S&P 500 stock price index. The S&P 500 stock price index monitors the performance of stocks from 500 significant companies listed on the stock exchanges in the United States. These companies are carefully selected by Standard & Poor's. Chen's study relied on the utilization of the Two-State Markov Switching model as a parametric methodology, whereas the Bry and Boschan algorithm was preferred for non-parametric methods.

The identification of bearish conditions was conducted by utilizing macroeconomic variables, including but not limited to economic growth, interest rates, inflation rates, money supply, and exchange rates. By utilizing these signs, Chen was able to determine the occurrence of a bearish phase in the S&P 500 stock price index, comparing it to previous times. The researcher's findings indicated a tendency for macroeconomic indicators to have more accuracy in predicting stock index returns while demonstrating a lesser ability to foresee market directional conditions.

In a similar spirit, Kole and van Dijk (2010) extended their investigation of the MSCI stock price index, specifically examining periods characterized by bearish and bullish market conditions. The MSCI stock price index, established by Morgan Stanley Capital International, comprises a total of 1546 global stock companies. This index serves as a benchmark for evaluating the performance of the global stock market. This study collected a diverse range of macroeconomic data, such as industrial output indices, inflation rates, and interest rates, among others, to forecast forthcoming stock market circumstances.

Building upon the research conducted by Shiu-Sheng Chen (2009), individuals with expertise in the field sought to develop a series of quantitative methodologies aimed at analyzing and predicting stock market conditions in various countries. This study aimed to investigate the predictive power of macroeconomic variables in forecasting bull and bear stock markets in China and Taiwan. The research utilized a two-state Markov transition model for this purpose. It has been revealed that certain variables, including inflation rates and changes in the real exchange rate, play a crucial role in predicting bear markets in China.

Conversely, for Taiwan, the focus moves to interest rate spreads and unemployment rates as key indications for bear market predictions. It is worth noting that the expansion of industrial production does not possess significant prediction ability for bear markets. This implies that markets in developing nations may be influenced more by capital movements rather than actual economic activity.

The pivotal variable in this study is the trajectory of the LQ45 stock price index, influenced by a suite of macroeconomic indicators that reflect the real sector's activity, external trade factors, commodity prices, liquidity in the economy, and global economic trends. This research posits hypotheses to explore these complex relationships.

The activity of the real sector is a mirror of the economy, and the indicators chosen here include motorcycle and car sales, retail sales, and cement sales—all of which are proxies for economic momentum in Indonesia. Motorcycle and car sales numbers provide insights into consumer confidence and discretionary spending (Ullah & Zhou, 2003), while retail sales offer a glimpse into consumer behavior and purchasing power (Siringo et al., 2023). Cement sales can be a harbinger of construction activity and infrastructure development, a sector crucial in regional development (Sukwika, 2018; Siringo et al., 2023). The hypothesis is that these indicators are significantly correlated with the direction of the LQ45 stock market.

H1: Motorcycle sales are related to the direction of the LQ45 stock market condition.
H2: Retail sales are related to the direction of the LQ45 stock market condition.
H3: Car sales are related to the direction of the LQ45 stock market condition.
H4: Cement sales are related to the direction of the LQ45 stock market condition.

External factors such as export and import values play a pivotal role in shaping the economic landscape. High export values can indicate robust industry performance and, by extension, suggest a positive impact on the stock market (VO, 2019). Conversely, import values can reflect domestic demand and purchasing power, with higher import values potentially signaling a stronger economy and a positive market outlook (Aremo, A., Olabisi, O., & Adeboye, O., 2020). These external trade indicators are hypothesized to have a meaningful relationship with the direction of the LQ45 stock market (Kim, S. and Choi, M., 2016).

H5: Export value is related to the direction of the LQ45 stock market condition.
H6: Import value is related to the direction of the LQ45 stock market condition.

Commodity prices play a significant role in Indonesia's economic landscape, with nine key factors influencing these prices. The most notable is the price of oil, particularly the widely traded West Texas Intermediate (WTI) and Brent crude oils. WTI, a benchmark in the U.S., is primarily used in gasoline production, while Brent, produced in the North Sea, is of higher quality due to its low sulfur content and closely aligns with Indonesia's Crude Price (ICP). As Indonesia is a net oil importer, fluctuations in these oil prices can lead to changes in domestic fuel prices, potentially impacting inflation and interest rates (Ayu, 2020).

Interest rates, another crucial factor, represent the cost of borrowing money. In Indonesia, various types of interest rates are considered, including the 7-Day (Reverse) Repo Rate (7DRR), which has replaced the BI Rate as the benchmark (Sanica, I., et al., 2018). Deposit interest rates vary based on the duration of deposits, categorized into one-month, three-month, and 12-month terms. Loan interest rates, divided into working capital and investment loans, reflect the cost to borrowers for banking services. Additionally, the exchange rate of the Indonesian Rupiah against the dollar is a vital indicator (Robiyanto, R., 2018). Inflation, measured by the Consumer Price Index (CPI), indicates the continual rise in the cost of goods and services, affecting the standard of living and economic stability (Damayanti, S. and Jalunggono, G., 2022).

H7. Oil prices are related to the direction of the LQ45 stock market.
H8. The benchmark interest rate is related to the direction of the LQ45 stock market.
H9. The one-month deposit interest rate is related to the direction of the LQ45 stock market.
H10. The three-month deposit interest rate is related to the direction of the LQ45 stock market.
H11. The twelve-month deposit interest rate is related to the direction of the LQ45 stock market.
H12. The working capital loan interest rate is related to the direction of the LQ45 stock market.
H13. The investment loan interest rate is related to the direction of the LQ45 stock market.
H14. The exchange rate of the Rupiah is related to the direction of the LQ45 stock market.
H15. Inflation is related to the direction of the LQ45 stock market.

Liquidity in an economy, which is closely linked to the volume of money in circulation, is categorized into narrow money (M1) and broad money (M2), as outlined by Samuelson and Nordhaus (2004). Narrow money includes base money and demand deposits, representing the most liquid assets available in the economy. In contrast, broad money extends to include not only narrow money but also savings accounts and credit limits, thus reflecting a broader spectrum of liquidity. This distinction between narrow and broad money is crucial for understanding financial market dynamics, particularly in examining how different levels of liquidity, from highly liquid assets to more diverse monetary instruments, impact the behavior of Indonesia's LQ45 stock market.
H16. Narrow money is related to the direction of the LQ45 stock market.
H17. Broad money is related to the direction of the LQ45 stock market.

The Indonesian stock market's performance is not solely dependent on domestic economic activities but is also heavily influenced by international economic developments, particularly those in the United States. The U.S., as an economic superpower, exerts a significant impact on the global economic landscape, with its economic indicators often serving as a bellwether for global market trends. Indicators such as the U.S. Purchasing Managers' Index (PMI) and Industrial Production Index (IPI) are instrumental in providing timely insights into the business environment and industrial output, respectively. When these indicators are on the upswing, they generally signal a robust U.S. economy, which can lead to an appreciation of stock index prices and bolster global market sentiment, including that of Indonesia's LQ45 (Eric Inkoom Danso, 2020).

Consumer sentiment, as measured by the Consumer Confidence Index (CCI), along with the Fed Fund Rate and inflation rates in the U.S., plays a pivotal role in shaping market expectations and investor confidence. High consumer confidence typically correlates with increased spending and, by extension, a more vigorous stock market. Conversely, high-interest rates and inflation can dampen consumer spending and borrowing, potentially leading to a bearish stock market. The interconnectedness of these economic variables with stock market performance underscores the influence of U.S. economic health on international markets, including Indonesia's (Adam, 2015).

Furthermore, the Coincident Economic Index and the Leading Economic Index (LEI) provide a snapshot of current economic conditions and a forecast of the economic trajectory, respectively. These indices are critical in predicting the short-term performance of the U.S. economy and, by extension, can have a consequential impact on the global stock markets. A positive LEI often presages an improving U.S. economy, which can result in heightened stock market indices and a favorable global stock market climate. This ripple effect is felt in markets far and wide, influencing the direction of the LQ45 index in Indonesia.

H18. The US PMI Manufacturing has a relationship with the direction of the LQ45 stock market.

H19. The US PMI Services has a relationship with the direction of the LQ45 stock market.

H20. The Industrial Production Index has a relationship with the direction of the LQ45 stock market.

H21. The Consumer Confidence Index has a relationship with the direction of the LQ45 stock market.

H22. The Fed Fund Rate has a relationship with the direction of the LQ45 stock market.

H23. Inflation in America has a relationship with the direction of the LQ45 stock market.

H24. The Coincident Economic Index has a relationship with the direction of the LQ45 stock market.

H25. The Leading Economic Index has a relationship with the direction of the LQ45 stock market.

Research Method

The research being conducted employs a quantitative methodology to investigate the correlation between macroeconomic indicators, including real sector activity, external factors, pricing factors, economic liquidity, the global economy, and the movement of the LQ45 stock price index. The research employs a rigorous and systematic approach to analyze numerical data, obtaining secondary data from reputable sources such as the CEIC. In this theoretical framework, macroeconomic indicators are seen as independent variables, whilst the direction of the LQ45 stock price index is regarded as the dependent variable. The objective of this study is to identify the periods characterized by bearish and bullish trends in the LQ45 index, analyze the macroeconomic indicators that have a significant influence on the index, and forecast its future trajectory.

The X-13ARIMA-SEATS approach is used to minimize seasonal variations in data sets like car sales and cement consumption. This software, developed by the US Census Bureau, combines the ARIMA model, X13-ARIMA's spectral method, and SEATS's signal extraction strategy to enhance accuracy in adjusting seasonally complex data. The general multiplicative seasonal ARIMA model for a time series zt can be written as follows:

$$\phi(B)\Phi(B^s)(1-B)^d(1-B^s)^D z_t = \theta(B)\Theta(B^s)e_t$$

B : backshift operator → $Bz_t = z_t - 1$

s : *seasonal* period

ϕB : nonseasonal operator AR → $\phi(B) = (1 - \phi_1 B - \cdots - \phi_p B^p)$
ΦB^s : *seasonal* operator AR → $\Phi(B^s) = (1 - \Phi_1 B^s - \cdots - \Phi_P B^{P_s})$
θB : nonseasonal operator MR → $\theta(B) = (1 - \theta_1 B - \cdots - \theta_q B^q)$
ΘB^s : *seasonal* operator MR → $\Theta(B^s) = (1 - \Theta_1 B^s - \cdots - \Theta_Q B^{Q_s})$
e_t : error at periode ke-t
$(1-B)^d$: *non seasonal differencing* ordo d
$(1-B_s)^D$: *seasonal differencing* ordo D

A better development of the ARIMA model arises by incorporating a time-varying mean function, modeled with linear regression effects. More explicitly, consider the formulation of a linear regression equation for a time series, denoted as yt:

$$y_t = \sum_i \beta_i x_{it} + z_t \Leftrightarrow z_t = y_t - \sum_i \beta_i x_{it}$$

Diana:
y_t: time series (dependent)
ex_{it} : regression variable observed alongside yt
β_i: regression parameter
z_t: regression error and assumed to follow an ARIMA model

Combining those two equations yields the general regARIMA model used by the X-13-ARIMA-SEATS program. This model can be expressed in a single equation as:

$$\phi(B)\Phi(B^s)(1-B)^d(1-B^s)^D\left(y_t - \sum_i \beta_i x_{it}\right) = \theta(B)\Theta(B^s)e_t$$

Result and Discussion

Bry-Boschan Algorithm

The Bry Boschan algorithm is used to identify turning points in a series y(t), a time series data such as GDP, industrial production, and stock price indices, to determine bearish and bullish periods in the LQ45 stock price index. The original data from the time series is referred to as Y(t) and the log of Y(t) is denoted as y(t).

A peak represents a turning point where the upward trend in the data shifts to a downward trend. A peak is defined at time t if

$$y_{t-k}, \dots, y_{t-k+1} < y_t > y_{t+1}, \dots, y_{t+k}$$

A trough signifies a turning point where the downward trend in the data transitions to an upward trend. A trough is defined at time t if

$$y_{t-k}, \dots, y_{t-k+1} > y_t < y_{t+1}, \dots, y_{t+k}$$

The BryBoschan algorithm uses the SymmetricWindow parameter k, which is adjusted based on research needs. The time series is partitioned into expansion and contraction periods, with expansion periods being bearish and contraction periods being bullish.

Binomial Logistic Regression

The LQ45 stock price index prediction is modeled using binomial logistic regression, a method similar to multiple linear regression. It examines the relationship between independent variables and a dichotomous dependent variable, such as success or failure, using a model with two values. The logistic regression model is given by:

$$\ln\left[\frac{\pi(\boldsymbol{x_i})}{1-\pi(\boldsymbol{x_i})}\right] = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_k x_{ki}$$

The ratio $\frac{\pi(x_i)}{1-\pi(x_i)}$ is called the odds ratio of an event. The equation above is the logit transformation of probability π(x_i), also known as the log odds and is denoted by g(x_i). Thus, the log odds equation can be written as:

$$g(\boldsymbol{x_i}) = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_k x_{ki}$$

$\boldsymbol{x_i}$: observation vector of i, with i = 1,2,..., n

n: number of observations

$\beta_1, \ldots$,βk: parameters indicating the relationship between independent variables and a dependent variable with only 2 values.

According to Hosmer and Lemeshow (2000), testing of parameters is necessary to determine the role of parameters or independent variables on the dependent variable. Partial parameter testing is conducted to observe the influence of independent variables on the dependent variable singly and also to determine if the independent variables in question are suitable for inclusion in the model. Partial testing is performed using the Wald test statistic. The hypotheses tested are:

$$H_0: \beta_j = 0$$
$$H_0: \beta_j \neq 0 \ ; j = 1,2, \ldots, p$$

The test statistic for the Wald test, or test W, is:

$$W = \left[\frac{\hat{\beta}_j}{SE(\hat{\beta}_j)}\right]^2$$

with:

$\hat{\beta}_j$: estimator of β_j

$SE(\hat{\beta}_j)$: *standard error* of $\hat{\beta}_j$

The W test statistic follows a chi-square distribution with 1 degree of freedom. The decision rule for the W test statistic is to reject H0 if the test statistic $W > \chi^2_{(\alpha,1)}$ or if the p-value < α. This χ^2 is the chi-square value from the chi-square table with 1 degree of freedom and a significance level of α. If the result is that H0 is rejected, it can be interpreted that $\beta_j, j = 1,2, \ldots, p$, has a significant effect on the dependent variable at the significance level α.

Descriptive Analysis

Descriptive statistics play a crucial role in the field of data analysis, providing a simplified overview and summary of the key aspects of a data set (Peren, 2021). In Table

1, several statistical metrics are utilized to analyze the dataset, including the Mean, Standard Deviation (St. Dev), Minimum (Min), Maximum (Max), and the Augmented Dickey-Fuller Test (ADF). By carefully examining each variable, the objective is to provide a clear and initial understanding of the patterns and variances within the data points. The Augmented Dickey-Fuller Test (ADF) is an essential tool for determining whether a series has a unit root, which is necessary to understand its stationarity and required for further time-series data analysis.

Table 1 Descriptive Statistics of All Variables

No	Variable	Mean	St. Dev	Min	Max	ADF
1	LQ45 Index	840,261	138,210	496,027	1105,762	-2,818
2	Motorcycle Sales	533148,564	130731,003	21851,000	750829,000	-5,621
3	Cement Sales	4988,732	976,513	2555,800	7331,700	-7,617
4	Retail Sales	175,153	43,101	90,600	249,786	-5,180
5	Car Sales	83430,763	19907,500	3551,000	115979,000	-4,991
6	Export Value	15440,600	3474,785	9649,504	27862,094	-4,892
7	Import Value	14359,766	2750,893	8438,627	22150,550	-4,727
8	Oil Prices	75,580	27,100	20,660	128,140	-4,846
9	Benchmark Interest Rate	0,056	0,013	0,035	0,078	-2,477
10	1-Month Deposit Interest Rate	6,067	1,481	2,830	8,580	-2,623
11	3-Month Deposit Interest Rate	6,317	1,556	2,970	9,430	-2,686
12	12-Month Deposit Interest Rate	6,709	1,406	3,270	9,120	-3,308
13	Working Capital Loan Interest Rate	11,173	1,462	8,400	13,750	-1,731
14	Investment Loan Interest Rate	10,871	1,384	8,130	13,240	-2,558
15	Rupiah Exchange Rate	12475,975	2219,297	8508,000	16367,005	-1,716
16	Inflation (CPI - Consumer Price Index)	0,209	0,238	0,046	3,000	-4,551
17	Broad Money	4804574,134	1726352,449	2066480,990	8528022,306	-4,561
18	Narrow Money	1225057,774	519435,255	490083,790	2608796,660	-4,529
19	US PMI Manufacturing	54,527	3,912	41,800	63,800	-4,725
20	US PMI Services	56,175	3,136	41,700	67,600	-6,238
21	Industrial Production Index (IPI)	1,383	4,173	-17,879	17,332	-5,883
22	Consumer Confidence Index (CCI)	94,979	25,676	40,900	137,900	-7,045
23	Federal Funds Rate (FFR)	0,636	0,858	0,050	4,100	-2,813
24	US Inflation	2,298	1,320	0,603	6,643	-3,912
25	Coincident Economic Index (CEI)	99,402	6,446	86,100	109,400	-6,460
26	Leading Economic Index (LEI)	100,596	10,477	80,900	117,800	-3,830

Seasonal Adjustment with X13ARIMA-SEATS

The shopping behavior of consumers and government spending can be quite fluctuating due to specific seasons, encompassing sectors such as car and motorcycle sales, retail products, and cement. The use of the X13ARIMA-SEATS methodology for Seasonal Adjustment (SA) provides significant insight into the seasonal patterns associated with macroeconomic and social variables. These phenomena become especially evident during certain intervals, such as election cycles, holidays, and religious celebrations, when many components, including government expenditures and public spending patterns, tend to exhibit substantial fluctuations. In the context of considerable diversity, the use of SA analysis facilitates the exploration of how various sectors respond to external conditions. Typically, graphical representations show striking sales fluctuations, indicating either substantial growth or decreases before these events.

In applying this method, R-studio software is utilized. Before implementing X13ARIMA-SEATS, data visualization with ggplot2 is conducted to observe the general patterns of motorcycle, car, retail, and cement sales data before the seasonal adjustment. The application of the X13-ARIMA-SEATS method through the function of the sea from the seasonal package involves data decomposition to identify and remove seasonal effects, resulting in an adjusted time series. This adjusted data is then saved in Excel format, which will be used for further discussion in the following subsections.

The application of the X13ARIMA-SEATS method to sales data produces more consistent and season-independent data, allowing for a clearer understanding of the fundamental patterns driving sales dynamics across various industries. The following four graphs illustrate the empirical results obtained from applying this methodology, specifically highlighting data that show seasonal patterns in different industries such as motorcycle, vehicle, retail, and cement sales. The results of this seasonal adjustment will eliminate the seasonal bias in the data, making it more stationary for the next methods, which also include the development of a predictive model for the direction of the LQ45 stock price.

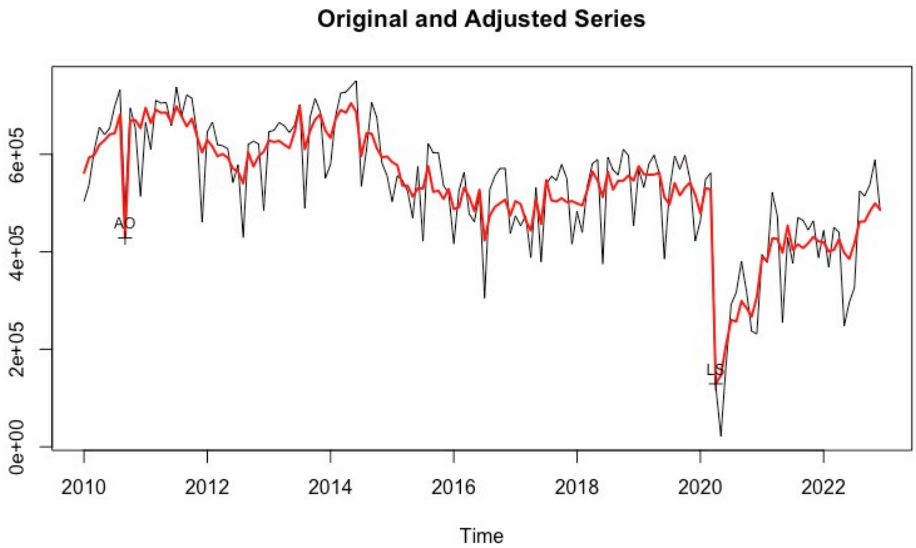

Figure 1 Seasonal Adjustment Results for Motorbike Sales.

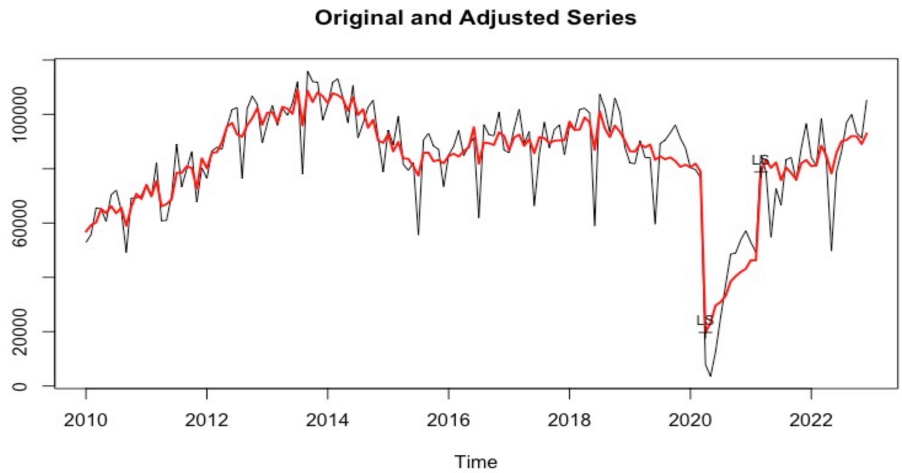

Figure 2 Seasonal Adjustment Results for Car Sales

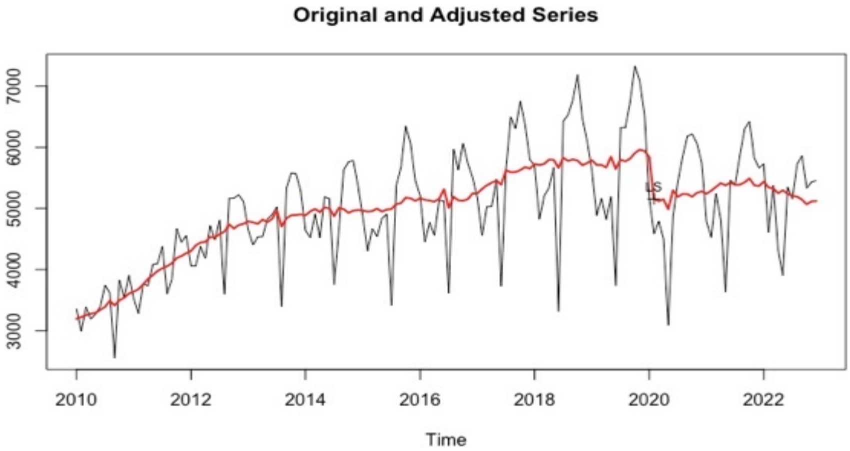

Figure 3 Seasonal Adjustment Results for Retail Sales

Identifying Turning Points with the Bry-Boschan Method

The use of stock indices as economic indicators is a common practice in many countries, including for detecting and analyzing macroeconomic business cycles. The Bry-Boschan method has been applied to the LQ45 stock index data, which comprises 45 stocks with high liquidity and significant market capitalization on the Indonesia Stock Exchange. Turning points within the provided time series data will be extracted by running a script written in R, specifically the "BCDating" package. Within the BCDating package, the BBQ() function is utilized to generate a series of turning points, distinguishing periods of expansion or bullish phases and recession or bearish phases applied to the LQ45 stock index. To view the results of the Bry-Boschan method, functions like show() and summary() are employed. The following are the periods generated by the Bry-Boschan method.

	Phase	]Start	;End]	Duration	LevStart	LevEnd	Amplitude
1	Expansion	<NA>	2010M10	NA	NA	673	NA
2	Recession	2010M10	2011M1	3	673	598	75.6
3	Expansion	2011M1	2011M7	6	598	730	132.0
4	Recession	2011M7	2011M9	2	730	623	107.2
5	Expansion	2011M9	2012M3	6	623	713	89.9
6	Recession	2012M3	2012M5	2	713	646	66.9
7	Expansion	2012M5	2013M4	11	646	857	211.4
8	Recession	2013M4	2013M8	4	857	701	156.1
9	Expansion	2013M8	2015M3	19	701	962	260.9
10	Recession	2015M3	2015M9	6	962	705	257.0
11	Expansion	2015M9	2016M3	6	705	840	135.4
12	Recession	2016M3	2016M5	2	840	820	20.3
13	Expansion	2016M5	2018M1	20	820	1106	285.7
14	Recession	2018M1	2018M6	5	1106	909	196.8
15	Expansion	2018M6	2019M1	7	909	1039	130.0
16	Recession	2019M1	2019M5	4	1039	983	56.1
17	Expansion	2019M5	2019M7	2	983	1022	39.6
18	Recession	2019M7	2020M3	8	1022	691	331.3
19	Expansion	2020M3	2021M2	11	691	945	253.6
20	Recession	2021M2	2021M7	5	945	823	121.7
21	Expansion	2021M7	2022M4	9	823	1085	262.4
22	Recession	2022M4	<NA>	NA	1085	NA	NA

	Amplitude	Duration
Exp=]T;P]	180.1	9.7
Rec=]P;T]	138.9	4.1

Figure 4 The resulting period is based on the Bry-Boschan method.

Figure 4 shows the periods based on the Bry-Boschan method, which has been segmented into various bullish and bearish periods during the observed timeframe from January 2010 to 2022. Bullish phases indicate periods where the level (Lev) demonstrates growth, whereas bearish phases indicate periods of level decline. For instance, the first bullish phase occurred between January 2011 and July 2011, with the level rising from 598 to 730, denoting an amplitude increase of 132.0. Subsequently, a bearish phase between July 2011 and September 2011 showed a level drop from 730 to 623, with an amplitude decrease of 107.2. The longest bullish period was recorded between May 2016 and January 2018, with the index increasing from 820 to 1106, with an amplitude of 285.7, reflecting significant growth during that time. Conversely, the longest bearish phase was from July 2019 to March 2020, marked by a sharp decline from an index of 1022 to 691.

In general, when comparing the bullish and bearish phases in this summary, the average amplitude and duration for bullish phases (Exp) are 180.1 and 9.7 (possibly in months), whereas for bearish phases (Rec) they are 138.9 and 4.1. This reflects that, historically, in the observed data, bullish phases tend to have longer amplitudes and durations compared to bearish phases. This suggests that despite the occurrence of bearish periods, the growth (bullish phases) between these periods tends to be greater and last longer than the declines (bearish phases).

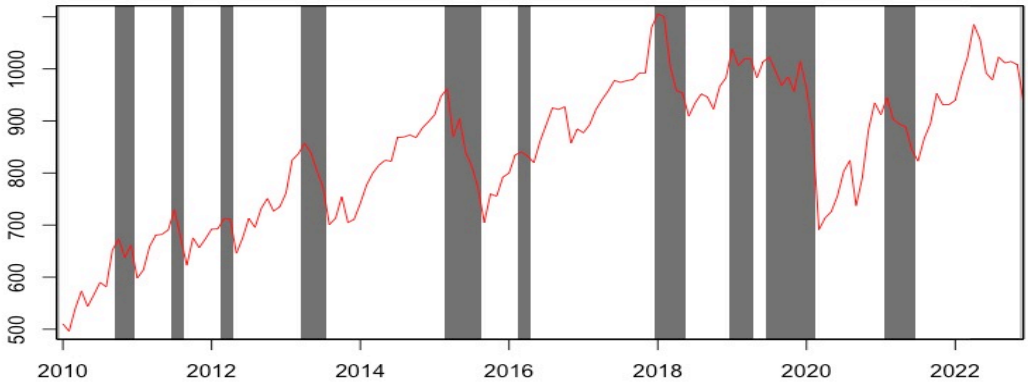

Figure 5 The resulting visualization based on the Bry-Boschan method.

Once the bearish and bullish periods have been determined, the plot () function is used to represent what the periods look like in a graph, offering a visual perspective on how the stock index has fluctuated between growth and decline over specific periods. Figure 5 is the visualization results of the bullish and bearish periods generated by the Bry-Boschan method. Periods colored gray indicate bearish periods, while uncolored periods indicate bullish phases.

Binomial Logistic Regression Prediction Model

Binomial logistic regression is a statistical technique used to test the relationship between a binary dependent variable (values of 1 and 0) and one or more independent variables. Within the framework provided for utilizing the same R software used in previous methods, the binomial logistic regression model has been run using the lm () function with a binomial distribution family. The predictors in this study include a variety of variables, namely motorcycle sales, cement sales, retail sales, car sales, export volume, import volume, oil prices, benchmark interest rates, deposit interest rates, working capital loan interest rates, investment loan interest rates, the Indonesian Rupiah exchange rate, inflation, monetary aggregates (M1 and M2), and an index describing the global economy, especially that of the United States.

The R script begins by loading the caret package so that the lm () function can be used to process data into a prediction model. The analyzed data is read from an Excel file using the read_excel() function. Thereafter, the Date column is converted to the Date data type, and subsequently, the data is transformed into a tsibble (time series tibble) object with Date as the index. The binomial logistic regression model is then applied to the data using the glm() function. The dependent variable (to be predicted) is the bearish or bullish period generated by the Bry-Boschan method and several independent variables (predictors) as previously described. The results of this model are then summarized using the summary() function to present the modeling outcomes, as shown in the following figure.

```
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.4352  -0.1563   0.1437   0.4537   2.4169

Coefficients:
                                Estimate Std. Error z value Pr(>|z|)
(Intercept)                    2.267e+01  9.757e+01   0.232  0.81625
data_adj$Motor                -3.710e-05  1.521e-05  -2.439  0.01472 *
data_adj$Semen                 4.407e-03  3.701e-03   1.191  0.23380
data_adj$Retail               -2.675e-01  9.243e-02  -2.894  0.00381 **
data_adj$Mobil                 5.553e-05  7.472e-05   0.743  0.45737
data_adj$`Val X`              -2.517e-04  3.275e-04  -0.769  0.44212
data_adj$`Val I`              -1.693e-04  3.309e-04  -0.512  0.60890
data_adj$`Harga Minyak`       -1.240e-01  5.319e-02  -2.332  0.01971 *
data_adj$`Suku Bunga Acuan`   -2.377e+02  1.195e+02  -1.989  0.04673 *
data_adj$`Dep 1 bulan`         9.507e+00  3.048e+00   3.119  0.00182 **
data_adj$`Depo 3 bulan`        1.070e+00  2.863e+00   0.374  0.70871
data_adj$`Depo 12 bulan`      -3.472e+00  2.190e+00  -1.585  0.11289
data_adj$`Pinjaman Modal Kerja` -1.255e+01  4.314e+00  -2.909  0.00363 **
data_adj$`Pinjaman Investasi`  6.163e+00  5.487e+00   1.123  0.26132
data_adj$`Nilai Tukar Rupiah`  3.286e-03  1.226e-03   2.681  0.00734 **
data_adj$`Inflasi (IHK)`      -2.521e+01  8.973e+00  -2.809  0.00496 **
data_adj$M1                    5.315e-05  1.956e-05   2.717  0.00658 **
data_adj$M2                   -2.338e-05  9.141e-06  -2.558  0.01053 *
data_adj$`US PMI M`            4.278e-01  2.088e-01   2.049  0.04044 *
data_adj$`US PMI S`            7.949e-02  1.957e-01   0.406  0.68465
data_adj$IPI                  -3.123e-01  1.629e-01  -1.917  0.05520 .
data_adj$CCI                  -2.523e-02  5.671e-02  -0.445  0.65633
data_adj$FFR                  -2.168e+00  1.144e+00  -1.896  0.05801 .
data_adj$`Inflasi US`          3.100e+00  1.270e+00   2.441  0.01464 *
data_adj$CEI                   9.719e-01  1.193e+00   0.815  0.41516
data_adj$LEI                  -3.552e-01  4.185e-01  -0.849  0.39603
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 195.704  on 155  degrees of freedom
Residual deviance:  93.699  on 130  degrees of freedom
AIC: 145.7

Number of Fisher Scoring iterations: 8
```

Figure 6 Results from the Binomial Logistic Regression Method

The binomial logistic regression model produces several relevant pieces of information regarding the relationship between the independent variables and the dependent variable, bearish and bullish periods. Variables that significantly affect the bearish and bullish periods (significance level of 5%) are motor sales, retail sales, oil price, 1-month deposit interest rate, working capital loan interest rate, rupiah exchange rate, inflation, M1, M2, US PMI manufacture, and US inflation. The model used to perform forecasts only uses independent variables that significantly affect the bearish and bullish periods of the LQ45 stock market (Bursac et al., 2008). The resulting model is:

$$\begin{aligned} Y = \ln\left(\frac{1-p}{p}\right) &= 22{,}67 - 0{,}00003710 \times \text{Motor} - 02675 \times \text{Retail} \\ &\quad - 0{,}1240 \times \text{Harga Minyak} - 237{,}7 \times \text{Suku Bunga Acuan} \\ &\quad + 9{,}507 \times \text{Dep 1 bulan} - 12{,}55 \times \text{Pinjaman Modal Kerja} \\ &\quad + 0{,}003286 \times \text{Nilai Tukar Rupiah} - 25{,}21 \times \text{Inflasi} + 0{,}00005315 \times \text{M1} \\ &\quad - 0{,}00002338 \times \text{M2} + 0{,}4278 \times \text{US PMI M} + 3{,}100 \times \text{Inflasi US} \end{aligned}$$

If the value of each independent variable in the model is entered to predict the future direction of the LQ45 stock market, according to (Tibshirani, 1996), the interpretation of the p-value is as follows:

$$p = \frac{e^Y}{1 + e^Y}$$

- If $p > 0.5$, then the model predicts that the market will be in a bullish condition because the probability is greater than that of a bearish market.
- Conversely, if $p < 0.5$, then the model predicts that the market will be in a bearish condition because the probability is smaller than that of a bearish market.

```
Confusion Matrix and Statistics

          Reference
Prediction  0  1
         0 36  9
         1 14 97

               Accuracy : 0.8526
                 95% CI : (0.787, 0.9042)
    No Information Rate : 0.6795
    P-Value [Acc > NIR] : 6.208e-07

                  Kappa : 0.6523

 Mcnemar's Test P-Value : 0.4042

            Sensitivity : 0.7200
            Specificity : 0.9151
         Pos Pred Value : 0.8000
         Neg Pred Value : 0.8739
             Prevalence : 0.3205
         Detection Rate : 0.2308
   Detection Prevalence : 0.2885
      Balanced Accuracy : 0.8175

       'Positive' Class : 0
```

Figure 7 Results from the Confusion Matrix

To test whether the resulting model is good enough to perform forecasts, a confusion matrix is used, and its results are presented in Figure 4.8. Here is the interpretation of the results from the confusion matrix using R software:

- True Negative (TN): 36 - The model correctly predicted the negative class as negative.
- False Positive (FP): 9 - The model incorrectly predicted the positive class as negative.
- False Negative (FN): 14 - The model incorrectly predicted the negative class as positive.
- True Positive (TP): 97 - The model correctly predicted the positive class as positive.

The model has performed well, achieving an accuracy rate of 85.26%. This indicates that the model has successfully classified approximately 85.26% of the data correctly. The 95% confidence interval related to the precision of the model ranges from

78.7% to 90.42%. This range suggests that the actual accuracy of the model lies within these bounds. The No Information Rate (NIR), with a value of 0.6795, serves as a benchmark and represents the proportion of the most dominant class. The p-value obtained is 6.208e-07, indicating a high level of statistical significance in the relationship between the accuracy of the model and NIR.

This finding confirms that the model's performance is far superior to random guesses based on the most dominant class. The Kappa value of the model, at 0.6523, indicates that the quality of this model is quite good, exceeding the expectations of chance. In particular, a Kappa value exceeding 0.6 is generally viewed as an indication of strong classification performance. Therefore, it can be concluded that the model produced is quite good for use in predicting the direction of the LQ45 stock market state.

Conclusion

This research concludes that investor attention and sentiment significantly impact the volatility and stock prices in the Indonesian stock market. The study effectively demonstrates the utility of advanced statistical techniques, including X13 ARIMA SEATS, Bry-Boschan algorithms, and Binomial Logistic Regression, in understanding the complex interplay between market dynamics and macroeconomic indicators. It highlights the critical role of factors such as motor and retail sales, oil prices, benchmark interest rates, and the Rupiah exchange rate in influencing the LQ45 index, which comprises the 45 most liquid stocks in Indonesia. Furthermore, variables like motor sales, retail sales, oil price, 1-month deposit interest rate, working capital loan interest rate, rupiah exchange rate, inflation, M1, M2, US PMI manufacture, and US inflation are identified as having a significant effect on the bearish and bullish periods of the market at a 5% significance level.

The predictive model employed in the study integrates binomial logistic regression and the Bry-Boschan algorithm, showing an impressive accuracy rate of 85.26% in forecasting the direction of the stock market. This high level of precision is invaluable for investors and analysts, providing a reliable tool for making informed investment decisions in a market that often experiences rapid and unpredictable changes. The effectiveness of the model in navigating the complexities of the stock market is a significant advancement in financial market analysis, offering a nuanced understanding of how investor sentiment and macroeconomic indicators shape market trends. These insights are crucial for developing sophisticated investment strategies.

Overall, the research significantly contributes to understanding how investor sentiment and attention, along with macroeconomic indicators, affect stock market behavior. This knowledge lays the foundation for more informed and effective investment strategies. Looking ahead, it would be beneficial for future research to delve deeper into how microeconomic factors and information technology, such as social media and online news, influence investor sentiment and, in turn, the dynamics of the stock market. This exploration could open new avenues in stock market analysis and lead to the development of more advanced predictive tools.

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