PRICE VOLATILITY OF LAKATAN BANANA IN DAVAO CITY

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ABSTRACT

This paper attempted to measure the univariate time series of the price of Lakatan Banana in Davao City. The primary aim of the study is to analyze the price trend and degree of price volatility. Hence, this study sought to present the trend of market volatility changes of Lakatan bananas, assess the peak and low of prices in time series, and impart price volatility information of Lakatan bananas in Davao City. Furthermore, researchers

forecasted the time series. The study used a time series of secondary data obtained from the Philippine Statistics Authority (PSA) covering the year 1997-2020, monthly basis. Moreover, the data was statistically treated using the ARCH model for capturing the price volatility and ARIMA model in forecasting the series. The ARCH(1) and ARIMA (2,1,2) are the best fitted models to continue the analysis. The ARCH(1) findings indicate that there is a lot more volatility towards the year 2020 and the diagnostics of ARIMA (2,1,2) model indicate that the forecasted price from 2021-2025 is consistent.

Keywords: *ARCH; ARIMA; Retail Price; Lakatan; Volatility*

INTRODUCTION

Bananas are grown extensively in the Philippines. It grows a variety of bananas including the Cavendish, Cardaba/Saba, Latundan, and Lakatan. The prices of these banana types vary from one another (Gueco, 2021). Since banana production began, it has had issues with Moko disease, sigatoka leaf mark, banana freckles, banana bunchy top virus, and fusarium wilt. For farms without the tools to control the illnesses, the effects of these diseases are severe (Ayaand Nas, 2017).

Among the banana varieties in the Philippines, banana lakatan variety recorded the third largest share in production with 10.2 percent of the total banana output in 2020. Among the regions in the Philippines, region XI (Davao Region) recorded the largest share in production with 23.8 percent of the total banana lakatan output in 2020 (PSA, 2021). The share of Davao City in the volume of production of banana lakatan in the Davao region in 2020 is 11.59% (PSA, 2022).

Among the banana varieties available in retail price surveys, banana lakatan is the most expensive (PSA, 2022). Furthermore, in Davao City, banana lakatan varieties recorded the second largest share in production in 2020 (PSA, 2022).

In a perfectly clear sense, volatility refers to fluctuations in economic variables over time, such as the price (FAO et al., 2011). This study focuses in particular on changes in Lakatan banana prices. When prices move in a steady trend or according to a predictable seasonal pattern, price changes are not necessarily risky. During price swings are significant and unexpected, they become challenging, creating uncertainty that increases danger for vendors, buyers, manufacturers, and governments and may lead to unwise decisions. Price changes that deviate from the market‘s fundamentals are challenging because they may lead to poor decisions. According to Rahman (2019), prices change as a result of a variety of circumstances. Changes in supply and demand, shifts in the cost of labor or raw materials, adjustments to government regulations or taxation, and shifts in economic circumstances like inflation or recession are some of the

most frequent reasons for price fluctuation. Events like natural catastrophes, political unrest, and shifts in consumer preferences can also have an impact on price.

Researchers considered the commodity banana because banana is one of the most important fruit crops in the Philippines in which the largest plantation is located in the Davao Region. In accordance with the Department of Agriculture's Philippines Banana Industry Roadmap Report (2019-2022), Lakatan is very competitive in the domestic market since it is produced for domestic consumption and not for exportation. Additionally, compared to other types offered in PSA, Lakatan is the most costly variety in Davao City, which gives researchers an idea to explore its price volatility. Moreover, there are very few studies that look at the cost of goods in the Philippines, particularly in Davao City, where main industries like cocoa, bananas, and coconuts are located.

It is crucial to examine the trend and volatility of the retail price of Lakatan bananas because the higher the volatility the higher the risk for the stakeholders. Businesses must include and get the support of stakeholders since they are the owners of the areas, procedures, or systems where the project needs to successfully transform (Pincot, 2021). Also with the inflation problem existingtoday, the financial crisis is being present. This study may be used to further the conversation and body of information regarding the banana industry. Therefore, the present study has been specifically designed to identify the price volatility and to forecast the price of Lakatan banana in Davao City. For the said purpose, Auto-regressive Conditionally Heteroscedastic (ARCH) and Autoregressive Integrated Moving Average (ARIMA) are applied.

Bananas are one of the Philippines' most known fruit crops. Musa acuminata cultivar, commonly known as Lakatan Banana, appears to be the most prevalent variety in Manila, and it is cultivated across the Philippines. It is among the most popular dessert bananas, largely grown by small-scale banana growers and consumed by the local market.

The study of Jaime et al. (2013) reveals that the current marketing situation of Lakatan bananas is for the domestic market. It is being cultivated for local consumption and the productivity of the fruit is decreasing due to the influence of companies who are widely cultivating Cavendish bananas. The Lakatan banana has a high demand, but because of a lack of decent promotion, it has become common for consumers and much less profitable for producers. However, due to decreasing demand for Cavendish bananas, Lakatan bananas have a possibility of being exported. Lakatan bananas have a continuous demand in the present market since they are regarded as nutritious food. However, it is not very profitable when compared to the market's future profits.

In a competitive market, Lakatan bananas are in great demand right now, but they are not being exported to other nations due to a shortage of supply. In terms of distinction, it is widely marketed alongside other types, with

the price set to be cheap in comparison to the quality. Local individuals prefer the commodity since it is a basis of their diets, although Lakatan bananas are insignificant in terms of export and import in international trade. One reason for this is that it does not appeal to the tastes and preferences of foreigners. Furthermore, because foreign languages favored the Cavendish type, the manufacturers avoided bulk manufacturing. However, if the Lakatan bananas are properly promoted and given sufficient attention, they may be able to reach the international market. Due to the cultural differences between the other countries and the people of the Philippines, other Asian countries may be interested in purchasing the product. (Jaime et al., 2013).

Price volatility is a measurement of a commodity‘s price variations. Volatilityquantifies the daily variation in the price of the commodity. The measurement of price variations in the markets is also provided by volatility. Businesses may suspend their investment and other proposals or boost their risk management initiatives if volatility increases or significantly changes. The expenses associated with these activities sometimes result in higher costs for producing and consuming products and services (EIA, 2003).

Harvey (2011) claimed that it is an assessment of risk based on the standard deviation of asset return. Volatility is a term used in economics to describe the volatility of returns of an asset over the course of a certain time period. Volatility indices are also available. These 1-9 scales, where a higher rating indicates a greater uncertainty.

In accord with the study of Hailu and Weersink (2011), both producers and consumers may observe the overt effects of price fluctuations in the commodities markets. Fears about a ―silent tsunami‖ that was sweeping the underprivileged who couldn‘t able to buy the nourishment they needed arose as a result of the dramatic increase in prices of crop translated into higher food costs in poorer countries. Although the producers benefit most from the higher average prices, the subsequent volatility places stricter and greater requirements on risk management of price for producers.

Furthermore, increased volatility has led to the liquidation of midsize and small businesses because it has an impact on the costs related to financial status. Other grain enterprises are refusing to buy grains from producers for future usage in order to deal with the hedging costs and volatility. (Hailu and Weersink, 2011)

In addition to their study of Hailu and Weersink (2011), back in 2007-2008,a number of variables led to the rise in degree of volatility and prices. For most crops, the stock-to-use ratio has decreased as production levels have flattened due to sustained low pricing. The value of the US dollar has fallen in relation to other currencies, giving international buyers more purchasing power with regard to goods. These buyers came from nations like India and China, whose GDPs have grown far faster than the world

average.

Lestari et al., (2022) performed a similar study on the price volatility of red chili in Semarang Regency from January 2019 to February 2020. The study states that inflation can be positively impacted by price changes. These significant changes may increase the price volatility. Thus, future price uncertainty increases in direct proportion to volatility (Fameliti and Skintzi, 2022)

The study‘s main goal is to measure the volatility of Lakatan Banana retail price. Hence, this study sought to present the trend of market volatility changes of Lakatan Banana, assess the peak and low of prices in time series, and impart price volatility information of Lakatan Banana in Davao City.

The researchers ought to research the price volatility of Lakatan banana for the economy‘s activity relative to the market situation of Lakatan banana.

Therefore, the present study has been specifically designed to identify the price volatility of Lakatan banana in Davao. The conclusions of this study will help society, government, and consumers seeing that price fluctuations are not a new incidence in the market.

This research will serve as a foundation for developing or enhancing government policies, rules, and regulations aimed at lowering price volatility in the

Philippines. Since the government plays an important role in maintaining a stable economy, it regulates the equilibrium pricing and distribution.

For the local administration of Davao City, this study will assist in developing a clear understanding of establishing the retail price of the Lakatan banana from its local producers. Lakatan banana growers may be able to utilize the findings of this study to help them make pricing decisions for their crops. This may enable them to gain the upper hand since the study will provide information about the possible future prices of Lakatan bananas. For business owners, it will enable them to anticipate pricing fluctuations that may occur in a short period and create strategies beforehand that will less likely have no negative impact on customer satisfaction.

Consumers can benefit from this research since they will be the one who will be affected by the government's regulations and policies, which will always be in the best interests of society. Apart from that, customers would have a better grasp of our economy's pricing fluctuations. This would encourage customers to be more cautious in their finances and to recognize that it is wise to refrain from spending more money than they earn because the market is uncertain and future pricing is also unpredictable.

This study will help investors estimate potential future fluctuations since higher price volatility frequently equates into increased risk. In addition, this study may

benefit investors by creating investment possibilities in addition to estimating future fluctuations. In addition, this study will serve as a guide for future researchers in the field of economics. Researchers in the subject of economics will find this paper useful as a reference. This will act as a guideline for researchers who will continue to improve and expand this study to gain a better knowledge of price volatility.

To better comprehend the notion of time series and the continued application of the models, it is crucial to define them first. A time series is a group of random variables that have been indexed by the chronological sequence in which they were obtained. Several techniques could be applied in the context of time series analysis to comprehend how the data behaved over time and to create forecasts (Dinardi, 2019). Several models will be evaluated and further examined in this work, especially the ARIMA and ARCH models.

This study is anchored to the ARCH model proposed by Engle (1982) that lets these existing values serve as variables for estimation. Hence, the model facilitated the use of the data to find the most appropriate values for anticipating the variance.

The ARCH model is concerned in simulating the series' variance's volatility. ARCH models were applied to real-time data on stock prices, commodity prices, bond prices, GDP, inflation rates, and unemployment rates. Importantly, there should never be a serial correlation in any series where there are seasonal effects or trends.

In accordance with the study of Hume (2020), ARCH is closely related to ARIMA Model but varies on the second component which is the CH, in which it models the last squared residuals at each previous point in time. Instead of using the term of variance or squared residual, volatility is a much preferred term in this model. The CH from the model will be predicting the future volatility as part of the wider ARCH Model. The ARCH model becomes more accurate if there are changes in ―volatility clusters‖. In addition, relying only on the ARIMA model could not capture the volatility in aspect. Pairing it with the ARCH model, which presents coefficients that can offer insights and clarity to the volatility clustering. ARCH Model also tests the stationary of the time series using Dickey Fuller Test then checking the presence of volatility before its forecast.

The Generalized Autoregressive Conditional Heteroskedasticity or GARCH model, which also has a moving average component, extends the ARCH model. GARCH is somehow the same or it is equivalent to the ARMA Model. It only has an autoregressive component.In a series when ARIMA is regularly used, ARCH would also work well (Kumar, 2020).

In addition, this study aims to forecast time series thus, it is anchored to George Box and Gwilym Jenkins who created the ARIMA model in the 1970s inan effort to use mathematics to characterize variations in time series.

This model's goal is to minimize the difference in values generated by the model and the observed ones as closely as feasible to zero. It is based on an adjustment of observed values.

In order to manage and measure risk, price derivative assets, develop trading strategies, and understand the dynamics of time series data, it is crucial to assess the correctness of time-varying models. Future volatility is predicted using a variety of time-varying volatility models. Numerous statistical techniques are frequently employed to estimate volatility, however in many forecasting analyses, autoregressive time series models like ARIMA or Auto Regressive Integrated and Singh, 2019)

As claimed by Ariton (2021), the addition of an integration component to the ARMA model results in the ARIMA model. ARIMA models are to be used with non-stationary time series, while ARMA models must be used with stationary time series. A stationary time series is one in which the variance and mean, among other statistical parameters, stay constant across time. Unfortunately, most real- world time series are not stationary, and transformations are frequently required to make them so. The transformation process is referred to as integration.

METHOD

Research Data Source

Lakatan is in demand in the domestic market supported by the Department of Agriculture on its Philippines Banana Industry Roadmap Report (2019-2022). Furthermore, according to the retail price survey, Lakatan is the most expensive variety in Davao City compared to other varieties available in PSA thus, giving researchers an idea to study its price volatility.

The researchers also chose retail price because of the final price of its goods sold to consumers from an accessible market. The study included secondary data (panel data) from the online collection of data of the Philippine Statistics Authority and contained monthly data on retail prices of Lakatan bananas in Davao from the years 1997-2020. The data also presents the retail price differences and changes of Lakatan bananas.

Research Design

Researchers employ available data, sometimes referred to as secondary data, in this study. The researchers used the quantitative method which is typically used to describe work that involves thousands, hundreds or perhaps one hundred thousand observations. In quantitative research, researchers use statistics or numbers to quantify. The methodology of quantitative research is deductible. It is guided by theory; theory is where it all begins and finishes (Stockemer et al., 2019). In

addition, the research design used for this study is time-series analysis research design. Time-series analysis (TSA) is suitable for longitudinal studydesigns with a single subject or research unit that are monitored repeatedly across time at regular intervals (Goodwin et al., 2020). The collected information were analyzed and organized in order to improve the research's superior effectiveness. Census records, information that is collected by state agencies, internal records, and evidence collected for other research purposes are all common secondary data sources.

Statistical Treatment of Data

The research statistical treatment used for the study was Autoregressive Conditionally Heteroscedastic (ARCH) and Autoregressive Integrated Moving Average (ARIMA). The researchers utilized ARCH and ARIMA Model to test, assess, and forecast the price volatility predictions of Lakatan banana and to know how volatile the price of Lakatan banana in Davao City. This section briefly discussed the process of the time series tests.

Normality Test

As the researchers utilized Stata software for the analysis of the time seriesdata, checking for normality tests became easy. The normal option in Stata's histogram adds the normal density curve that corresponds to the mean and standard deviation of the displayed data. The quantile function, denoted as f(Q(P)), can also be used to indirectly calculate the density function. For instance, if P were 0.5, the density at the median would be f(Q(0.5)).

P is really determined as the so-called plotting positions (p i) connected to the values of a sample of Y of size n and rank I where y (i) is the order statistics (y (1) = y (i)). <= y (n) (n). One straightforward formula is p i = I - 0.5) / n. The majority of other rules belong to the family I - a)/(n - 2a + 1), which is indexed bya.

Stationary

A unit root is utilized to ascertain if a time series is stationary in time series analysis. The null hypothesis asserts that time series have a unit root, while the alternative hypothesis says that time series are stationary.

The initial unit root tests are valid if an AR(1) with white noise errorsadequately represents the time series yt. Although many financial time series is dynamic, a straightforward AR(1) model cannot accurately capture its dynamic nature. Said and Dickey (1984) modified the basic autoregressive unit root test to allow any ARMA(p, q) models with ambiguous orders; this test is recognized as the augmented Dickey-Fuller (ADF) test. The ADF test compares the null hypothesis of I(1) with the alternative that a time series is I(0), supposing that the dynamics in the data have an ARMA structure. In calculating the test regression, the ADF test is the basis.

A straightforward AR model is as follows:

$$Y(t) = c + \varphi 1Y(t-1) + \varepsilon(t)$$

Where the Y(t) represents the time series‘ value at time t and c is a constant term. φ1 is the autoregressive coefficient that represents the weight of the previous value of the time series in the current prediction. Y(t-1) represents the time series‘ value at time t-1 and ε(t) represents the error term, which describes the difference between the actual value of the time series at time t and the predicted value

Autocorrelation and Partial Autocorrelation Functions

Autocorrelation and partial autocorrelation are measures of the relation between present and previous series values, indicating which past series values are most effective in forecasting future values. Using this information, you may construct the ARIMA model's process structure. More specifically, Autocorrelation Function (ACF) is the correlation between series of data at lag k that are separated by k intervals and Partial Autocorrelation Function (PACF) represents the correlation between series values at lag k while considering the values of the intervals between them.

The x-axis of the ACF plot denotes the lag at which the autocorrelation is computed. Meanwhile, the y-axis displays the correlation value (between 1 and 1).A spike at lag 1 indicates a high connection between each value in the series and the value that came preceding it in an ACF plot, a spike at lag 2 indicates a strong correlation in between value and the value that came two points earlier, and so on.

ARCH Model

The analysis of time series volatility and the forecast of future volatility is performed using the statistical model known as autoregressive conditional heteroskedasticity (ARCH). In the financial industry, ARCH modeling measures risk by offering a volatility model that more closely resembles actual markets. The ARCH model predicts that times of high volatility are followed by even higher volatility, while periods of low volatility are followed by further low volatility.

Simply put, an AR(p) model that has been applied to a time series' varianceis an ARCH(p) model.

ARCH(1):

A time-series {ϵ(t)} provides at each point in time by $\epsilon(t) = w(t)*\sigma(t)$where zero denotes white noise and w(t) is the unit variance.
Variable $(x(t)) = \sigma^2(t) = a0+a1 * \sigma^2(t-1)$

The conditional variance is guaranteed to be positive if $a0 > a0$, $a1$ $a0$.

$a0$ and $a1$ are model parameters. The lagged square error is $\sigma 2(t-1)$.

We refer to ϵ(t) as an ARCH (autoregressive conditional heteroskedasticmodel) model of order unity (1).

$\epsilon(t) = w(t)* \sigma(t) = w(t)* \sqrt{(a0 + a1 *\epsilon^2(t-1))}$

likewise ARCH(2):

$\epsilon(t) = w(t)* \sigma(t) = w(t)* \sqrt{(a0 + a1 * \epsilon^2(t-1) + a2 * \epsilon^2(t-2))}$likewise ARCH(p):

$\epsilon(t) = w(t) * \sqrt{(a0 + a(p) * \sum \epsilon^2(t-i) (t-i)}$

where:

The ARCH model's lag squared residual error inclusion parameter is p.

The square error's number of logged periods is given by the expression I = (1,2,3,-,-,-,-, -, p).

Interpretation:

1. If the error is high during the period (t-1) as well, the probability ofthe error value during the period (t) being larger is more heightened.
2. If the error is small during the period (t-1), the value inside sqrt willbe low, which results in a lessened error in (t).
3. Keep in mind that with a positive variance, $a1 \geq 0$.
4. $a1 < 1$ must hold in order for the stability condition to hold, or else ϵ(t) will explode (progressively get higher over time).

Reminder: ARCH(1) should only ever be applied to a series that has already through enough model fitting to result in discrete white noise in the residuals, as was previously mentioned.

ARIMA Model

A statistical analysis technique called Autoregressive Integrated Moving Average (ARIMA) uses time-series data to comprehend or predict future trends. Economic research frequently uses this method to forecast future stock prices. An ARIMA model is generally categorized as a "ARIMA(p,d,q)" model, where **p** represents the total number of autoregressive terms, **d** represents the number of nonseasonal deviations required for stationarity, and **q** represents the number of lags in the forecast errors in the prediction equation.

The following is how the forecasting equation is generated:

(1) Let y denote the d^{th} difference of Y, which appears to mean: If
d=0: $y_t = Y_t$

If d=1: $y_t = Y_t - Y_{t-1}$

If d=2: $y_t = (Y_t - Y_{t-1}) - (Y_{t-1} - Y_{t-2}) = Y_t - 2Y_{t-1} + Y_{t-2}$

The general forecasting equation for y is:

$$\hat{y}_t = \mu + \phi_1 y_{t-1} + \ldots + \phi_p y_{t-p} - \theta_1 e_{t-1} - \ldots - \theta_q e_{t-q}$$

(2) An autoregressive model of pth-order: AR(p), has the generic form:

(2.1) $Y_t = \varphi_0 + \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \cdots + \varphi_p Y_{t-p} + \varepsilon_t$

Where Y_t stands for the response (dependent) variable at time t, and $Y_{t-1}, Y_{t-2}, \cdots, Y_{t-p}$ represents the response variable at time delays $t-1, t-2, \ldots, t-p$, where the coefficients to be estimated are denoted by respectively, the $\varphi_0, \varphi_1, \varphi_2, \cdots, \varphi_p$ and ε_t is the error term at time t.

(3) A moving average model of qth-order: MA(q), has the generic form.

(3.1) $Y_t = \mu + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q}$

Where Y_t stands for the response (dependent) variable at time t, μ denotesthe constant mean of the process, $\theta_1, \theta_2, \cdots, \theta_q$ denotes the coefficients to be estimated, ε_t is the error term at time t, $\varepsilon_{t-1}, \varepsilon_{t-2}, \cdots, \varepsilon_{t-q}$ indicates the error in

earlier time frames that are included in the response Y_t.

Forecasting Accuracy Method

The accuracy of a forecasting technique is measured by the term MAD, or Mean Absolute Deviation. It is determined by averaging all of the absolute changes over a specific period, then calculating the absolute difference between the anticipated and actual values. A more accurate forecasting system has a lower MAD value, which means that the forecasted values are closer to the actual values. On the other hand, a higher MAD value denotes a less precise forecasting technique since it signifies that the predicted values are farther from the actual values. When evaluating the accuracy of a forecasting approach, MAD is frequently combined with additional accuracy metrics like mean squared error (MSE) or root mean square error (RMSE).

$$MAD = (1/n) \sum |Ai - Fi|$$

Whereas MAD is the mean absolute deviation and n stands for the number of time series‘ periods. Ai represents the every period‘s actual value while Fi is the forecasted value for each period.

Mean Squared Error (MSE) is a metric used to assess the precision of a forecasting technique. It is determined by taking the squared difference between the predicted value and the actual value, averaging all squared differences throughout the specified period, and then calculating the difference between them. When evaluating the accuracy of a forecasting approach, MSE is frequently combined with other accuracy metrics like mean absolute deviation (MAD) or root mean squared error (RMSE).

$$MSE = (1/n) \sum (Ai - Fi)^2$$

Whereas MSE is the mean squared error, n is the number of time series‘ periods, Ai is the every period‘s actual value and Fi is the forecasted value for each period.

Mean Absolute Percentage Error (MAPE) is a forecasting method's accuracy and is calculated by dividing the anticipated value by the actual value, then taking the absolute difference between the two. The result is then multiplied by 100 to express the error as a percentage, and the average of all of the error percentages over a given time period is calculated. A lower MAPE value indicates a more accurate forecasting method, as it means that the anticipated values are closer to the actual values. On the other hand, a higher MAPE value indicates a less accurate forecasting method, as it means that the forecasted values are further from the actual values. MAPE is often used in combination with other accuracy measures, such as mean absolute deviation (MAD) or mean squared error (MSE), to provide a more comprehensive evaluation of a forecasting method's accuracy. However, one limitation of MAPE is that it can be affected by the presence of outliers or extreme values in the data, which can cause the error percentages to be distorted.

$$MAPE = (1/n) \sum |(Ai - Fi)/Ai|$$

Whereas MAPE is the mean absolute percentage error, n is the number of time series‘ periods, Ai is the every period's actual value and Fi is the forecasted value for each period.

Research Procedures

The purpose of the study is to evaluate the price volatility of Lakatan Banana in Davao City, and valid data was collected to provide accurate findings. However, before conducting this research, the required consent and authorization were obtained from both the class adviser and the research adviser.

The researchers began by seeking and collecting data that the study would use to forecast price volatility for Lakatan bananas. The Philippine Statistics Authority's internet database was utilized to find and collect data for the study. Then, researchers gathered data on the monthly retail pricing of Lakatan bananas in Davao City from 1997 to the latest recorded data. Next, once all the needed data was collected, the researchers utilized Stata, a statistical software for Windows and Mac Computers, to build a statistical relationship with the data we obtained and use the relationship to forecast future data values. The researchers will send all the gathered data to a statistician for analysis of the data.

RESULTS AND DISCUSSIONS

Price Trend Information of Lakatan Banana

The figure shows the trend of monthly retail price of

Lakatan bananas in Davao City from 1997-2020. It exhibits price fluctuation in years 2010, 2014, 2017, and 2020. Retail prices of Lakatan bananas during these years were affected by disease, natural calamities, and other issues that will be discussed further in the next discussion.

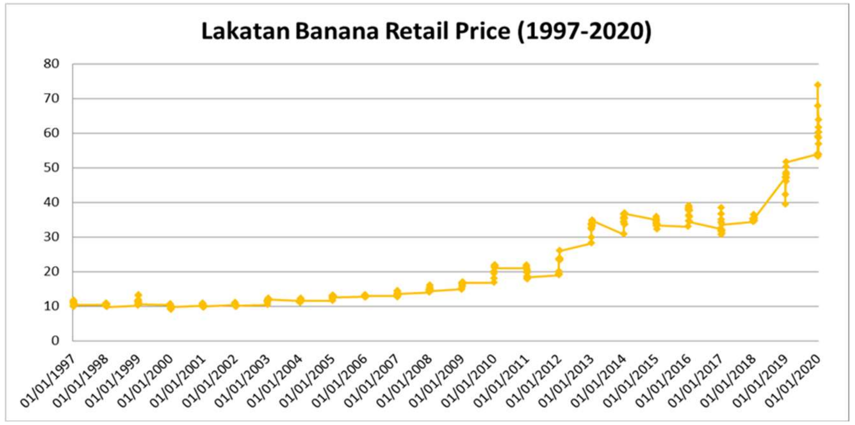


Figure 1. Price Trend 1997-2020

Retail price increased from ₱11.40 in 2004 to ₱20.50 in 2010 with a percentage change of 79.82%. In 2009, the first case of the Fusarium Wilt, also known as the Panama disease, in Calinan, Davao City was recorded by the Department of Agriculture Davao. (Lumawag, 2019)

Retail price decreased from ₱20.50 in 2010 to ₱19.80 in 2011, but increased to ₱34.91 in 2014 with a percentage change of 76.31%. Small banana farmers in the Davao Region have been hit by a ―double whammy‖ of the devastation caused by typhoon ―Pablo‖ and the cost of rebuilding their destroyed crops due to the financial crisis (Cascaro, 2012). In 2014, crop yields in the region dropped, according to the Southern Mindanao Regional Agriculture and Fishery Council (RAFC), as the lack of rain has already harmed some areas (Dinoy et al., 2014).

Retail price decreased from ₱34.91 in 2014 to ₱33.25 in 2017, but increased to ₱61.65 in 2020 with a percentage change of 85.41%. Panama disease, a serious infection, is threatening the banana industry. The disease was shown to have a greater impact in Calinan in Davao City, Davao del Norte, and Panabo City (Cortez, 2019).

Retail price in quarter basis increased from ₱49.97 in fourth quarter of 2019 to ₱55.43 in the first quarter of 2020. During this time, production of lakatan bananas decreased in Davao City. The production of bananas reached 8,264.00 metric tons during the fourth quarter of 2019 and reached 5,722.28 metric tons in the first quarter of 2020. (PSA, 2022) Retail price in quarter basis increased from ₱55.43 in first quarter of 2020 to ₱68.48 in the second quarter of 2020. During this time, production of lakatan bananas decreased in Davao City. The production of bananas reached 5,722.28 metric tons during the first quarter of 2020 and reached 5,413.20 metric tons inthe second quarter of 2020. (PSA, 2022) bananas increased in Davao City. The production of bananas reached 5,413.20 metric tons during the second quarter of 2020 and reached 5,612.15 metric tonsin the third quarter of 2020. (PSA, 2022)

Retail price in quarter basis decreased from ₱59.08 in the third quarter of 2020 to ₱58.00 in the fourth quarter of 2020. During this time, production of lakatan bananas increased in Davao City. The production of bananas reached 5,612.15 metric tons during the third quarter of 2020 and reached 8,765.00 metric tons in the fourth quarter of 2020. (PSA, 2022)

Retail price in monthly basis increased from ₱53.26 in second month of 2020 to ₱73.75 in the fourth month of 2020 with a percentage change of 38.47%. Banana prices were not subject to a price freeze during the start of the pandemic in March, yet there were dramatic increases in prices seen. These prices were already significantly higher than they were in 2018 and 2019 before this (Palo et al, 2020). The pandemic has, however, had an impact on the local export businesses' ability to produce bananas. Even if there is a high demand for bananas, lockdowns slow down production since they restrict employees from crossing borders if they do not live close to the plantations, as well as the movement of cargo and shipments (Francisco, 2020).

ARCH Model

To start with the analysis, first check the stationary result of the time series data through the Dickey-Fuller Test. As per the results of the test, the variable is non-stationarity with an insignificant p value of 0.9899.

Test Statistic	DF CV 1%	DF CV 5%	DF CV 10%	p-value
0.702	-3.457	-2.879	-2.570	0.9899 NS

Table 1. Dickey-Fuller Test

*Significant at 5% NS=Not Significant
No. of obs=287

To transform the time series into stationary, researchers used the method of first differencing using the Augmented Dickey-Fuller Test. Test results presented a stationary time series therefore proceed to check the presence of volatility using the ARCH Model, with the consideration of the volatility clusters presented in the trend.

Table 2. Dickey-Fuller Test (1st Difference)

*Significant at 5% NS=Not Significant
No. of obs=287

Checking for normality is required to continue the

Price_d1	-.0251612	.0168375	0.135NS
_cons			
ARCH L1	2.384011	.1328808	0.000*
_cons	.4270944	.0223314	0.000*

*Significant at 5% NS= Not Significant No. of obs=287

analysis. The histogram looks like a bell shape and has a high peak while others are relatively heavy (See Appendix F).

Using the regression in identifying the autocorrelation, the time series are significant with the p-value of 0.000 (See Appendix F). From the LM test, results show the p-value has a less than the five percentage significance level which indicates the effect of ARCH.

The coefficients generated using the ARCH Regression Analysis are presented in Table 1. ARCH model regression utilized 287 observations with results revealed that the ARCH L1 is significant with a p-value lower than five percentage significance level which is 0.000, has a positive coefficient, and average return is log

Test Statistic	DF CV 1%	DF CV 5%	DF CV 10%	p-value
-17.408	-3.457	-2.879	-2.570	0.000*

-.025. According to Frost (2017), a positive coefficient proposes that as the output increases, the input tends to increase; a negative coefficient indicates an increase in output, decreasing the input. Furthermore, the results from the table showed the ARCH model correctly examined the trend in time series.

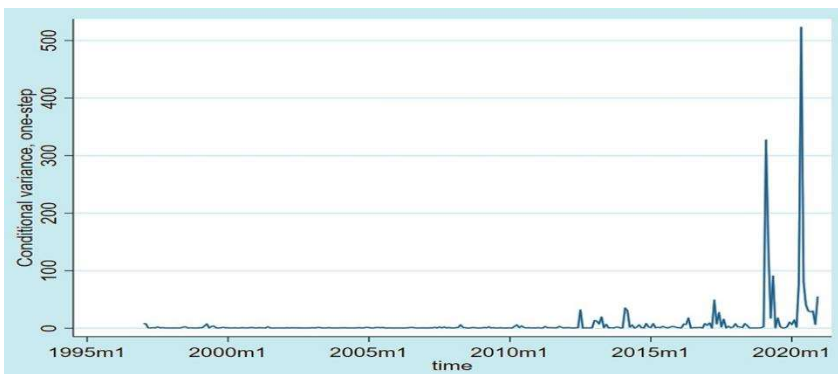
Table 3. ARCH Model Regression

Variable Coefficient Standard Error P-Value

The figure 2 shows that there is a lot more volatility towards the year 2020. This is due to the occurrence and belief of the people that banana was one of the remedies of the COVID disease. After news of claims circulated on social media that bananas might treat or prevent people from developing the coronavirus sickness 2019, the price of bananas sold in the market increased from its normal selling rates (Valdez, 2020). On this false assertion, the Department of Health had clarified and released a statement. It will take further research and testing to determine the banana's contribution to COVID-19 defense (Valeza, 2020).

Figure 2. Variance of the Series

ARIMA Model



The ARIMA model is used to forecast a non-stationary time series. Identification for the stationarity tests consist of the graph, correlogram and formal tests.

The graph indicates a positive trend. It means that the variable is non- stationary (See Appendix G). Then, correlogram indicates a slow decay. It means that the variable is non-stationary (See Appendix G).

To further test the stationarity, it was done through the Dickey-Fuller Test. This test compares the stationary alternative to the null hypothesis of an ARIMA process (Cheung and Lai, 1995). The trend has the result from p-value of 0.02. It means that the trend was significant. Therefore, it was appropriate to include the trend in the test. Results showed that p-value (0.731) is higher than the significance level. Thus, the null hypothesis (Price has a unit root) cannot be rejected. It indicates that the time series is non-stationary.

Table 4. Augmented Dickey-Fuller Test
McKinnon p-value for Z(t) = 0.7315 NS
*Significant at 5% NS=Not Significant

Variable	Coefficient	Standard Error	P-Value
price L1	-.0293932	.0168625	0.082NS
trend	.0063543	.0027438	0.021*
cons	-.093196	.2075714	0.654NS

No. of obs=287

Checking stationarity for the first differences are applied and conducted with the Unit Root tests again. The results of Augmented Dickey-Fuller test with first differences revealed to have a smaller value (0.000) than the significance level. Therefore, the variable in first differences is stationary. The variable is non- stationary but applying first differences, the variable is stationary. Therefore, the researchers used the ARIMA model because of the method of differencing.

Variable	Coefficient	Standard Error	P-Value
price LD	-1.067348	.0613125	0.000*
cons	.1850245	.104519	0.078NS

Table 5. Augmented Dickey-Fuller Test (Lag Difference)
McKinnon p-value for Z(t) = 0.0000*
*Significant at 5% NS=Not Significant
No. of obs=287

Auto-correlation Function is used to determine ―q.‖ The lags that exceeded the confidence band are 2, 7, etc. The researchers chose 2 because the researchers do not want to include many lags in the model because of parsimony (See Appendix G). Partial Autocorrelation Function is used to determine ―p.‖ The lags that exceeded the confidence band are 2, 7, etc. The researchers chose 2 because the researchers did not want to include many lags in the model because of parsimony (See Appendix G).

The researchers identified one possible model to estimate: ARIMA (2,1,2). is 1 because the time series in the first differences is stationary according to theresult with the ADF Test.

The coefficients generated using the ARMA

Regression Analysis are presented in Table 2. The findings of the ARIMA model regression showed that the AR L1, AR L2, MA L1, and MA L2 are significant with p-values less than

5% significance threshold, which is 0.000. Additionally, it shows that whereas MA L1 and MA L2 have positive coefficients, AR L1 and AR L2 have negative coefficients. In this case, the coefficients of AR L2 and MA L2 are closer to zero which means that the most recent observations are more closely connected to the present observations than the earlier observations (Javlacalle, 2014). Thus, the estimated ARIMA Model (2,1,2) are best fitted for

Variable	Coefficient	Standard Error	P-Value
ar L1	-1.083195	.036299	0.000*
ar L2	-.9819837	.0421607	0.000*
ma L1	1.048547	.0532223	0.000*
ma L2	.8855902	.0583287	0.000*

forecasting the series.

Table 6. ARIMA Model Regression
*Significant at 5% NS=Not Significant
No. of obs=287

The results of the Eigenvalue stability condition showed that the AR and MA roots lie inside the unit circle. It indicates that the AR and MA parameters satisfy the stability and invertibility conditions respectively (See Appendix G).

With the results from the diagnostic test that satisfies the conditions, the model is fit for forecasting. The figure below showed that in years 2021 to 2025, the price trend became consistent. However, the forecasted data is not always perfect. According to Reid and Sanders (2012) it is quite hard to make an accurate and precise forecasting of data. Forecasters are aware that they must accept complexity and unpredictability of the underlying system being forecasted. In making well-informed decisions, it is essential to estimate future results that are as precise and trustworthy as feasible.

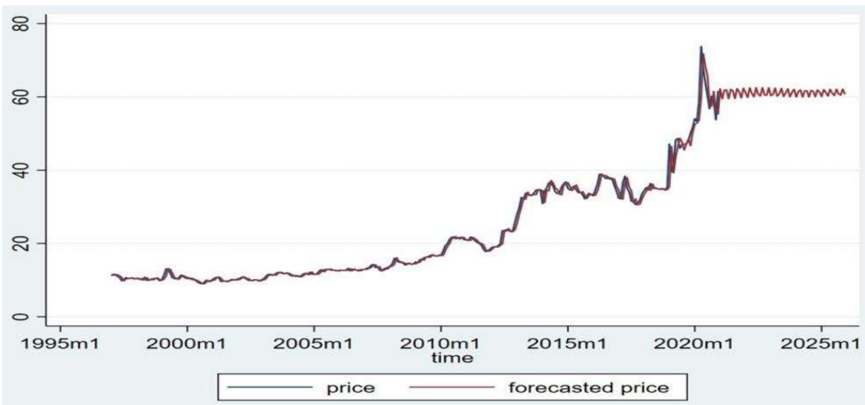


Figure 3. Forecasting

To further check the accuracy of the forecasted value, forecasting methods were used and compared with each other using MAD, MSE, and MAPE (See Appendix G). The results showed that the MAD accuracy value was 4.298515 while the MSE had 30.38302 accuracy value

and the MAPE had 6.777018 accuracy value.

According to Vivek (2020), the forecast error should be as low as possible in measuring the accuracy. Out of all forecasting accuracy methods used, MAD has the lowest value. Therefore, among the three accuracy methods, the researchers identified the MAD method with the value of 4.298515 as the more accurate forecasting method.

	MAD	RMSE	MAPE
Test Data	4.298515*	5.512079	6.777018

Table 7. Forecasting Accuracy Methods
*More Accurate Forecasting Method

CONCLUSION AND RECOMMENDATION

Conclusion

The research results showed that the price volatility of Lakatan Banana in Davao City is consistent however in the year 2020, the volatility is higher than the previous years. The potential reason for its high volatility is because of the pandemic which affects the consumer's spending behavior. The study used ARCH(1) and ARIMA(2,1,2) models as the best fitted model for capturing volatility and forecasting the Lakatan Banana retail price on a monthly basis. The researchers were able to forecast from 2021 until 2025. As for the concluding observation, the volatility of Lakatan Banana in Davao City is consistent with minimal volatility. The forecasted years were unaffected by the high volatility of price in 2020 and showed a consistent trend. In addition, both ARCH and ARIMA models only measure the volatility and monitor the fluctuations of the Lakatan banana but do not provide a reason for the existence of its volatility.

Furthermore, this study is supported by the work of Dinardi (2019), in which he used models for forecasting such as ARIMA and ARCH to predict the behavior of future stock returns. The ARIMA model is appropriate to be used in his work however the ARCH model is not appropriate because the time series does not present the ARCH effect. The work of Lestari et al. (2022) in which they used the ARCH-GARCH model to forecast the price volatility of red chili. Their work indicated that the data price of red chili in Semarang Regency starting January 2019 to February 2020 is volatile. In addition, our study is also being supported by the work of Ramesh et al. (2019), in which they utilized ARIMA to forecast the banana production in India. They forecast India's banana production for the years 2020–2025 using ARIMA (0,1,2) and data from the country's banana cropproduction from 1951–2019.

Recommendation

When the price volatility of lakatan bananas is stable, it is a good opportunity for farmers to focus on improving their production efficiency and cost-effectiveness. Some recommendations for farmers in this situation may include: First, implementing good agricultural practices (GAPs) to improve crop health and yield. This

may involve optimizing irrigation and fertilizing, controlling pests and diseases, and properly pruning and training plants. Second, diversifying their crops to spread risk and increase income stability. This could involve growing other fruit or vegetable crops alongside bananas, or even raising livestock or bees for additional income. Third, improving their supply chain management to reduce waste and increase profits. This may involve working directly with buyers, such as supermarkets or wholesalers, to negotiate better prices and reduce intermediaries in the supply chain. Fourth, investing in technology and infrastructure to increase efficiency and reduce costs. This could include using precision agriculture techniques, such as sensors and drones, to optimize irrigation and fertilizing, or investing in storage and transportation facilities to reduce post-harvest losses. Fifth is seeking out opportunities to add value to their products such as through processing or packaging. This may involve partnering with processors or developing their own value-added products, such as banana chips or purees.

When the price volatility of lakatan bananas is high, it can be challenging for farmers to plan and make informed decisions about their operations. In this situation, some recommendations for farmers may include: First, diversify the crops that are being grown on the farm. By growing a variety of crops, farmers can reduce their reliance on any one particular commodity and potentially mitigate the impact of price fluctuations. Second, consider entering into price risk management strategies, including futures contracts or hedging, to help protect against volatility in price. Third, consider forming partnerships or joining a cooperative with other farmers to increase bargaining power when selling crops. This can help to stabilize prices and provide a more stable income stream for the farm. Fourth, look for opportunities to add value to the crops being produced, such as byprocessing them into value-added products like dried bananas or banana chips. This can help to increase the overall profitability of the farm. Fifth, keep an eye on market trends and stay informed about any potential changes in demand or supply that could affect the price of bananas. This will allow farmers to make more informed decisions about their farming operations. Therefore, it is recommended for future researchers to apply demand and supply analysis.

As for the future researchers, they are recommended to try testing the GARCH Model to get a more generalized result of volatility. Moreover, rather than focusing on price volatility, they should consider studying the factors affecting the price of Lakatan bananas, particularly the future prices predicted by the model.

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