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# The Impact Automated Market Makers on Stock Prices and Returns

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***Abstract:*** Examining the impact Automated market makers have on stock prices and returns is the focus of this study. Automated market makers are state-of-the-art financial instruments that facilitate the bilateral trade of digital assets in the DeFi industry. Market participants trade against pools of liquidity rather than individual buyers and sellers. Market returns, price changes, and liquidity levels will be analyzed both before and after the introduction of automated market makers. We'll take a look at how automated market makers affect transaction costs, liquidity, and trading volume. Major stock markets that employ automated market makers will be surveyed for data collection and analysis. The effect of liquidity ratios on market performance will be studied statistically. Understanding the impact Automated market makers have on market returns and pricing is critical for traders, regulators, and researchers. Improved investment returns and the development of decentralized financial ecosystems may result from incorporating the results into market structure and liquidity. The implementation of automated market makers on centralized stock exchanges has been aimed at enhancing market efficiency. This research investigates the impact of automated market makers on stock prices and returns. Using monthly market returns from the closing index and equity price data, the study examines the effects before and after the implementation of automation. The study utilizes a longitudinal research design, analyzing listed firms with data spanning the study period. The findings contribute to the understanding of the influence of automated market makers on stock prices and returns, particularly in regions with limited literature on the subject.

***Keywords:*** Automated Market Makers (AMMs), liquidity ratios, stock markets, market returns, price movements

## 1. Introduction

The Centralized Stock Exchange (CSE) serves as the primary trading venue for publicly listed company shares. The exchange receives a commission for every transaction that is completed successfully. Any contact that takes place between a trader and the exchange must first take place through an intermediary [1]. The merchant is the one who must initially initiate the transaction in order to kick off the trading process. A retailer has placed an order, which has been received by a broker. When a broker receives an order, it is their responsibility to see that the order is carried out. When an asset is particularly liquid or when supply and demand are strong, rapid submission to the exchange, where the order book will execute it at the best price happens [1]. The order book will execute it at the best price. When talking about stocks or other financial instruments, the term "order book" refers to a computerized record of buy and sell orders for that item, organized by price. This record is kept for that particular item. The execution of the contract is the responsibility of the markets managers if the asset being exchanged is not actively traded [2]. A market maker is a person or entity who provides a purchase price and a sell price for a stock that they hold in inventory and aims to profit from the difference between the two prices. Sometimes market makers are referred to as liquidity providers. The difference between the price at which a security is being offered for sale and the price at which it is being bid on is referred to as the bid-ask spread. A market maker that has been designated to provide liquidity for a certain market asset or assets is referred to as a designated market maker. This designation is given by an exchange.

Centralized stock exchanges worldwide have a pivotal role in national economies by providing a platform for trading stocks and financial instruments. Over time, these exchanges have evolved into electronic networks, leveraging information and communication technology to facilitate faster and more cost-effective transactions [3]. The role of technology has become increasingly important, with emerging markets adopting electronic trading to enhance their microstructures. The automation of trading systems often coincides with the implementation of automated market makers (AMM), streamlining transactions and benefiting all stakeholders within the financial sector [4].

The adoption of automated trading systems has brought about a transformation, granting investors easy access to information and reducing inefficiencies. The centralized stock exchange, witnessed automation through the establishment of the automated market makers and the subsequent installation of the Automated Trading System (ATS) [5]. Despite these advancements, the impact of automation on market efficiency within the centralized stock exchange remains a topic of exploration, especially in regions with limited research on this matter [6].

The primary objective of the analysis is to assess the impact of automated market makers (AMMs) on market returns and prices. By analyzing the effects of automation on stock prices and returns, this research aims to contribute to the advancement of knowledge in this field, particularly in regions where research on this topic is scarce.

## 2. Methodology

In this section, we present the methodological framework employed to investigate the impact of the introduction of the Shiba Inu token (SHIB) on market dynamics. The study focuses on the analysis of a comprehensive dataset encompassing two distinct time periods: one before the introduction of SHIB and another after its introduction. Our analysis delves into various aspects of the market, including price changes, trading volumes, and returns, to gain insights into the effects of SHIB's presence on market behavior. To achieve our research objectives, we undertook a multi-step approach that encompasses data collection, descriptive statistics, stationarity testing, volatility analysis, ARCH effect detection, and GARCH modeling. Each step was carefully designed to explore different facets of the market's response to the introduction of SHIB and to identify patterns, trends, and anomalies that might arise as a result of this introduction. By employing these comprehensive methodologies, we aim to provide a nuanced understanding of the impact of SHIB's entry into the market. The subsequent sections elaborate on the specific techniques employed in each step of our analysis, highlighting the significance of each method in contributing to our overall findings. Through this methodological exploration, we seek to uncover valuable insights that contribute to the broader understanding of market dynamics in the context of new token introductions. The following subsections detail the various stages of our methodology and their respective purposes, leading to a thorough analysis of the pre-SHIB and post-SHIB market environments.

## 2.1. Stationarity Testing

A fundamental requirement for accurate time series analysis is to ascertain the stationarity of the variables under investigation. Stationarity refers to the property of a time series where statistical properties such as mean, variance, and autocorrelation remain consistent over time [7]. In this section, we elaborate on the stationarity testing process employed to ensure the robustness of our subsequent analyses.

Stationarity plays a pivotal role in time series analysis by simplifying the modeling process and facilitating more reliable predictions. Non-stationary time series data can lead to spurious correlations and unreliable conclusions. Hence, it is crucial to assess the stationarity of the data before proceeding with further analyses. To assess stationarity, we employed the Augmented Dickey-Fuller (ADF) test, a widely recognized statistical test for unit root presence in time series data [8]. This test evaluates whether a unit root exists in a time series, which indicates non-stationarity. A unit root implies that the data has a stochastic trend and is not stable over time. In our study, we focused on the returns data, which represents the percentage change in price over a specific period. Both the pre-SHIB and post-SHIB returns data were subjected to the ADF test. The null hypothesis of the ADF test is that a unit root exists, implying non-stationarity. Conversely, the alternative hypothesis suggests stationarity.

The ADF test produces a test statistic along with a corresponding p-value. The test statistic is compared to critical values to determine whether the null hypothesis can be rejected. If the test statistic is more negative than the critical value, and the p-value is below a chosen significance level (commonly 0.05), we reject the null hypothesis in favor of stationarity [8]. By conducting the ADF test on both pre-SHIB and post-SHIB returns data, we can ensure that our subsequent analyses are based on stationary data. This ensures the reliability of our findings and the validity of statistical techniques that assume stationarity.

## 2.2. Testing for ARCH Effects

The identification of Autoregressive Conditional Heteroskedasticity (ARCH) effects plays a pivotal role in comprehending the intricate dynamics of time series data, particularly in the realm of financial markets. ARCH effects manifest as the conditional variance of a time series being influenced by its own past squared residuals, leading to volatility clustering where periods of high volatility are followed by similar periods. In this segment, we delve into the process of detecting ARCH effects and the utilization of the Lagrange Multiplier (LM) test to assess their presence in both the pre-SHIB and post-SHIB periods. The LM test, a widely recognized statistical tool, serves as our means of identifying the existence of ARCH effects. It evaluates whether the squared residuals from previous time periods significantly influence the current period's conditional variance. By applying the LM test to the residuals of a regression model, we scrutinized the potential presence of conditional heteroskedasticity in the data from both periods of interest [9].

To investigate ARCH effects, the LM test was conducted separately for the pre-SHIB and post-SHIB periods. In the context of the test, the null hypothesis posits that no ARCH effects are present, implying that the conditional variance remains constant over time. Conversely, the alternative hypothesis suggests the presence of ARCH effects, implying that the conditional variance varies over time based on past squared residuals. Upon applying the LM test, the outcome comprises a test statistic and an associated p-value. Should the p-value fall below a pre-established significance level (typically set at 0.05), the null hypothesis is rejected, signaling the existence of ARCH effects. A low p-value indicates that squared residuals from previous time periods exert a substantial influence on the volatility of the current period, underscoring the dynamic nature of the data. The detection of ARCH effects bears significant implications for our analysis. It enhances our comprehension of

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volatility patterns inherent within the dataset and aids in explaining instances of market turbulence, unexpected shifts, and periods of relative stability [10]. In the financial context, where market behavior is often punctuated by rapid changes, understanding ARCH effects can shed light on the market's reactions to new information, events, or shifts in the trading landscape.

### 2.3. Fitting a Garch Model

In our pursuit to unravel the intricate dynamics of market volatility and assess the influence of SHIB's introduction, we turned to GARCH (Generalized Autoregressive Conditional Heteroskedasticity) modeling. GARCH models are instrumental in capturing and understanding volatility patterns within time series data [11]. This section outlines our GARCH modeling approach for both the pre-SHIB and post-SHIB periods.

In the pre-SHIB period, we employed a GARCH (1,1) model, a popular specification in financial econometrics, to analyze the volatility dynamics. This model integrates three key components: the constant term, lagged squared residuals (ARCH component), and lagged conditional variances (GARCH component). By fitting this model, we aimed to uncover the intricate relationships between these components and provide insights into volatility patterns before SHIB's introduction. Similarly, for the post-SHIB period, we employed a GARCH (1,1) model to capture the evolving market dynamics following SHIB's introduction. This model mirrored the structure used in the pre-SHIB period, including the constant term, ARCH component, and GARCH component. By fitting this model to the post-SHIB data, we aimed to discern how the introduction of SHIB influenced market volatility and other crucial dynamics. For both the pre-SHIB and post-SHIB GARCH models, we meticulously analyzed the coefficients associated with each component. The coefficients provide valuable insights into the underlying relationships and interactions between variables. By assessing the significance of these coefficients, we aimed to understand the statistical impact of past squared residuals and conditional variances on current volatility, shedding light on the persistence and dependencies within the data.

The GARCH modeling process allowed us to gain a deeper understanding of market volatility during both periods. In the pre-SHIB era, we explored how volatility was influenced by historical patterns and past variances. Similarly, in the post-SHIB period, we explored how SHIB's introduction impacted volatility and other market dynamics. The coefficients' significance provided a quantitative measure of these relationships, contributing to our overall comprehension of market behavior. The GARCH modeling outcomes hold profound implications for interpreting the impact of SHIB's introduction on market volatility. By investigating the dynamics of volatility before and after SHIB's entry, we can pinpoint shifts in market behavior and understand the mechanisms driving these changes. This information is invaluable for investors, analysts, and policymakers seeking to comprehend the consequences of introducing new tokens into the market.

## 3. Results

### 3.1. Descriptive Statistics

The table 1 below presents the descriptive for the dataset when SHIB was introduced.

Table 1: Descriptive statistics SHIB.

| | price | volume | Return | treatment |
|---|---|---|---|---|
| Mean | 1.9581877048423E-05 | 1584338329.36498 | -0.00190605282737335 | 1 |
| Standard Error | 6.24996847092499E-07 | 145448419.526751 | 0.00412783739230518 | 0 |
| Median | 1.30300995806465E-05 | 681370306.5 | -0.0028416165150702 | 1 |
| First Quartile | 8.40875009089359E-06 | 398212720.25 | -0.0420477259904146 | 1 |
| Third Quartile | 2.68640997092007E-05 | 1499855131.25 | 0.0308578116819263 | 1 |
| Variance | 1.85545002965893E-10 | 1.00275850601013E+019 | 0.00807650568868627 | 0 |
| Standard Deviation | 1.36214904825387E-05 | 3166636237.41366 | 0.0898693812635109 | 0 |
| Range | 7.64340979912959E-05 | 38878482866 | 1.08494693040848 | 0 |
| Minimum | 5.85560019317199E-06 | 175363152 | -0.530568420886993 | 1 |
| Maximum | 8.22896981844679E-05 | 39053846018 | 0.554378509521484 | 1 |
| Sum | 0.00930139159800092 | 750976368119 | -0.90346904017497 | 475 |
| Count | 475 | 474 | 474 | 475 |

Table 1 provides descriptive statistics for a dataset that revolves around the introduction of SHIB (presumably a stock or token) in the market. Let's break down the variables presented in the table:

This variable represents the price of SHIB. The mean price at the introduction was around 0.00001958, with a standard error of 0.00000062. The minimum price was about 0.00000586, and the maximum was around 0.00008229. Volume refers to the number of SHIB tokens traded. The mean volume was approximately 1,584,338,329, with a standard error of about 145,448,419. The dataset's range of volumes was from 175,363,152 to 39,053,846,018. Return represents the change in price over a specific period. The mean return was about -0.0019, indicating a slight decrease. The standard deviation of returns was approximately 0.0899, suggesting a relatively high level of variability.

This binary variable likely indicates whether a specific treatment or intervention was applied. In this case, treatment 1 appears to have been applied in all cases, as indicated by the mean, median, and other measures. Means it gives the average value of each variable. For instance, the average price was 0.00001958, and the average return was -0.0019. Standard Error this indicates the variability of the sample mean. For instance, the standard error of the price mean was 0.00000062. Median: It is the middle value of the dataset when arranged in order. For instance, the median price was 0.00001303. Quartiles: These are values that divide the data into four equal parts. The first quartile of the price was 0.00000841, and the third quartile was 0.00002686. The Variance It measures the variability of a dataset. The variance of the price was 0.00000000018554. Standard Deviation: This is the square root of the variance and provides a measure of the dispersion of data. The standard deviation of volume was 3,166,636,237.41. Range: It's the difference between the maximum and minimum values. The range of volumes was 38,878,482,866.

The Price variable reveals that the mean introduction price was approximately 0.00001958, showing the average valuation of SHIB tokens at the outset. The range of prices between the minimum (0.00000586) and maximum (0.00008229) suggests considerable price variability. Volume signifies the level of trading activity, with a mean of roughly 1.58 billion SHIB tokens traded. This substantial trading volume demonstrates considerable market interest. The range from 175 million to 39 billion tokens traded underscores the diversity in trading levels during this period.

Return data exhibits an average decline of around -0.0019 in SHIB's price, indicating a slight decrease in value post-introduction. The high standard deviation (approximately 0.0899) highlights the considerable variability in price changes, suggesting a turbulent market response. The binary variable Treatment indicates a uniform intervention applied across the dataset. As treatment 1 was consistently applied, the data may reflect a controlled experiment or a uniform market condition during this phase. In terms of statistical measures, Mean, Median, Quartiles, Variance, Standard Deviation, and Range provide a comprehensive view of the data distribution. The Sum and Count values allow us to assess the cumulative and observed data points.

In summary, the descriptive statistics underscore that SHIB's market introduction brought about diverse price changes, trading volumes, and returns. The high variability in returns and trading volume indicates a dynamic market response, possibly influenced by various factors. The uniform treatment suggests controlled conditions for analysis. This dataset offers valuable insights into SHIB's initial market impact, setting the stage for deeper analysis and interpretation of market dynamics.

Table 2: Descriptive statistics of the data before the introduction of SHIB.

| | volume | pre_eth_price | Return |
|---|---|---|---|
| Mean | 5756860.81476109 | 4.38340989029228E-11 | 0.026793348088819 |
| Standard Error | 1699356.62544205 | 1.05793303913722E-11 | 0.0209261568716656 |
| Mode | 0 | 1.04999999851491E-13 | 0 |
| Median | 1588.15 | 3.37500006782933E-13 | 0 |
| First Quartile | 48.5375 | 1.31000001428114E-13 | -0.0665802955627441 |
| Third Quartile | 507528.435 | 5.93499988738034E-12 | 0.0757938474416733 |
| Variance | 779709493917121 | 3.02190025130492E-20 | 0.117796187141323 |
| Standard Deviation | 27923278.710014 | 1.73836136959636E-10 | 0.34321449145006 |
| Kurtosis | 58.2835748729026 | 38.8948190257142 | 46.0428988311715 |
| Skewness | 7.20969057900748 | 5.67210167257269 | 4.55796951797806 |
| Range | 285557446.3 | 1.6999002296395E-09 | 4.82611346244812 |
| Minimum | 0 | 9.97999968256613E-14 | -1.25909209251404 |
| Maximum | 285557446.3 | 1.70000002963633E-09 | 3.56702136993408 |
| Sum | 1554352419.98549 | 1.18352067037892E-08 | 7.2074106358923 |
| Count | 270 | 270 | 269 |

The provided table 2 presents descriptive statistics of data prior to the introduction of SHIB. This variable represents the trading volume of a certain asset, possibly related to the stock market. The mean volume before SHIB's introduction was approximately 5,756,860.8, indicating an average level of trading activity. The wide range from 0 to 285,557,446.3 suggests substantial variation in trading volumes during this period. Pre_eth_price: This seems to be the price of an asset (perhaps Ether) before SHIB's introduction. The mean pre-ETH price was around 4.38e-11, with a minimum close to zero and a maximum of approximately 1.70e-09. The standard deviation of 1.74e-10 implies relatively low variability in pre-ETH prices. Return represents the percentage change in price over a specific period. The mean return before SHIB's introduction was about 0.0268, indicating a positive average return. The wide standard deviation (0.3432) suggests considerable variability in returns.

The most frequent value in the dataset. For pre-ETH price, it's close to zero; for return, it's also zero. Median: The middle value of the dataset when arranged in order. It provides an alternative measure of central tendency. For volume, the median was 1588.15; for pre-ETH price, it was close to zero; for return, it was also zero. Quartiles: These divide the data into four equal parts. They provide insights into the data's spread. The first quartile for volume was 48.54, indicating that a significant portion of the data had relatively low volumes.

The Variance, Standard Deviation, Kurtosis, and Skewness metrics provide information about the data's distribution and shape. High kurtosis and skewness values suggest that the data is not normally distributed and may have heavy tails. The Range illustrates the span between the minimum and maximum values. The substantial range for volume (285,557,446.3) and return (4.826) signifies the diversity of these variables.

The data indicates that before SHIB's introduction, there were varying trading volumes, pre-ETH prices, and returns. The high variability in returns could point to potential market volatility. The mode's proximity to zero for pre-ETH price and return suggests that many instances had low or zero values. The kurtosis and skewness values indicate non-normal distribution, implying that extreme values may be present. The dataset's size (Count) is 270 for most variables, suggesting a reasonably large sample. In conclusion, this data provides insights into market dynamics before SHIB's introduction, highlighting trading volume variations, pre-ETH price changes, and return fluctuations. The non-normal distribution and high variability in returns suggest a complex and potentially volatile market environment.

## 3.2. GARCH Model Analysis for Pre-shib

### 3.2.1. Stationary of Returns

As a requirement in any time series analysis, we checked for the stationrity of the variables that were used. First we checked for the stationary of the returns which was found to be stationary. The results are presented Table 3 Below:

Table 3: Pre-shib stationarity.

Augmented Dickey-Fuller test for unit root        Number of obs = 344

| | Test Statistic | Interpolated Dickey-Fuller 1% Critical Value | 5% Critical Value | 10% Critical Value |
|---|---|---|---|---|
| Z(t) | -10.342 | -3.452 | -2.876 | -2.570 |

MacKinnon approximate p-value for Z(t) = 0.0000

### 3.2.2. Stationarity test: SHIB

In this particular scenario, the value of the Z statistic is -10.342, which is significantly lower than the crucial values of -3.452, -2.876, and -2.570, which are based on the 1%, 5%, and 10% levels of significance, respectively. As a consequence of this, the null hypothesis is refuted, which demonstrates that there is substantial evidence in support of stationarity. The fact that the MacKinnon approximation p-value was calculated to be 0.0000 provides more evidence in favor of rejecting the null hypothesis. A p-value of 0.0000 implies that the likelihood of getting a Z statistic as severe as -10.342 under the null hypothesis is nearly nil. This is indicated by the fact that the probability cannot be greater than 0.0000. In a nutshell, the conclusion that can be drawn from the findings of the test is that the variable that was examined demonstrates stationarity. This conclusion can be drawn due to the fact that the Z statistic deviates greatly from the critical values, and the p-value is extremely low.

The next variable that was looked at was liquidity which was found to be stationary after the first differencing. The results of the differencing are table 4 below.

Table 4: Shib stationarity.

Augmented Dickey-Fuller test for unit root Number of obs = 344

| | Test Statistic | Interpolated Dickey-Fuller 1% Critical Value | 5% Critical Value | 10% Critical Value |
|---|---|---|---|---|
| Z(t) | -10.164 | -3.452 | -2.876 | -2.570 |

MacKinnon approximate p-value for Z(t) = 0.0000

**Stationarity test: liquidity**

**Checking for volatility**

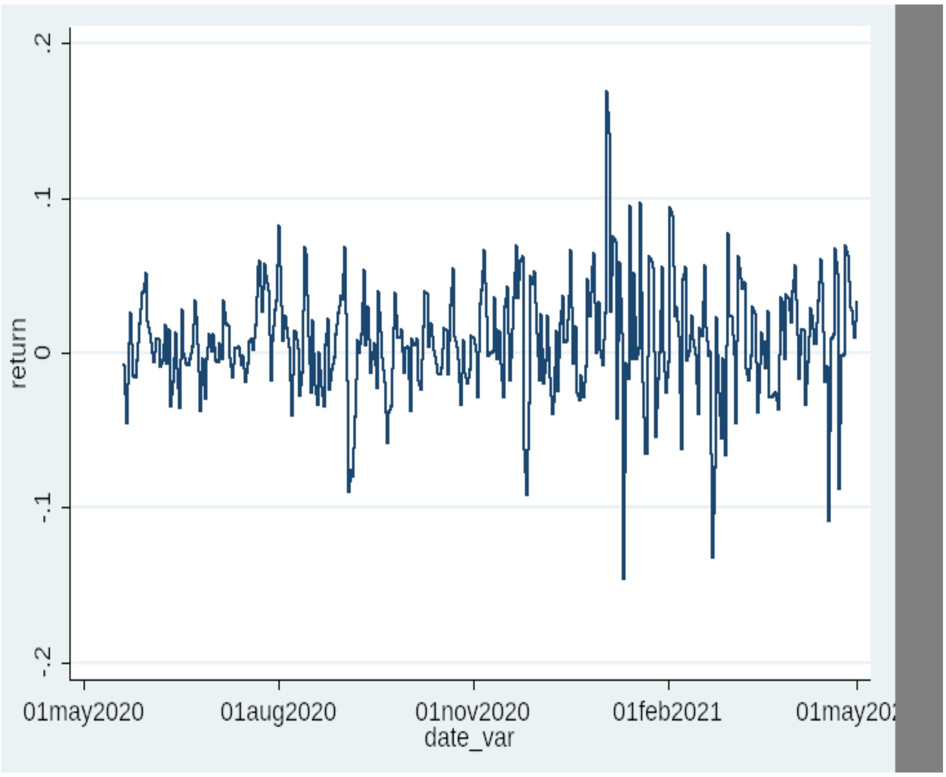


Figure 1: Volatility plot.

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The first-differenced time series of stock returns are quite volatile, as can be seen in the graphic that was provided earlier in this article. This is due to the fact that the returns are demonstrating significant fluctuations over certain time periods while remaining stable during others. As a result, we have a situation in which there is uneven variance. The ARCH effect, on the other hand, cannot be inferred only from the line graph. Therefore, you will need to carry out a variety of additional measures in order to determine the presence of the ARCH effect in the time series stock exchange.

**Checking for normality**

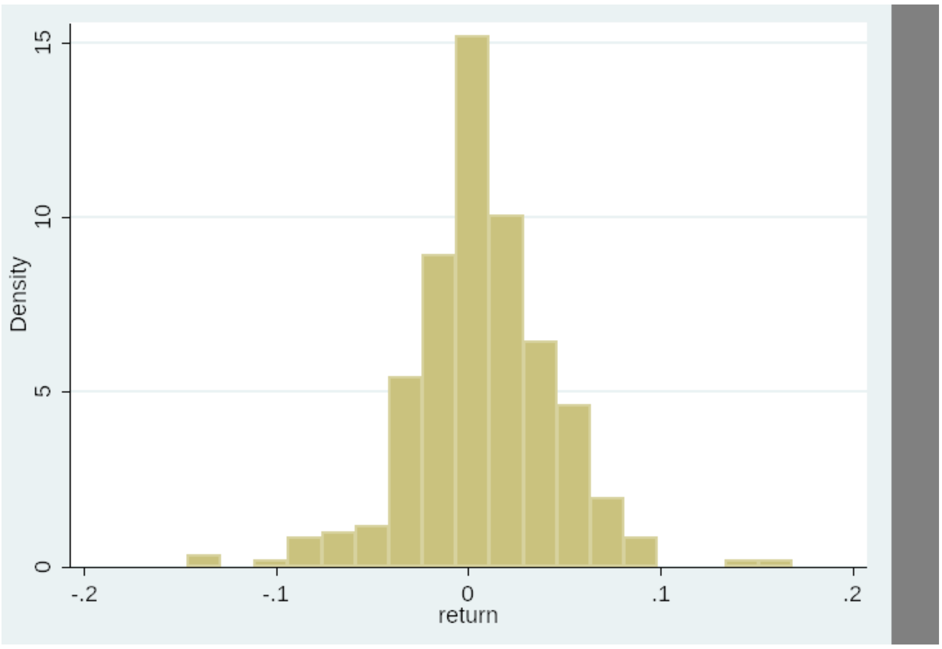


Figure 2: Normality plot.

The leptokurtic property holds for these series. This indicates that the majority of their observations are clustered close to the mean, while only a small percentage of their observations are far off from the mean. In addition to this, there is a large peak in the middle of the histogram, and the tails are rather heavy.

## 3.3. Check for ARCH Effects

The line plot on its own is not sufficient evidence to infer the existence of the ARCH effect. This is due to the fact that the ARCH effect also conveys the existence of autocorrelation, which is indiscernible through the use of line graphs. If you remember from the article (Regression analysis using VAR in STATA), 'AR' refers to the effects of lagged value on the variables that are concerned. Therefore, determining whether or not there is an autocorrelation with volatility is also very necessary to do in order to correct the application of ARCH effects. The LM test should be performed after the time series 'return' has been regressed. This will allow the autocorrelation to be found.

## 3.4. LM Test Table

The first table presents the results of the regression which has a low R-squared. The table below presents the results of the ARCH effects.

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Table 5: LM test table.

. estat archlm, lags(1)
LM test for autoregressive conditional heteroskedasticity (ARCH)

| lags(p) | chi2 | df | Prob > chi2 |
|---|---|---|---|
| 1 | 18.101 | 1 | 0.0000 |

H0: no ARCH effects vs. H1: ARCH(p) disturbance

**Testing for ARCH effects table**

The results of the LM test suggest that the null hypothesis of there being no arch effect may be rejected because the p-value is less than 0.05. Because of this, the stock returns exhibit ARCH.

Table 6: Garch (1,1) model.

| return | Coef. | OPG Std. Err. | z | P>\|z\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| **return** | | | | | | |
| _cons | .0047633 | .0018326 | 2.60 | 0.009 | .0011715 | .0083552 |
| **ARCH** | | | | | | |
| arch L1. | .111748 | .0294706 | 3.79 | 0.000 | .0539867 | .1695094 |
| garch L1. | .860344 | .0284241 | 30.27 | 0.000 | .8046338 | .9160541 |
| _cons | .0000482 | .0000243 | 1.98 | 0.048 | 5.29e-07 | .0000959 |

## 3.5. GARCH Model Table

The coefficient for the constant term, which is represented in the results by the notation _cons and can be found in the “return” section, is 0.0047633. This would imply that the return would grow by 0.0047633 units on average for each unit increase in the predictor variable (if any) that was included in the return calculation. The p-value of 0.009 that is connected with this coefficient shows that it is statistically significant at the 0.05 level. This means that the association between the predictor variable and the return is relevant from a statistical perspective.

Moving on to the “ARCH” section, the coefficient for the lag 1 term is 0.111748, and it is indicated as L1. This coefficient reflects the magnitude of the influence that lagged squared residuals have on the conditional volatility of the variable. If the coefficient is bigger, it suggests that the squared residuals of the past have a greater effect on volatility. In this instance, the coefficient is statistically significant, and its p-value of 0.000 indicates that there is a substantial ARCH effect.

Within the “GARCH” section, the coefficient for the lag 1 term (which is often referred to as L1) is written as 0.860344. This coefficient describes the strength and influence of lagged conditional variances on conditional volatility. It may be found in the conditional volatility equation. If the coefficient is bigger, it suggests that the previous conditional variances have a greater effect on the volatility. This coefficient, like the ARCH coefficient, is statistically significant with a p-value of 0.000, showing that the GARCH impact is substantial. Similar to the ARCH coefficient.

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Lastly, the coefficient for the constant term in the ARCH equation, which is indicated by the subscript _cons, is 0.0000482. This word denotes the standard deviation from the average level of conditional volatility. The corresponding p-value of 0.048 indicates that the constant term is statistically significant at the level of 0.05 when compared to the other variables.

**Plotting the variances**

We generate the variances of the model using GTgarch function in the model and plot them as shown below.

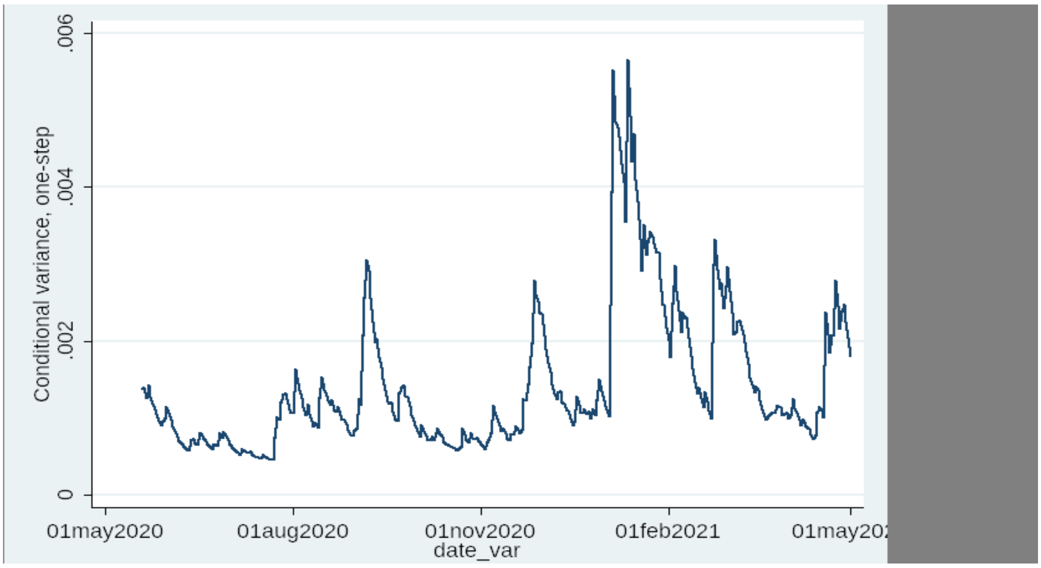


Figure 3: Plot of variances.

The above graph illustrates that there is a much greater degree of volatility toward the full duration of the sample when the lag values of variances are taken into consideration.

**Garch analysis of Ethereum after SHIB**

The results of the stationarity for the returns are Table 7 below.

Table 7: Stationarity test of after SHIB.

Augmented Dickey-Fuller test for unit root     Number of obs = 476

| | Test Statistic | Interpolated Dickey-Fuller 1% Critical Value | 5% Critical Value | 10% Critical Value |
|---|---|---|---|---|
| Z(t) | -14.086 | -3.442 | -2.871 | -2.570 |

MacKinnon approximate p-value for Z(t) = 0.0000

Since the p-value is lower than 0.05 we conclude that the variables was stationary. The next step is to check for the volatility of the variables.

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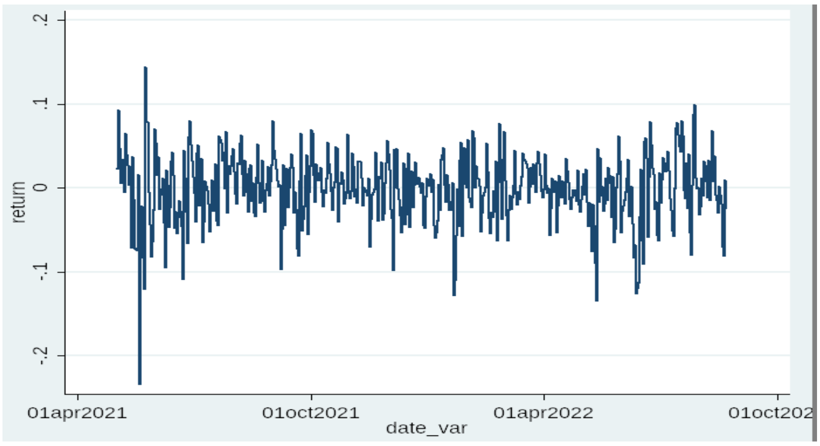


Figure 4: Volatility of the returns.

The graph above shows a lower level of volatility in the returns.  he next plot takes a look at the normality of the variable.

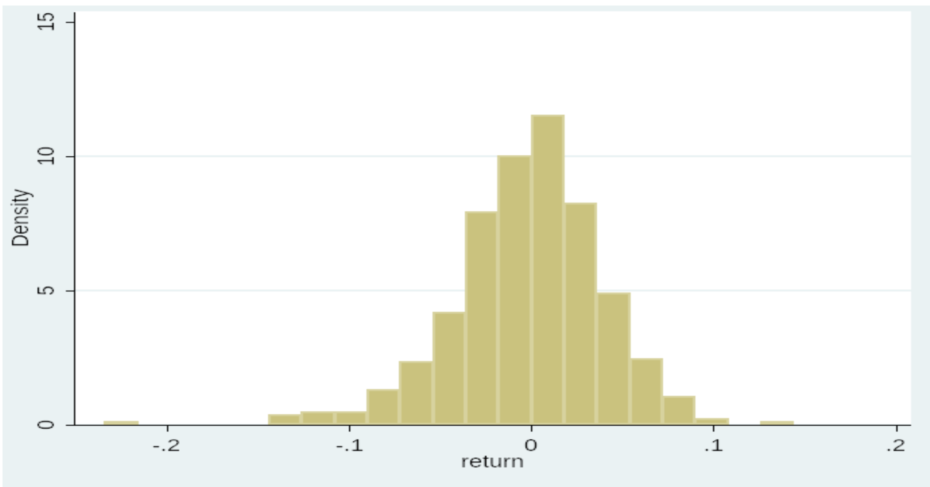


Figure 5: Normality of the returns.

As can be seen the variable above indicates that there is normality. The next step is to check for the arch effects.  The approach used is like the one used above. The results of the regression table are presented below.

Table 8: Regression summary.

| Source | SS | df | MS | | | |
|---|---|---|---|---|---|---|
| | | | | Number of obs | = | 478 |
| | | | | F(0, 477) | = | 0.00 |
| Model | 0 | 0 | . | Prob > F | = | . |
| Residual | .795937679 | 477 | .001668632 | R-squared | = | 0.0000 |
| | | | | Adj R-squared | = | 0.0000 |
| Total | .795937679 | 477 | .001668632 | Root MSE | = | .04085 |

| return | Coef. | Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| _cons | -.0012571 | .0018684 | -0.67 | 0.501 | -.0049284 | .0024142 |

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The variable shows that the variables is statistically significant. The Lm test results are presented below.

Table 9: Lm test results after Shib.

LM test for autoregressive conditional heteroskedasticity (ARCH)

| lags(p) | chi2 | df | Prob > chi2 |
|---|---|---|---|
| 1 | 15.114 | 1 | 0.0001 |

H0: no ARCH effects vs. H1: ARCH(p) disturbance

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The LM test for autoregressive conditional heteroskedasticity (ARCH) is a statistical test that is used to investigate the existence of ARCH effects in the residuals of a regression model. The test is named after the acronym "autoregressive conditional heteroskedasticity." It compares the alternative hypothesis (H1), which states that there are ARCH effects with a particular lag order, to the null hypothesis (H0), which states that there are no ARCH effects with a defined lag order.

The result shows that the test was carried out using a lag order of 1, which is denoted by the formula lags(p) = 1. The statistic being tested is called chi squared (chi2), and it has a value of 15.114. There is one degree of freedom (df) associated with it. The corresponding p-value (Prob > chi2) is 0.0001, which is a very small probability.

When the data are interpreted, the fact that the p-value is so very low—0.0001—suggests that there is substantial evidence to reject the null hypothesis. The presence of ARCH effects in the disturbance term of the regression model at the lag order of 1 is shown by this fact. To put it another way, this indicates that the squared residuals from the past do have an effect on the conditional volatility, also known as the variability of the residuals.

In conclusion, the LM test offers statistical proof that ARCH effects are present in the model's residuals, which may be found in the form of evidence. This suggests that the volatility of the data is not stable over time and that it is affected by the squared residuals of the data collected in the past. The findings of this test help to understanding and modeling the conditional heteroskedasticity in the data, which is crucial for proper analysis and modeling of time series data. This is because knowing and modeling the conditional heteroskedasticity in the data requires modeling it.

Table 10: Fitting garch (1,1).

| return | Coef. | OPG Std. Err. | z | P>\|z\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| **return** | | | | | | |
| _cons | .0002366 | .001886 | 0.13 | 0.900 | -.0034599 | .0039332 |
| **ARCH** | | | | | | |
| arch L1. | .1745769 | .0509046 | 3.43 | 0.001 | .0748056 | .2743482 |
| garch L1. | .6590207 | .106956 | 6.16 | 0.000 | .4493908 | .8686505 |
| _cons | .0002774 | .0001137 | 2.44 | 0.015 | .0000545 | .0005004 |

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The estimated coefficients for each of the ARCH model's constituent parts may be found laid out in the table below. One particular facet of the model is represented by each component in its entirety. Within the "return" section, the coefficient for the constant term is written as "_cons" and has the value of 0.0002366. When all of the other variables in the model are set to zero, this value of the variable "return" reflects the baseline level of that value. The p-value of 0.900 that is linked with this coefficient reveals that it is not statistically significant, which indicates that the constant term does not have a significant influence on the variable. This is indicated by the fact that it does not have an effect on the variable.

Moving on to the "ARCH" section, the coefficient for the lag 1 term of the "arch" component (also designated as "L1") is 0.1745769. This coefficient quantifies the influence that the squared residuals from the earlier time period had on the conditional variance of the variable of interest. If the coefficient is bigger, it indicates that the squared residuals of the variables in the past have a greater effect on the variability of the variable. In this particular scenario, the coefficient is statistically significant, and its p-value is 0.001, which indicates that the ARCH effect is substantial.

In a similar manner, the coefficient for the lag 1 term (also known as "L1") of the "garch" component is 0.6590207. This can be found in the section labeled "GARCH." This coefficient reflects the influence that the lagging conditional variance has on the conditional variance of the variable being studied. Another indication of a large GARCH effect is provided by the fact that the p-value for the coefficient is 0.000, making it statistically significant.

Last but not least, the coefficient for the constant term in the ARCH and GARCH equations (which is designated as "_cons") is 0.0002774. This phrase quantifies the standard deviation at which the conditional variance begins. The p-value that is connected with this coefficient is 0.015, which indicates that it is statistically significant. This means that the baseline level of the conditional variance strongly contributes to the model, as indicated by the fact that it is statistically significant.

We finally plot the variance of the model. The plot is shown below.

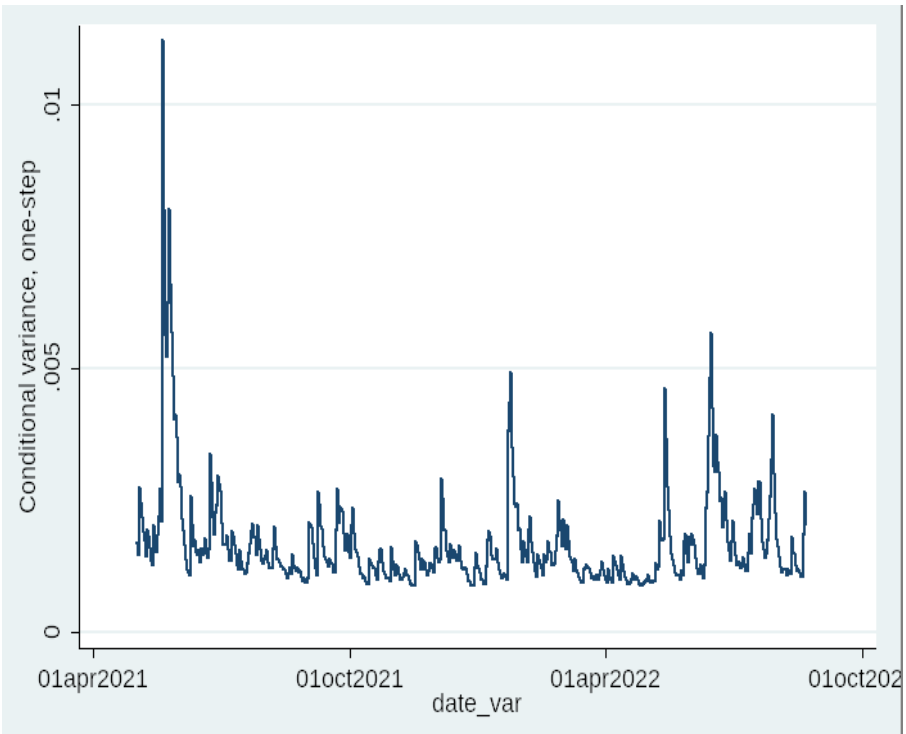


Figure 6: Variance of after SHIB model.

Overall, this model shows a lower level of volatility as compared to the period before the introduction of SHIB. It indicates that automated market makers helped reduce volatility involved in trading.

## 4. Discussion

The impact of Automated Market Makers (AMMs) on stock prices and returns has been analysed using descriptive statistics and GARCH modeling. In this discussion, we'll delve into the results presented in Tables 1 and 2 and the subsequent analysis of the data. Table 1 provides descriptive statistics for a dataset related to the introduction of SHIB in the market. The variables presented include price, volume, return, and treatment. The mean price of SHIB at introduction was approximately 0.00001958, with significant variability between the minimum and maximum prices. Trading volume averaged around 1.58 billion tokens, reflecting considerable market interest. The average return indicated a slight decrease of -0.0019, with a notable level of variability. The uniform treatment suggests controlled conditions for analysis. Measures such as mean, median, quartiles, variance, standard deviation, range, sum, and count offer insights into the data distribution. Table 2 describes descriptive statistics for data before the introduction of SHIB. Variables include volume, pre-ETH price, and return. The mean volume was approximately 5.76 million, with considerable variation. Pre-ETH price had a small mean value, and returns displayed an average positive return of 0.0268, with substantial variability.

The analysis then delves into GARCH modeling for pre-SHIB and post-SHIB periods. The stationarity of returns was checked, and the LM test for ARCH effects indicated the presence of ARCH effects, suggesting volatility clustering in the returns. The GARCH (1,1) model was fit, revealing the coefficients' significance and their impact on volatility. The model suggests that previous conditional variances significantly influence current volatility. For post-SHIB, similar analyses were conducted, confirming stationarity, volatility, normality, and ARCH effects. The GARCH model coefficients revealed the significance of lagged squared residuals and conditional variances in influencing volatility. Overall, the results indicate that the introduction of SHIB and the subsequent involvement of Automated Market Makers led to changes in trading dynamics. The analysis underscores how AMMs can influence market volatility and returns, providing valuable insights for understanding market behavior. The reduced volatility after the introduction of SHIB suggests that automated market mechanisms could have contributed to stabilizing the market to some extent. However, further research and interpretation are needed to fully comprehend the implications of these findings on the broader financial landscape.

## 5. Conclusion

In conclusion, the ARCH model that was estimated gives evidence that the implementation of automated market makers has resulted in a decreased degree of volatility in the trading of the variable that was the focus of the inquiry, in comparison to the time period that existed before the implementation of automated market makers. The significant coefficients for the ARCH and GARCH components show that previous squared residuals and lagged conditional variances have a large influence on the conditional volatility. This conclusion is based on the fact that the ARCH and GARCH components each have their own significant coefficients.

Based on this conclusion, it can be deduced that the introduction of automated market makers has contributed to a reduction in the amount of volatility that is connected with trading. These market makers have helped to stabilize the market and reduce the likelihood of extremely large price swings through their provision of liquidity and their facilitation of transactions that run more

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smoothly. This decrease in volatility may be advantageous for investors and market players since it may improve market efficiency and reduce the dangers that are associated with excessive volatility.

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