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# Behavioral finance research of the Tehran Stock Exchange by mathematical round numbers in the Tehran Stock Exchange's overall index

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**Abstract**

The formation of market interactions is directly affected by the decision-making of market players. This paper seeks to assess the presence of behavioral finance on the Iranian financial market as a factor influencing market participants' decisions. The current study evaluates the existence of behavioral finance on the Iranian capital market by focusing on the phenomena of "price clustering" in the total index of the Tehran Stock Exchange. It proposes a new criterion for identifying behavioral bias in the financial market. One of the reasons for the lack of uniformity in the distribution of data in the total index of Tehran securities is the propensity of individuals to make individual decisions based on the index of total securities of Tehran. People use the total index as a criterion for making decisions, and when the total index reaches round numbers, their purchasing and selling behavior changes. The results of the study validate the phenomena of price clustering in round numbers in Tehran's total stock index. In actuality, the lack of uniform distribution in the total index numbers of Tehran stock is an appropriate indicator of the existence of behavioral finance on the Tehran Stock Exchange. The main differentiating aspect of this study is the introduction of the overall index as a new measure compared to individual symbols for demonstrating behavioral bias in the financial market, which has been employed in previous studies.

*Keywords:* Behavioral finance, price clustering, total index, round numbers

*JEL Classification:* G10, G11, G19

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## 1. Introduction

In recent years, one of the most distinguishing characteristics of Iran's economy has been the high volatility of key economic variables. The high volatility of economic variables makes it an ideal subject of study for scholars who can analyze economic phenomena and concerns in diverse ways. The allocation of resources in the economy in the most efficient manner is the primary and most essential function of the economic system, which is accomplished by the markets. The fair price for any commodity or resource is determined to achieve this optimal allocation.

In numerous of these studies, the causes and mechanisms of the capital market phenomenon of behavioral finance have been identified. How should we determine the existence or nonexistence of this phenomenon, given that the question is still open? In other words, does this phenomena of human irrationality or behavioral finance exist in a market, and what is the best criterion for demonstrating its existence or nonexistence? This study examines the most significant indicators of the presence or absence of behavioral finance in the capital market. The primary distinction between this study and others is its emphasis on the suitability of the total index as a criterion for demonstrating the presence of behavioral finance.

## 2. Theoretical Foundations

In recent decades, the issue of determining the fair price (Fair Price), which is derived from the intrinsic value of each commodity, has been raised as market efficiency and efficient market theory, and has been challenged under a variety of headings, including behavioral economics and behavioral finance. In fact, the increased depth of economic research employing other sciences such as psychology and sociology to eliminate additional economic assumptions and make them real has led to the emergence of new scientific subfields within the field of economics, such as behavioral finance and behavioral economics [1].

Behavioral economics has posed a threat to the market's efficiency by broadening psychological models and the rationality of people's economic actions (rational assumption). In fact, behavioral economics has challenged the central role of the market in classical economics, which is the optimal allocation of market resources, often known as market efficiency [2].

Due to the significance of the capital market, the existence of numerous examples that are clear examples of behavioral economics, and the extent of research conducted in the capital market in the field of behavioral economics, behavioral finance is used as a term to describe capital market behaviors that confirm behavioral economics.

Rezaei & Elmi [13] refers to behavioral finance as a discipline of finance that employs psychological ideas to explain stock market oddities. In academic publications during the 1990s, behavioral finance emerged to explain the irrational behavior of investors. It was investigated how groups behave on the current financial market [4].

Behavioral finance contends that the irrationality of certain financial phenomena can be explained. This subject has two facets: 1. Arbitrage restriction based on the argument that rational traders are unable to exclude irrational causes. 2. Psychologies that catalogue the expected forms of deviations from reason [3].

Price clustering is one of the biases noticed in the capital market, and it involves the preference for certain numbers over others. In this phenomenon, certain prices are more prevalent than others. For instance, when more people deal in round numbers, the frequency of round numbers in transactions is greater [5].

Given that the process of discovering prices in an efficient market is random and that it is impossible to foresee the movements of stock and market prices, the non-uniformity of the number distribution contradicts the random walk hypothesis [7].

## 3. Clustering

Clustering is a numerical anomaly linked to investors' irrational behavior. There is a great deal of clustering among round dollar and half dollar stock prices. According to Harris's [6] definition, price clustering occurs when traders utilize specific prices to explain market conditions. There are numerous articles on the clustering of transactions at the end of numerical sequences Harris [6]; David et al. [7]. The use of entire rounds and half that simplifies the trading procedure is consistent with the theories of the behavioral finance school of thought, as it reduces the cost of transaction calculations.

Psychological barriers in round numbers reflect the market's inefficiency. According to the market efficiency hypothesis, numbers should not have a preference for one another, and it is also impossible to have a lucrative strategy. But despite psychological barriers, some numbers will alter the process as soon as they are seen, and a lucrative plan can be developed in this case [12].

According to Fama (1970), under certain circumstances, markets may not be efficient, i.e., prices may not transfer all available information. The efficient market hypothesis is basically an extension of the theory of expected utility, as it claims that markets would be efficient by definition if people behaved rationally, that is, to maximize their profits [12].

The phenomena of price clustering or psychological limits leads certain traders to exploit information connected to price figures or psychological limits to predict the market, which is in opposition with market efficiency.

In uncertain price environments, investors are urged to trade in round numbers. The term for this phenomenon is resolution hypothesis [9].

There are multiple causes for the clustering of round prices:

- The resolution hypothesis is one of the hypotheses pertaining to the phenomena of price clustering under uncertain situations, stating that price clustering is more prevalent in smaller, more volatile enterprises;
- Anchoring and round phobia give a focus point for decision-making, resulting in more price clustering around round values than other numbers;
- Convenience is a notion referring to ease of comprehension and less calculations. The likelihood of making a mistake when using round numbers is extremely low. And people's tendency to disregard duplicate information boosts their propensity to trade in round quantities [10];
- Transaction costs are addressed by the negotiation hypothesis. According to the negotiation hypothesis, traders employ round numbers to cut transaction costs and accelerate business transactions. Using round numbers in highly volatile environments decreases the risk associated with doing transactions. And the cost of obtaining accurate prices encourages prices to converge on round numbers [6].

In general, the preceding ideas are given as explanations for price clustering in round numbers. The important question is whether price clustering in individual stocks might signal the presence of behavioral finance in the market, but behavioral finance examines irrational behavior. Therefore, the round numbers in the price of individual stocks can be viewed as bounded rationality, a reasonable behavior described by Simon [5].

One of the reasons for the presence of behavioral finance in the capital market (stock market) is the efficacy of buyers' and sellers' judgments when the total index hits a price level. Round prices can be mentioned among these prices. In other words, when the prices of various symbols are influenced by the trajectory of the total index, it is evidence of behavioral finance or market inefficiency [11].

This study investigates the round numbers in the overall stock market index, which cannot be justified by the reasons stated in bounded rationality. The round numbers in the individual stock index can therefore be deemed to have a rational logic based on the hypotheses made. The impact of individual stocks on the total index and the existence of a trend in the total index may be the strongest sign of irrational behavior and proof of the existence of behavioral finance in the stock market [13].

The volatility of the Iranian capital market can be attributed to the existence of a trend in the overall index and the impact of individual stocks on the overall index. Because despite the influence of individual decisions from the overall index, a new source of driving force is created in the market, which causes a positive regression in the stock price, and in a way, attraction and repulsion in the round numbers as a source of volatility in the stock market causes an increase in volatility in the market. In fact, one of the benefits of this study is the introduction of a behavioral variable as a source of pointing volatility increase.

## 4. Literature Review

The primary objective of this study is to uncover behavioral finance perspectives not before explored. The purpose of the majority of previous domestic and international studies was to examine the reasons for the emergence of behaviors that resulted in the emergence of a new subfield of economics known as behavioral finance, whereas this study examines the presence or absence of behavioral bias in the Iranian capital market. On the other hand, previous studies have only examined the individual index of stocks as a criterion for investigating the existence of behavioral finance, whereas the establishment of the law of round numbers in the individual index cannot accurately express irrational behavior for the reasons discussed in this study. Or the irrationality of people, the index of the entire stock market has been studied as a more accurate criterion for the existence of behavioral finance in this study.

In a study titled "Intraday patterns of price clustering in Bitcoin," Ma & Tanizaki [8] looked into the phenomenon of price clustering in Bitcoin (BTC) with yen (JPY) as its unit of measure (JPY). They provided two answers based on tick-by-tick information. The first was the presence or absence of price clustering in BTC/JPY transactions, and the second was the variation in the size of price clustering over the course of a trading day. The last two digits of the BTC price were found to cluster at the numbers that end in '00' with the use of statistical measurements. Additionally, at the precise hour intervals, the scales of BTC/JPY clustering at '00' tended to fall. This study added to the growing body of knowledge about price clustering and investor behavior.

In a study titled "A study of network negative news based on behavioral finance analysis of abnormal fluctuation of stock price," Chung et al. (2022) examined the model of how actual bad news affects stock prices, and provided evidence using China's A-share listed companies as an example. According to studies, bad news increases stock price volatility and causes excess returns before 1 day and after 4 days. The less the stock price will fluctuate in response to bad news, the better the company is performing [13].

In a study titled "Are there psychological barriers in Asian stock markets?," Lobao (2019) looked for signs of psychological barriers at round numbers in six of the biggest Asian stock markets. This paper checked the index trailing digits for uniformity and calculated the differential effects of being above or below a potential barrier using regression and generalized autoregressive conditional heteroskedasticity (GARCH) analysis. The markets of South Korea and Taiwan showed the strongest evidence of restrictions. Japan and Hong Kong showed a very slight indication of obstacles, and Singapore and China's stock markets show very little evidence of psychological hurdles. These results cast doubt on the idea that Asian markets are efficient and back up the idea that certain of these markets can benefit from technical analysis tactics.

Isidore & Christic [4] in a study titled "A behavioral finance perspective of the stock market anomalies", following an explanation of the basics of classical financial theory, introduced the ideas of behavioral finance and prospect theory before discussing stock market oddities from the viewpoint of behavioral finance. Anomalies like Short-term momentum, Long-term reversal, Weekend anomaly, and Value premium anomaly are caused by behavioral biases that are discussed. Because there is so much stock information available and there are so many stocks available for investment, stock market investors experience a great deal of anxiety when making decisions. Investors who are experiencing anxiety will act irrationally and display behavioral biases. As a result, stock prices deviate from the norm, leading to unusual stock market behavior.

In a study titled "Round number price barriers in US stock market," Lam (2018) investigated whether round number price barriers exist on the American stock market. He demonstrated how the pricing barriers caused stock values to cluster around multiples of $10. A long-short portfolio built around a price barrier and held for a week results in a 17 basis point weekly return (8% annually), which was an anomalous future return pattern. After accounting for many conditions, the amount of such an extraordinary return remains unchanged. He provided evidence in support of the left-digit-bias barrier channel.

In a 2016 study titled "Clustering of prices and stability of stock prices," Blaua & Griffith used an unconventional method to determine the factors that influence volatility by analyzing how pricing frictions affect the stability of stock prices. They specifically evaluated the claim that clustering on round pricing increments would make financial markets more erratic. Stocks with a higher degree of clustering had likely less informative pricing and display greater volatility, which could be one explanation for the clustering-induced volatility. Additional tests indicated that the causal relationship should flow from clustering to volatility rather than the other way around. Given that they saw a high, positive correlation between price clustering and stock price volatility, their multivariate analyses appeared to support this paper's hypothesis.

In a study titled "Price clustering and natural resistance points in the Dutch stock market: A natural experiment," Sonnemanse (2014) used data mining to test two round number hypotheses as well as the theory of anomalistic digits. The hypothesis of round numbers has not been confirmed, but the hypothesis of anomalistic digits, or decimal numbers close to the wise penny and stupid dollar numbers (buying and selling imbalance around the round numbers), has been confirmed, according to the results obtained from the data of the Dutch stock exchange [2].

## 5. Research Methodology

The clustering method was utilized in this study. Using MATLAB software, this method specifies the cumulative centers of the data in the total index.

The $\chi^2$ statistic was used to examine the homogeneity of the data shown below.

$$\chi^2 = \sum \frac{(O_{t-E_t})^2}{E_t} \tag{1}$$

$O_t$ is the frequency of observed prices near round numerals.
$E_t$ represents the anticipated frequency assuming a uniform distribution.

The test's hypotheses are as follows:

H0: The distribution of numbers in the Tehran Stock Exchange's total index is uniform.

H1: The distribution of numbers in the Tehran Stock Exchange's total index is not uniform.

This study investigates the overall index from 2009 to 2021. This period's high economic volatility in Iran has resulted in a rise in the total index and given a foundation for the study of influencing factors in behavioral finance theory. The period under review coincides with the period of the $10^{th}$, $11^{th}$ and $12^{th}$ governments in Iran, during which the economic and political conditions, as a result of the economic volatility in the $10^{th}$and $13^{th}$ governments, the total index were similar and characterized by high levels of volatility and uncertainty.

## 6. K-Means Clustering: Optimizing Cost Function Mathematically

Steps in K-Means Algorithm:

1. Input the number of clusters(k) and Training set examples.
2. Random Initialization of k cluster centroids.
3. For fixed cluster centroids assign each training example to closest centers.
4. Update the centers for assigned points
5. Repeat 3 and 4 until convergence.

## 7. Defining a Cost Function

After each iteration we get k Centroids with assignment of training examples to respective clusters. So our objective function is defined as- Summation of euclidean distance of each training example with its cluster center and this is summed over $k$ clusters. We can write it in this way:

$$J = \sum_{j=1}^{k} \sum_{i=1}^{m} a_{ij} \left\| x_i - \mu_j \right\|_2^2$$

Where:
if $x_i \in j$ Cluster:
$a_{ij} = 1$
else:
$a_{ij} = 0$

## 8. Cost Function

*Minimizing the Cost Function:*

Minimizing the cost function depends upon the two steps of iterations, After each full iteration our aim is to keep minimizing the cost function.

*Step A:*

First step is choosing the optimal assignment of variable a for fixed centers $(\mu_1, \mu_2 \ldots, \mu_k)$.

In order to minimize the total euclidean distance for fixed centers we will choose $a = 1$ for each training examples which lies closest to a certain cluster center.

This can be achieved by using the equations below:

$$J = \sum_{j=1}^{k} \sum_{i=1}^{m} a_{ij} \left\| x_i - \mu_j \right\|_2^2$$

$$a_{ij} = 1 \text{ if } j = \operatorname{argmin}_j \left\| x_i - \mu_j \right\|_2^2$$

*Step B:*

This involves finding the optimal centers ($\mu$) for fixed assignment of points (i.e. for fixed $a$). For this case we set the gradient with respect to $\mu$ as 0 for fixed $a$.

$$\frac{\partial J}{\partial \mu_j} = 0$$

*Step 1:*

This can be thought as summation over $k$ clusters . So when we find derivate with respect to certain cluster. We can write cost function as:

$$J = \sum_{j=1}^{k} \sum_{i=1}^{m} a_{ij} \left\| x_i - \mu_j \right\|_2^2$$
$$J = \sum_{i=1}^{m} a_{ij} \left\| x_i - \mu_1 \right\|_2^2 + \sum_{i=1}^{m} a_{ij} \left\| x_i - \mu_2 \right\|_2^2 + \cdots\cdots \sum_{i=1}^{m} a_{ij} \left\| x_i - \mu_j \right\|_2^2 \cdots + \cdots \sum_{i=1}^{m} a_{ij} \left\| x_i - \mu_k \right\|_2^2$$

Derivative with respect to $j$th cluster:

$$\frac{\partial J}{\partial \mu_j} = \frac{\partial \sum_{i=1}^{m} a_{ij} \left\| x_i - \mu_j \right\|_2^2}{\partial \mu_j}$$

*Step 2:*

Expanding the euclidean norm term we can write like this:

$$\left\| x_i - \mu_j \right\|_2^2 = (x_i - \mu_j)^T (x_i - \mu_j)$$
$$x_i^T x_i - x_i^T \mu_j - \mu_j^T x_i - \mu_j^T \mu_j = x_i^T x_i - 2x_i^T \mu_j + \mu_j^T \mu_j$$
$$\frac{\partial J}{\partial \mu_j} = \frac{\partial \sum_{i=1}^{m} a_{ij} (x_i^T x_i - 2x_i^T \mu_j + \mu_j^T \mu_j)}{\partial \mu_j}$$

*Step 3:*

Now taking the gradient we arrive at the following equations:

Taking the gradient we get

$$\frac{\partial J}{\partial \mu_j} = \sum_i a_{ij} (-2x_i + 2\mu_j)$$
$$\frac{\partial J}{\partial \mu_j} = \sum_i a_{ij} 2x_i + 2\mu_j \sum_i a_{ij} = 0$$

On rearranging we get:

$$\mu_j = \frac{\sum_i a_{ij} x_i}{\sum_i a_{ij}}$$

*Step 4:*

So for points assigned to $j$th cluster we know that $a_{ij} = 1$ So we get:

$$\sum_i a_{ij} = n_j$$

So final expression becomes:

$$\mu_j = \frac{\sum_{i \in j} x_i}{n_j}$$

*Step 5:*

In this step we will verify that this particular value corresponds to the minimum of the cost function and not maximum. For proofing this we will proof that hessian is an PSD or PD then this will be corresponding minimum for the cost function. So now lets find Hessain Matrix.

Lets think for cluster centers as a column vector given below:

$$\mu = \begin{pmatrix} \mu_1 \\ \mu_2 \\ \vdots \\ \mu_k \end{pmatrix}$$

$$\nabla_\mu^2 \boldsymbol{J} = \begin{pmatrix} \frac{\partial^2 \boldsymbol{J}}{\partial \mu_1^2} & \frac{\partial^2 \boldsymbol{J}}{\partial \mu_1 \mu_2} & \cdots & \mu_{1,k} \\ \frac{\partial^2 \boldsymbol{J}}{\partial \mu_2 \mu_1} & \cdots & \cdots & \\ \vdots & \vdots & \ddots & \vdots \end{pmatrix}$$

Gradient with respect to certain $j$th center we obtain was

$$\frac{\partial \boldsymbol{J}}{\partial \mu_j} = \sum_i a_{ij}(-2x_i + 2\mu_j)$$

Now further computing second gradient with respect to $j$ we will arrive will all diagonal elements of the hessian matrix and all non-diagonal elements will be 0.

$$\frac{\partial^2 \boldsymbol{J}}{\partial \mu_j^2} = 2\sum_i a_{ij}$$

So all the diagonal elements of the hessian matrix will be of this form for each $j$ from 1 to $k$. We can see that summation over a gives number of points belonging to a certain cluster $j$ (i.e. $n_j$)

$$2\sum_i a_{ij} = n_j > 0$$

This proves that all the diagonal elements will be greater then 0. Hence this matrix will have all its Eigen values as positive. Therefore this will be a positive definite matrix. Hence we can say that value corresponds to the minimum.

## 9. Conclusion

We can see that this simple calculus exercise supports the fact that value of $\mu$ which yields us the minimum cost function is equal to the mean of the training examples belonging to that cluster. This article was all about to justify the intution we follow to minimize the cost function mathematically.

## 10. Research Hypotheses

H1: The hypothesis of price clustering in round numbers in the total index is maintained.

H2: The frequency distribution of total index numbers is uniform.

H3: When volatility is greater, price clustering in the round and certain numbers in the whole index are greater, and the visibility of behavioral finance has increased.

Table 1: Results of goodness-of-fit test for the periods under study.

| Periods | $\chi^2$ statistic for goodness of fit test | $\chi^2$ for 5% confidence coefficient and degrees of freedom |
|---|---|---|
| 2009–2021 | 102.3 | $\chi^2_{0.05,\,12} = 21.9$ |
| 2009–2013 | 24.6 | $\chi^2_{0.05,\,12} = 21.9$ |
| 2013–2017 | 15.8 | $\chi^2_{0.05,\,12} = 21.9$ |
| 2017–2021 | 140.2 | $\chi^2_{0.05,\,12} = 21.9$ |

Source: Research calculations

Table 2: GARCH coefficient calculations.

| Variable | Coefficient | Std. Error | *Z*-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.036609 | 0.00764 | 4.793881 | 0.0000 |
| AD | 0.218629 | 0.04399 | 4.969767 | 0.0000 |
| BD | 0.279396 | 0.04251 | 6.571961 | 0.0000 |
| AU | 0.110816 | 0.05654 | 1.959869 | 0.0500 |
| BU | –0.51794 | 0.04968 | –10.4248 | 0.0000 |

Source: Research calculations

BD[1]: The ten-day period before crossing barriers in the downward mode;

AD[2]: The ten-day period after crossing barriers in the downward mode;

BU[3]: The ten-day period before crossing barriers in the upward mode;

AU[4]: The ten-day period after crossing barriers in the upward mode.

[1]Before downward

[2]After downward

[3]Before upward

[4]After upward

Examining the distribution of numbers in the total index with the MATLAB software, switching program, and clustering program reveals that price clustering has occurred for the numbers 10,000, 15,000, 20,000, 30,000, 50,000, 100,000, 200,000, 300,000, 500,000, 1,000,000, and 2,000,000. In addition, the frequency of transactions within 10% of the preceding digits has been greater than that of other numbers. Therefore, the first hypothesis, namely the premise of price clustering, is supported by the round data.

At the 5% confidence level, the hypothesis of data uniformity is rejected based on the goodness-of-fit test. The results of the goodness-of-fit test indicate that the $\chi^2$ statistic over the entire time is equal to 102.3, which is equivalent to 102.3. Given that $\chi^2_{0.05,\,12} = 102.3 > 21.9 = 12$ and 2.05, the hypothesis of the uniformity of the frequency distribution is rejected at the 95% confidence level.

Due to the similarities between the 10th and 12th governments (high political and economic volatilities such as international tensions and exchange rate jumps and high uncertainty), the third hypothesis examines behavioral finance in different periods and compares the relative political and economic stability during the period of the 11th government to that of the 10th government (2013 to 2017). According to $\chi^2$ statistic, between 2009 and 2013 was equal to 24.6, between 2013 and 2017 it was equal to 15.8, and between 2017 and 2021 it was equal to 140.2. It appears that the hypothesis of non-uniformity of numbers in the stock market index cannot be discarded at the 95% confidence level during the period when the economy has been generally stable. The hypothesis of data homogeneity will be denied, however, for the time periods 2009 to 2013 and 2017 to 2021, as determined by the goodness-of-fit test. The hypothesis of uniform data frequency is rejected during economic eras characterized by uncertainty and instability; as a result, the establishment of behavioral finance is strengthened.

In analyzing the dynamics of responses to round prices, the movement of prices around the barriers will be analyzed. The prices before and after the barriers will be examined in this method, also known as the conditional effect, and for this method, the opposing equation will be calculated using the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) methodology.

$$R_t = \alpha_1 + \alpha_2 BD_t + \alpha_3 AD_t + \alpha_4 BU_t + \alpha_5 AU_t + \alpha_6 V_{t-1} + \alpha_7 \varepsilon^2_{t-1} + \eta \tag{2}$$

Here, a 10-day timeframe is considered. Four time intervals surrounding the barriers will be investigated.

Given Equation 2, the coefficients reflect the buildup of numbers surrounding round numbers and are significant. On the other hand, the coefficients in the ascending state are more significant than those in the descending state, and based on the graphs and the studied periods, the reaction to the round numbers in the ascending state, which is associated with greater economic uncertainty in Iran, is greater than in the descending state, which occurs under less uncertain conditions.

## Findings

Investors and scholars have always been interested in investigating factors that affect the stock market. In recent years, behavioral finance has gained the interest of numerous scholars as the cutting edge of knowledge and the most modern method for analyzing financial factors and the stock market. Using relevant literature, this paper investigates the presence of behavioral finance with the total index. In fact, the prevalence of significant economic volatility in Iran and its acceleration to the stock market creates conditions that are less apparent in stable economies. Choosing the total index as the criterion to demonstrate the existence of behavioral finance on the Tehran Stock Exchange by utilizing price clustering in round and particular numbers distinguishes this study from others.

The years 2009 to 2021 are the focus of this investigation. This period is subdivided into 2009 to 2013, 2013 to 2017, and 2017 to 2021 subperiods. The first and third phases are characterized by high economic volatility, whereas the second period, which coincides with political stability as a result of the JCPOA and the stability of Iran's key economic markets such as foreign exchange, is characterized by low economic volatility. Based on the goodness-of-fit test, price clustering bias is demonstrated for specific numbers. However, when studying the periods separately, it is evident that the hypothesis of uniformity is supported for the years 2012 to 2016, but denied for the other two periods.

Examining the data for the aforementioned time period with the GARCH method reveals, however, that price clustering occurs more frequently during the market's rise, which correlates with large economic swings, than during the stock market's collapse.

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