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INITIAL PUBLIC OFFERING EFFECTS ON VOLATILITY IN US STOCK MARKET

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Abstract:
This paper aims to investigate the effect of Initial Public Offerings (IPOs) on stock market volatility in the United States using the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. The study utilizes daily data from January 2020 to October 2022 on the Standard & Poor's 500 Index (S&P 500) and IPO firms listed on the New York Stock Exchange (NYSE) their IPO dates during the same period. The GARCH model is employed to estimate the volatility of the S&P 500 index stock prices after the IPOs announcements during the first day, first five days, and first ten days. The study finds that IPOs significantly impact volatility in the US market, and the effect is more pronounced in the short term. We discovered that IPOs after their announcements during the first five days have a negative impact on other stock prices in the S&P500 index. The effects are stronger for the first day of initial public offering come to the market while there is a negative impact on the 10th day of IPOs in the market but it is not statistically significant. The downward-sloping demand curve hypothesis is supported by these findings. These results have important implications for investors, market regulators, and policymakers. Investors should be aware of the potential for increased volatility during periods of IPO activity and adjust their investment strategies accordingly. Market regulators may need to consider implementing measures to mitigate the impact of IPOs on market volatility. Policymakers may also need to consider the potential economic effects of IPOs and the associated increase in market volatility to ensure a stable and efficient stock market.

Keywords:
IPOs, US, S&P500, NYSE, Volatility, ARCH/GARCH, E-GARCH

1. Introduction

The impact of an IPO on the volatility of the US stock market is the subject of this study. When it comes to the theoretical and practical implications of IPOs for market participants and regulators, the question of whether or not they have a negative pricing impact on existing equities during the first ten days after their announcements is crucial. Near substitutes, or stocks whose price changes are highly correlated with the IPO company's industry's performance, are negatively impacted by the IPO. This is studied by Braun and Larrain (2009) look into this question by analyzing IPO listing activities in 22 emerging countries. Shi, Sun, and Zhang (2017). find that large Chinese IPOs have a negative effect on pricing across the board, not just for similar products. Both analyses evaluate IPO share trading in the listing month or the days immediately following the IPO listing date, based on actual market data. We extended the analysis to determine if the price of existing stocks would decrease on the first day, the fifth day, and the tenth day following the announcement of an IPO. while prior studies have concentrated on significant event days such as listing day, subscription day, offering day, etc. The purpose of this research is to ascertain if IPOs are detrimental to the stock market. The time frame of January 1, 2020, through September 30, 2022, was used in our analysis using ARCH/GARCH and E GARCH models.

A company's first-time selling shares of stock to the general public is called an "initial public offering" (Ritter,1998). During an initial public offering (IPO), there are different goals at play for investors, underwriters, and the issuing company. Underwriters act as a go-between for issuers and investors, and their goal is to build a strong reputation in the market. Companies that decide to go public typically seek the highest possible issue price to maximize their cash flow from the IPO. Investors prefer underpriced shares at a discounted price to maximize their profit. However, there are many other reasons for a company to go public besides raising capital for investment opportunities. These include: determining the firm's market value; enhancing the firm's image in the market; reducing the cost of capital; broadening the basis of ownership; allowing one or more principals to diversify personal assets; attracting analysts' attention; attracting venture capitalists; and attracting talent.

One of the most consequential choices a private company can make is whether or not to go public. This decision affects the very foundation of the company. It should come as no surprise that IPOs are of interest to academics, investors, and policymakers. Since IPOs have become increasingly common in recent years, many studies have been conducted on them (Shen & Wei, 2007). (Pagano, 1998).

U.S. and international companies from a wide range of industries choose to sell shares to the public in the United States by listing on a U.S. exchange because of the country's deep and liquid capital markets. Businesses try to go public for a variety of reasons, including the opportunity for higher valuations, the elimination of liquidity discount coupons, strict corporate governance guidelines, increased flexibility to offer workforce share incentives, extensive research industry expert coverage, and the availability of investment returns. In 1783, the United States saw its first initial public offering (IPO), and the NEW YORK stock exchange (NYSE) has now been in continuous operation for 240 years. U.S.-based companies listed on the NYSE and Nasdaq, the two largest stock exchanges in the country, had a combined market cap of nearly $40 trillion as of October 2022. The two markets are currently worth $22 and $17 trillion and are growing at a rapid rate. Over 15,000 IPOs have occurred in the United States since 1960. (Mujalovic, Halbhuber, & Bogdanov, 2022).

Investors use "styles" in asset pricing and capital allocation, according to the behavioral literature. Examples of easily discernible characteristics that investors use to classify assets include inclusion in the S&P 500 Index and a stock's book-to-market ratio. Since 2003 (Barberis & Shleifer). When an initial public offering (IPO) is released, investors may make changes to their portfolios to maintain the level of exposure they had hoped for across asset classes. In this procedure, some assets are purged at a higher rate than others because of their similarity to the IPO's aesthetic. For instance, a growth IPO may crowd out and depress the prices of other growth stocks as we move along the demand curve for growth if the demand for "growth" is sloping downwards (low book-to-market).

The CAPM forecasts an uncertain market reaction to equity issues, while the model with downward-sloping demands forecasts a negative one. Both models predict cross-sectional variation (i.e., some prices decreasing less than others or even increasing), but this does not affect the market-wide projections. Market reaction is typically negative, supporting a model with downwardly sloping demands, as shown by evidence from stock picking that shows periods of active issuing are followed by periods of poor stock return in the United States. Baker and Wurgler (2000)

Similar to the previous models, the IPO effect results from a change in long-term stock demand rather than short-term price pressure (Harris & Gurel, 1986). Pricing pressures are based on the idea that market makers will only buy stocks at a discount in the run-up to an initial public offering (IPO), thus compelling investors to liquidate existing holdings to fund the purchase of new shares. To fund the acquisition of the new asset, investors may liquidate similar stocks, and the discount amount may be related to the IPO covariance. When investors' cash reserves improve again, however, they buy back some of the shares they had sold, causing the price to rise to its previous level. Equities with a high IPO covariance should see a greater price increase in the time after the IPO if the initial effect is due to a lack of liquidity. The central tenet of the price pressure school of thought is that market prices will turn around after a major event, or, more precisely, after the event's resulting surge in demand. In many different contexts, such as index expansions, this has been the most distinguishing prediction (Kaul, Mohrotra, & Morck, 2000).

What follows is a synopsis or outline of the remaining parts of the paper. The literature is reviewed in the article's second section. Section 3 provides a high-level overview of the data and parameter setup. The methodology of the empirical tests is discussed in greater depth in Section 4 of this article. In Section 5, we present the empirical results and a battery of statistical tests; in Section 6, we draw conclusions and discuss policy implications.

2. Literature Review

According to Amarilysya (2021), an initial public offering (IPO) is the process by which a company or other issuer offers and sells securities to the public for the first time in the form of shares. In developed economies, initial public offerings (IPOs) are preferred to other forms of internal financing like secured loans and venture capital because of their speed and lower cost (Chemmanur, He, & Nandy, 2010). Moreover, an initial public offering (IPO) is the capstone of the startup funding life cycle.

Initial public offerings have been studied extensively in the academic literature (IPOs). IPOs have been shown time and time again to be underpriced and to generate excessive profits in the short term. More research is being conducted to learn if the performance of other listed equities on different event days is affected by IPOs. This article explores the ripple effect an initial public offering (IPO) has on the market. The purpose of this chapter is to provide a summary of the research done on the topic at hand. We will scour a wide range of resources for relevant content that advances the study's objectives.

The argument stems from the theory that the supply shock caused by a highly anticipated initial public offering (IPO) could cause a drop in demand for previously traded stocks. Baraun and Larrain (2009), building on the work of Grossman and Stiglitz (1980), propose a model in which the demand curve for stocks is assumed to fall. In addition, their model predicts that the covariance between IPO stock and market IPO issue size will increase as IPO size increases.

Literature on IPO effects on US volatility helps paint a complete picture. Our findings are consistent with those found in the vast literature on the topic of price changes caused by changes in supply. A supply shock occurs when there is an abrupt change in the availability of a product or commodity. As a result of an increase in output caused by a positive supply shock, prices fall. On the other hand, a negative supply shock causes output to fall and prices to rise.

The question of whether or not the price of other stocks is affected by an initial public offering (IPO) is an important one. The first to investigate the cross-stock IPO effect, Baraun & Larrain (2009) widened their focus on supply-side effects. Using event study methods, they analyzed 254 IPOs across 22 developing markets between 1989 and 2002 and found that none of the offerings caused a precipitous decline in stock price. They showed that portfolios with a high degree of covariance with the new asset experienced a price decline during the issue period. Securities with similar characteristics to the IPO in terms of size and book-to-market ratio saw a decline in relative price. These results are consistent with the supply mechanism since they are more pronounced when the supply shock was larger. The authors also note that substantial IPOs have the potential to affect market prices as a whole. They devise a precise means of determining whether or not large IPOs are having an antagonistic effect on individual Chinese markets.

According to Shi, Sun, and Zhang (2017), large IPOs in China have a negative effect on market prices overall, not just for similar stocks that are close to going public. Both investigations are grounded in the actual trading of IPO shares and examine the month of the IPO listing or the days before and after the IPO listing date. They take their time analyzing the IPO announcement and how it will affect the value and volatility of existing stocks that could be used as direct substitutes for the IPO shares. Circumstantial evidence shows that initial public offerings (IPOs) cause a crash in the value of Chinese stocks. On its first day of trading after being listed on the Shanghai Stock Exchange (SSE) on November 5, 2007, China Oil (PetroChina) had a market value of 70 billion yuan or about 45% of the day's total trading value on the SSE. From a morning high of 5,748 to a final tally of 5,634, the SSE Composite Index experienced a decline. Consequently, the negative theoretical and practical implications of an IPO's effect on existing share prices are a major concern.

According to Scholes, (1972) and Mikkelson & Partch, (1983), the demand curve for stocks should be skewed if companies in the market are not perfectly matched to one another (1985). There would be a negative effect on the equilibrium price of stocks that are close substitutes for IPOs if the supply of those stocks were to increase. Baraun and Larrain (2009) state that the primary reason for the negative cross-stock effect of an IPO is portfolio rebalancing. However, Shi, Sun, and Zhang (2017) discovered that Chinese investors speculated on the undervaluation of major IPOs by selling some of their existing shares to buy for IPO shares, temporarily lowering the price of existing stocks.

The portfolio rebalancing method expects a drop in market equilibrium prices, which, barring a temporary liquidity crisis, should be maintained for a long time. In contrast, the speculating argument anticipates a drop in price that should be quickly reversed. Both arguments, however, rely heavily on IPO share trading as their primary source of evidence.

Both of these hypotheses are consistent with the theory of the downward-sloping demand curve, which states that an increase in supply due to IPOs reduces demand for their near substitutes and, consequently, their prices in a market with different defects. In other words, adding a new asset to the portfolio is at the expense of current assets, assuming aggregate demand stays the same, so any price decline caused by rebalancing the portfolio should not be followed by a price recovery. However, due to liquidity or behavioral issues, the impact may be short-lived (Harris & Gurel, 1986). During the initial public offering (IPO) period, investors may sell their stock holdings and buy new shares for speculative or rebalancing purposes (attracted by IPO underpricing). The selling of stocks by investors would put downward pressure on their prices. Later, when liquidity has improved, these investors buy back the securities they sold, driving prices higher.

Market reaction to an initial public offering (IPO) is time-sensitive, occurring most frequently around the subscription date (T), when investors can submit subscriptions for shares, and the listing date (LD) when investors can trade the IPO shares on the stock exchange. A lot of people save up for the IPO subscription date. Investors no longer need to sell existing shares to purchase IPO shares thanks to the availability of these reserve funds. Previous studies of supply shocks have assumed, at least implicitly, that aggregate demand for the associated asset remains constant. Supply shocks are the primary driver of price changes in these stocks (Meidan, 2005). (Baraun & Larrain, 2009). Given that not every potential investor can afford to make a bet on the IPO with their own money, a portion of the subscription must still be generated by selling existing shares. Not all of the daily trading market amounts need to come from this fraction of the total frozen funds.

Since LD is the day on which IPO investors can trade in their shares, it is another important event day. Investors who speculate can buy shares in an initial public offering (IPO) and then sell them for a profit on the first trading day. In the meantime, regular investors can rebalance their holdings by selling current equities that closely parallel the IPO on or before LD and purchasing shares of the listing stock on LD. Because it provides a natural experiment to study the effect of an IPO announcement on the price of existing stocks, the study of China's IPO approval regime deserves your attention. What makes China's IPO approval system stand out is that after an IPO approval announcement is made, the supply of IPO shares will almost certainly increase. In China, however, where obtaining IPO approval is much more difficult, IPO approval guarantees the delivery of new shares; in fact, no Chinese firm has ever voluntarily withdrawn its IPO after receiving approval. In the United States, companies have more freedom during the initial public offering (IPO) process, and they can stop the distribution of shares at any time. The study found strong evidence that stock market declines following the approval or announcement of an IPO could be attributed to investors' anticipation of future share offerings. From 2004 to 2014, 1,056 initial public offerings (IPOs) were made on the Chinese stock market.

Before and following the IPO listing date, Shi, Sun, and Zhang (2017) also analyzed the effects on price. They found that the close substitute of an IPO had a negative price effect in the days leading up to the listing days of the IPO. After five trading days after the listing, there is some evidence to suggest that the price decline related to the IPO issue is reversed.

Larrain & Braun, 2005 looked into the impact of IPOs on the price of other publicly traded stocks. Quantitatively significant shifts in the availability of assets in emerging markets were the primary area of investigation. They found that new assets entering a market affect the prices of existing assets.

Hsu, Rocholl, & Reed, (2006) analyzed the stock price, operating performance, and survival chances of publicly listed businesses following a massive IPO in the market. Their research showed that competitors in the same industry see low stock price returns in the lead-up to their IPO and a precipitous drop in performance afterward. The results showed that other companies operating in the same industry felt the effects of the IPO. There are implications for investors who are weighing the risk and reward of businesses in industries where there is a high probability of new IPO entries, as suggested by the article's research.

The effect of stock issues on pricing was studied by Loderer, Cooney, and Van Drunen (1991) for regulated companies. Their studies focused on cross elasticity or the potential effect of shifts in the quantity of one asset on shifts in the value of another. The researchers looked into the impact IPOs had on the prices of other stocks and found that the negative price reactions they observed could not be attributed to the disclosure of information about the fundamentals of the companies involved.

The relationship between investor demand for IPOs and the subsequent performance of those companies has been studied by other researchers. According to (Hanley, 1993), equities that are priced below the initial filing range perform poorly on the first day and have a negative effect on other stocks already traded in the market, while stocks that are priced above the first listing range perform wonderfully despite being provided at a higher price.

Chintya et al. (2020) examined the impact of an IPO firm on a rival stock's performance in developing markets, and they were the first to provide empirical experiments on the short-term and long-term influence of IPO firms on the performance of their rival companies in Indonesia from 2010 to 2017. They found that the short-term effects of IPO stock performance are negative, while the long-term effects are positive.
Between 2010 and 2018, AVCI (2021) conducted research in Turkey to examine the valuation and intra-industry effects of initial public offerings (IPOs). And it was discovered that the stock prices of rival Turkish companies drop significantly after IPOs.
Nonetheless, there are still sizable IPOs that harm the performance of competitors. According to the research of Spiegel and Tookes (2020), competitors' performance typically declines after an IPO due to industry-wide trends.
Kupianen (2020) used data on Finnish IPOs from 2000 through late 2020 to examine if the stock prices and operating performance of competing firms were affected by IPOs. He found that stock prices drop sharply and noticeably right before and after the initial public offering (IPO) filing events, but only slightly after the IPO is completed.
Min (2020) investigated the impact of IPOs on the stock prices of existing competitors in the same sector on the Korean stock market. by looking at how the stock prices of similar companies responded to the news of their IPO and listing. The outcome suggests that rival companies' stock prices dropped after word of the IPO shares leaked out.

3. Data and Methodology

Quantitative research is the type of research that is being conducted here, and the data that is being utilized in this investigation is secondary data obtained from the Eikon Thomson Reuters database. The purpose of this research is to investigate the impact that a company's initial public offering has had on the stock market in the United States. The data are collected daily, which is the most frequent interval. - The schedule of daily initial public offering (IPO) dates that will take place on the NYSE market between January 1, 2020, and September 30, 2022; This is a series of the closing prices of the S&P 500 market index daily. All initial public offerings that were listed on the NYSE (New York stock exchange) during the aforementioned period make up this study's population. The method of sampling that was utilized in this research was non-probability sampling, and the technical analysis of the data that was carried out in this investigation consisted of testing the data with the assistance of the ARCH/GARCH and E-GARCH models. The S&P 500 is the volatility indicator that we use for the variable that we are studying. The quotes of the 500 largest American companies are used to calculate the S&P 500 (SPX), which is a market index. It is frequently regarded as the stock market indicator in the United States that is most representative of the overall market. To measure IPO dates, we made use of dummy variables for the first day, up to the fifth day, and up to the tenth day. The dates of NYSE-listed initial public offerings served as our independent variable. The New York Stock Exchange (NYSE), which has its roots in 1792, is currently the stock exchange that has the highest total market capitalization of its listed securities. It is also the oldest stock exchange in the world.

4. Methodology

The model that produces the least amount of squares is the cornerstone of applied econometrics. Given that applied econometricians are frequently tasked with predicting how much one variable will change in response to a change in another variable, it is easy to comprehend why this would be the case. However, econometricians are being asked more and more to forecast and evaluate the number of flaws in the model. In light of this circumstance, the problems revolve around volatility, and the conventional methods have been replaced by the ARCH and GARCH models.
The Auto-Regressive Conditional Heteroskedasticity/Generalized Auto Regressive Conditional Heteroskedasticity (ARCH / GARCH) method was applied in this time series data study that was conducted. In this particular investigation, the ARCH/GARCH approach was selected because the variance of the error occurred frequently, was not dependent on the independent variable, but frequently changed over time. Specifically, there is a period of extremely high volatility that follows a period of extremely low volatility. In both of these scenarios, there is a period in between. These types of fluctuations are examples of heteroscedasticity because there are multiple error variants in which the degree of the error varies based on the prior volatility (Nachrowi & Usman, 2007). The ARCH and GARCH models have demonstrated that there are helpful tools for analyzing time series data, particularly in

applications about the financial industry. When the objective of the study is to analyze and make predictions regarding volatility, these models are of great assistance. An explanation of each of the research models used in this study can be found in the following:

In the modeling and forecasting of asset dynamics, the GARCH model, also known as autoregressive conditional heteroscedasticity (ARCH), as well as its derivative models, are frequently utilized. Bollerslev, (1986) improved Engle's (1982) work by developing an approach that enables both autoregressive (AR) and moving average (MA) factors in heteroskedastic variance. Bollerslev's approach was published in 1986. This is an example of the generalized autoregressive conditional heteroscedasticity model is known as the GARCH (p, q) model. GARCH models are constructed to accurately reflect the effects of both positive and negative shocks on conditional volatility as well as other types of asymmetry. The provision of a volatility measurement that applies to the process of making financial decisions is the objective of this model. A generalized version of the GARCH model is used to express the variance.

ARCH (q)

$$\boldsymbol{\sigma}_t^2 = \alpha_0 + \sum_{i=2}^{q} \alpha_i \, \varepsilon_{t-i}^2$$

GARCH (1,1)$\boldsymbol{\sigma}_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \, \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \, \sigma_{j-i}^2$

where _t2 represents the conditional variance, _t represents the residual, and _0, I and _j stand for the parameters that need to be estimated. The presence of a positive variance necessitates the use of nonnegative values for the parameters _0, I, and _j. This implies that the volatility cannot have a mean that is either zero or negative, and the I and _j parameters must be less than 1 for the model to be considered acceptable. Additionally, they show that if there is a significant change in the share prices, the conditional variance predictions will improve. This is because the model will be able to capture the generalized characteristic of volatility clustering. Higher values of the I coefficient in financial data series indicate greater responsiveness of volatility to market shocks, whereas higher values of the j coefficient indicate market shock persistence. Both of these coefficients are measured in terms of their values in financial data series.

According to Brooks and Burke's research from 2003, the GARCH (1,1) model is sufficient for accurately representing the clustering of volatility found in financial data. According to the recommendations made by Brooks and Burke, we apply GARCH (1,1) with the equations that are listed below in this investigation.

Mean equation: - P_(t=) μ+ ε_t

Variance equation: - σ_t^2=α_0+α_1 ε_(t-i)^2+β_1 σ_(j-i)^2

with α_0 > 0 and α_1 ≥ 0 and β_1 ≥ 0 conditions

where P is the price of one share of stock at time t, is the average price of one share of stock, and _t is the price of one share of stock after taking into account any dividends. It is known as a conditional variance, and it indicates the variance during time t based on prior knowledge at time t-1. The value _t2 indicates this variance. The conditional variance equation is the combination of three parameters: a constant term, known as (_0; volatility news from the past time, known as _(t-i)2 or ARCH term; variance from the past time, known as _t2 or GARCH term; and the lag of the squared residuals computed from the mean equation. This indicates that the conditional variance of at time t has an effect not only on the volatility news from the most recent period but also on the conditional variance of the time before that.

First, the mean equation needs to be solved to obtain the regression residuals for the model. Only after this is done can the ARCH and GARCH effects be tested. The squared residuals series and the conditional variance are both produced using the lags in the subsequent step. The null hypothesis of no GARCH effects (that is, no volatility clustering in S&P500 index stock prices) states that the _0, _1, and _1 parameter must be nonnegative in favor of conditional variance 2 t to be nonnegative. This is because the nonnegative value of conditional variance 2 t favors the null hypothesis of no GARCH effects. As a measurement of volatility shock persistence, the sum of the coefficients _1 and _1 is expected to be less than 1, and this result is expected to be in line with expectations. When the sum of the coefficients is greater than one, the shock has a significant effect because of the magnitude of the difference.

The GARCH model with an exponential component

According to standard GARCH models, both positive and negative error components have an asymmetric influence on volatility. This influence can be either positive or negative. On the other hand, financial time series exhibit asymmetrical and nonlinear patterns for several reasons, including transaction costs, market conflicts, arbitrage restrictions, and a few more. (Aliyev, 2019). The fact that this is the case suggests that "bad news" or negative shocks may have a greater impact on conditional volatility than "good news" or positive shocks. The GARCH model does not take into account the effect that leverage has. The asymmetric influence of the media is accounted for by Nelson's Exponential GARCH (EGARCH) model, which was developed (in 1991). This model makes it possible to have an asymmetrical response to shocks in the conditional variance, and EGARCH (1,1) is represented as

$$\log \boldsymbol{\sigma}_t^2 = \alpha_0 + \sum_{i=1}^{p} \beta_i log\, \sigma_{t-1}^2 + \sum_{j=1}^{q} \alpha_j \left[\frac{\mathrm{I}\varepsilon_{t-j}\mathrm{I}}{\sigma_{t-j}} \left(\frac{\mathrm{I}\varepsilon_{t-j}\mathrm{I}}{\sigma_{t-j}} \right) \right] + \sum_{j=1}^{q} \alpha_j \left(\frac{\varepsilon_{t-j}}{\sigma_{t-j}} \right)$$

Mean equation: - $P_{t=} \mu + \varepsilon_t$

Variance equation: - $\ln \boldsymbol{\sigma}_t^2 = \alpha_0 + \beta_1 \ln (\boldsymbol{\sigma}_{t-1}^2) + \alpha_1 \left[\left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| - \sqrt{\frac{2}{n}} \right] - \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}}$

Where is meant to represent the leverage effects, which are responsible for the asymmetry in the model. If it is less than zero, it means that negative shocks (also known as bad news) cause greater volatility than positive shocks (also known as good news), whereas if is greater than zero, it means that positive shocks are more volatile than negative shocks.

If equals zero, this establishes that the model is symmetric. Since ln _t2 could potentially have a negative value, there are no significant restrictions placed on the parameters.

5. Results of Empirical Research

The generalized autoregressive conditional heteroscedasticity, also known as the GARCH (1, 1) model, was utilized to investigate the correlations between the independent variables (IPOs date) and the dependent variable (S&P500 closing price). This model was also utilized to test the hypotheses regarding the study.

To convert accurate data, the natural logarithm was used for the closing price of the S&P 500 index. Because the residuals were greater for wider ranges of the dependent variable when real values were used. Because of the adjustment, it became possible to compare and analyze the results in a meaningful way, even though the independent variable was treated as a dummy variable with values of either one (1) or zero (0). (0).

After that, the assumptions of stationarity, constant error variance, independence, and normality were tested against the data in natural logarithms to make certain that they had not been violated. This was done to determine whether or not the assumptions had been invalidated. For this purpose, this narrates is generated using EViews 12. The index either has a unit root or the data are not stationary, as was discovered by the Phillip Peron test, the Dickey-Fuller test, and the Kwiatkowski-Phillips-Schmidt-Shin test statistic. These three tests are considered to be the best unit root tests. After that, the log difference was used in place of the natural logarithm data to get observed contradiction. After that, ARIMA regression models in EViews 12 were used to analyze the data of the S&P500 series in natural logarithmic difference.

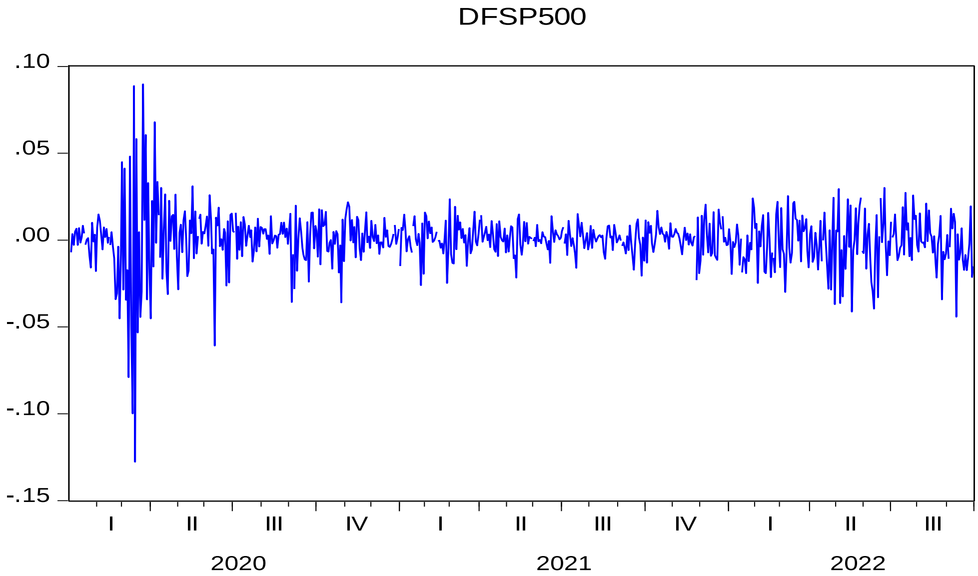

Figure:1 Daily prices of S&P 500

The clustering of the S&P 500 index's volatility for daily frequencies may be seen in the picture below. It spans the period from the first of January 2020 to the 30th of September 2022. The level of volatility has been relatively constant over time; however, there is a sizable void in the first three months of 2020, and the reason for this is the problem with covid-19. According to the graph, the level of volatility has grown somewhat but not significantly, and it has stayed rather high during the first three months of 2020. To mention that volatility clustering is a common effect in equity markets, consider the following graph, which shows that periods of low volatility are followed by periods of high volatility. Additionally, periods of higher volatility than those periods are followed by periods of higher volatility as well. As a consequence, the assumption that the variance remains constant over time might not be appropriate, and we might not incorporate all of the volatility that is present in the dependent variable. In the year 2020, there has been a significant decrease, which is the reason why volatility has increased.

The term "arch" refers to a series whose volatility varies over time (a property known as heteroskedasticity), and it is dependent on the autocorrelation of the lags that came before it. Hence, volatility models are carried out over stationary time series (mean) with non-constant variance, and that variance is going to be conditionally dependent on what his place in the preceding lags in the recent past. After determining the average of the univariate time series ARMA/ARIMA models, the next step is to determine whether or not the model displays periods of increased volatility by determining whether or not ARCH effects are present.

Table:1 ARMA models

	ARMA (1,1)	ARMA (2,1)	ARMA (1,2)	ARMA (2,2)
C	0.000142	0.000136	0.000135	0.000141
AR (1)	-0505492*	-0.057610	-0.208023**	-1.741996*
AR (2)		0.175429*		-0.884641*
MA (1)	0.281221*	-0.142563	0.008595	1.587623*

MA (2)			0.166272*	0.700350*
R^2	0.063469	0.073055	0.076767	0.144104
Adjusted R-squared	0.059385	0.067658	0.071392	0.137865
Akaike info criterion	-5.467211	5.474571	-5.478563	-5.550667
Schwarz criterion	-5.440970	5.441771	-5.445763	-5.511307
Hannan-Quinn criterion	-5.457062	5.461885	-5.465877	-5.535444

The significant level of *%1**%5 ***%10 is specified

After putting several ARMA (p, q) models through their paces, we chose the one that performed the best. The information criteria developed by Akaike, Schwarz, and Hannan-Quinn were used in the process of selecting the model that was found to be the most appropriate. Four potential ARMA models may be estimated using the mean equation of possible ARMA models. These models are denoted as ARMA (1,1), ARMA (2,1), ARMA (1,2), and ARMA (2,2). According to the findings of our study, the ARMA (2,2) technique has the lowest AIC, SBC, and HQC while also having the greatest adjusted r-square.

Table:2 Results of the LM test for the arch effect

ARCH 1	F-statistic	113.5195	Prob. F (1,689)	0.0000
	OBS*R-squared	97.74460	Prob. Chi-Square (1)	0.0000
ARCH 2	F-statistic	2.6673109	Prob. F (1,689)	0.0698
	OBS*R-squared	5.328049	Prob. Chi-Square (1)	0.0697

While trying to estimate the ARCH model, you will need to look at two parts: the mean equation and the variance equation. Each of these equations has two stages. To determine the mean equation, the first step is to ensure that the variables in question are in a stationary state. After this step has been completed, the second step is to choose a suitable ARMA or ARIMA model. The mean equation was brought up in the prior chapters of this discussion. After determining the value of the mean, we do a heteroskedasticity test to determine whether or not the arch effect is present in the data. The variance equation follows this step. Hypothesis H0 states that there is no existent ARCH impact up to the given lag. There are ARCH effects up to the given latency, as stated in hypothesis 1. In the event that the p-value is lower than 0.05, we will not accept the null hypothesis, and this will indicate that ARCH effects do exist.

To assess the hypothesis of whether or not this model has an ARCH effect, we calculate the estimates of the LM-test, also known as the Lagrange Multiplier Test. The results of the ARCH LM test are shown in this table. Given that the probability values for p = 0 are less than 0.05, the test concludes that the null hypothesis should be rejected;

hence, we may infer that this model has a significant ARCH effect. Adding two ARCH effects is acceptable, and the heteroskedasticity of two ARCH effects works just well in this model ARCH2; hence, we are unable to rule out the null hypothesis that H0 exists.

Table:3 GARCH (1,1) Findings For the dependent variable dlogs&p500, the period beginning on 1 January 2020 and ending on 30 September 2022

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000804	0.000387	2.080036	0.0375
AR (1)	-1.616212	0.092118	-17.54501	0.0000
AR (2)	-0.822547	0.089455	-9.195058	0.0000
MA (1)	1.552773	0.106336	14.60246	0.0000
MA (2)	0.782125	0.101273	7.722925	0.0000
Variance Equation				
C	7.06E-06	1.71E-06	4.120318	0.0000
RESID (-1) ^2	0.211632	0.036551	5.790005	0.0000
GARCH (-1)	0.766300	0.036296	21.11232	0.0000
GARCH 1,1 LM-test				
F-statistic		0.177334	` Prob. F (1,687)	0.6738
OBS*R-squared		0.177805	Prob. Chi-Square (1)	0.6733

Both the ARCH and the GARCH parameters are positive, and with a p-value of 0.0000, their positive values are very significant. We can draw the conclusion that the volatility is very persistent and clustering as a result of the fact that the GARCH coefficient value is larger than the ARCH coefficient value. Due to the fact that the total of the coefficients for the ARCH and GARCH parameters is very near to 1 (0.211632 + 0.766300), it may be deduced that any shocks encountered by conditional variance would be very persistent. Since the GARCH parameter is important, a substantial excess of stock share prices in either direction will cause future estimates of the variance to be high for an extended period. This will be the case regardless of whether the excess is positive or negative. At times of high volatility, this indicates that the GARCH model will perform better as a forecasting model than its counterpart, the ARCH model. Our ARMA 2,2 model is suitable for less than 5% of the data when it comes to the mean equation. Additionally, the LM-Test of GARCH 1,1 shows that it is suitable, which means that we are unable to reject the null hypothesis.

Table:4 the market situation on the first day after the IPO announcement was made

Variable	Coefficient	Std. Error	z-Statistic	Prob.	GARCH 1,1
C	1.25E-05	2.67E-06	4.683161	0.0000	Adjusted R-squared 0.079347
RESID (-1) ^2	0.168650	0.034886	4.834267	0.0000	Akaike info criterion -6.024535
GARCH (-1)	0.789883	0.036428	21.68321	0.0000	Schwarz criterion -5.965360
D1	-1.21E-05	3.25E-06	-3.726390	0.0002	Log-likelihood 2087.464
					ARCH2
Variable	Coefficient	Std. Error	z-Statistic	Prob.	
C	7.92E-05	8.76E-06	9.041935	0.0000	Adjusted R-squared 0.020988
RESID (-1) ^2	0.307828	0.060690	5.072165	0.0000	Akaike info criterion -5.928314
RESID (-2) ^2	0.445801	0.071681	6.219242	0.0000	Schwarz criterion -5.869140
D1	-3.67E-05	9.08E-06	-4.041168	0.0001	Log-likelihood 2054.268

					E-GARCH
Variable	Coefficient	Std. Error	z-Statistic	Prob.	Adjusted R-squared 0.091693 Akaike info criterion -6.059993 Schwarz criterion -5.994244 Log-likelihood 2100.698
C (6)	-0.866051	0.146591	-5.907930	0.0000	
C (7)	0.205734	0.048539	4.238536	0.0000	
C (8)	-0.159394	0.027654	-5.763799	0.0000	
C (9)	0.912553	0.014512	62.88287	0.0000	
C (10)	-0.234133	0.037644	-6.219636	0.0000	

We can see that the p-value of the dummy variable D1, when considered with the other variables in the variance equation, is lower than the 5% significance threshold. This indicates that the null hypothesis is not supported, and that the model is significant. There is a decreased value in the existing stocks with an amount of (-1.21E-05), which shows that the 1st day of the IPO announcement in the market will have a negative effect on the other shares outstanding in the exchange market. Because the coefficient of the dummy variable 1 for the first day of IPOs is negative, this means that there is a decreased value in the existing stocks. This model's initial offering day parameter had a probability value that was statistically significant at level 5% or even (0.0002) 1%. This was the lowest level at which statistical significance could be achieved. These results are consistent with what Shi et al. found in their investigation (2018). They concluded that offering day has a one percent chance of having a negative effect on the market return of the Shanghai Stock Exchange (SSE) Composite Index which is equal to 0.14% of the index's value. According to the findings of ARCH, the first trading day after initial public offerings (IPOs) were made available to the public had a negative impact on the share prices of the S&P500 index. While the E-GARCH result shows that the leverage effect in the stock exchange market for announcing IPOs had a negative (– 0.234133) impact on the previous shares in the market, share prices are expected to drop (-3.67E-05) on the first day of IPOs in the market. This indicates that 23% of IPOs coming to the market for the first day will have a negative effect on the other share prices in the S&P 500 market.

Table 5: The market's activity over the first five trading days following the IPO announcement

Variable	Coefficient	Std. Error	z-Statistic	Prob.	GARCH 1,1
C	1.55E-05	4.73E-06	3.265251	0.0011	Adjusted R-squared 0.080694 Akaike info criterion -6.017754 Schwarz criterion -5.958579 Log-likelihood 2085.125
RESID (-1) ^2	0.183867	0.034724	5.295051	0.0000	
GARCH (-1)	0.777005	0.036854	21.08360	0.0000	
D2	-9.10E-06	4.16E-06	-2.185562	0.0288	
					ARCH2
Variable	Coefficient	Std. Error	z-Statistic	Prob.	Adjusted R-squared 0.024114 Akaike info criterion -5.922745 Schwarz criterion -5.863571 Log-likelihood 2052.347
C	9.78E-05	1.94E-05	5.028792	0.0000	
RESID (-1) ^2	0.304058	0.060493	5.026330	0.0000	
RESID (-2) ^2	0.455311	0.065341	6.968235	0.0000	
D2	-4.15E-05	1.91E-05	-2.172114	0.0298	
					E-GARCH
Variable	Coefficient	Std. Error	z-Statistic	Prob.	Adjusted R-squared 0.092519 Akaike info criterion -6.029784 Schwarz criterion -5.964035
C (6)	-0.876032	0.151877	-5.768028	0.0000	
C (7)	0.273504	0.042999	6.360694	0.0000	
C (8)	-0.114257	0.025845	-4.420888	0.0000	
C (9)	0.916899	0.016370	56.01179	0.0000	

C (10)	-0.101907	0.038252	-2.664079	0.0077	Log-likelihood 2090.276

We can see that the p-value of the dummy variable D2 together with the other variables in the variance equation is lower than the 5% significance threshold of (0.0288), which indicates that the null hypothesis has been invalidated and the model is significant. Because the coefficient of the dummy variable 2 for the first five days of IPOs is negative, this indicates that there is a decreased value in the existing stocks with an amount of (-9.10E-06). This indicates that the first five days of IPOs in the market will have a negative effect on the other shares outstanding in the exchange market. According to the findings of ARCH, the first five trading days after the launch of initial public offerings (IPOs) had a negative impact on the share prices of the S&P500 index. Although the E-GARCH result reveals that the leverage effect in the market for stock exchanges for announcing IPOs had a negative (-0.101907) influence on the prior shares in the market, share prices are predicted to drop (-4.15E-05) on the first day that IPOs are traded in the market. This indicates that 10% of IPOs coming to the market for the first day would have a negative impact on the other share prices traded in the S&P 500 market. Although initial public offerings (IPOs) have a 23% impact on the volatility of stock prices, research has shown that this influence diminishes or disappears as the period under consideration lengthens. As a result, the impact of market volatility is best illustrated by looking at the shortest time frames.

Table:6 the first 10 trading days in the market after the announcement of the IPOs

Variable	Coefficient	Std. Error	z-Statistic	Prob.	GARCH 1,1
C	1.95E-05	1.00E-05	1.942041	0.0521	Adjusted R-squared 0.078599
RESID (-1) ^2	0.193968	0.035365	5.484813	0.0000	Akaike info criterion -6.015590
GARCH (-1)	0.771636	0.037659	20.48981	0.0000	Schwarz criterion -5.956416
D3	-1.25E-05	9.51E-06	-1.318608	0.1873	Log-likelihood 2084.379
					ARCH2
Variable	Coefficient	Std. Error	z-Statistic	Prob.	
C	0.000126	4.04E-05	3.131344	0.0017	Adjusted R-squared 0.029613
RESID (-1) ^2	0.316760	0.058362	5.427512	0.0000	Akaike info criterion -5.922178
RESID (-2) ^2	0.427390	0.066687	6.408910	0.0000	Schwarz criterion -5.863004
D3	-6.63E-05	3.93E-05	-1.684331	0.0921	Log-likelihood 2052.152
					E-GARCH
Variable	Coefficient	Std. Error	z-Statistic	Prob.	
C (6)	-0.895781	0.151888	-5.897635	0.0000	Adjusted R-squared 0.083303
C (7)	0.318646	0.045033	7.075788	0.0000	Akaike info criterion -6.021133
C (8)	-0.106925	0.026921	-3.971760	0.0001	Schwarz criterion --5.955383
C (9)	0.919771	0.016513	55.69827	0.0000	Log-likelihood 2087.291
C (10)	-0.071391	0.046925	-1.521384	0.1282	

We can see that the p-value of the dummy variable D3, when considered with the other variables in the variance equation, is lower than the 5% significance threshold. This indicates that the null hypothesis is not supported, and that the model is significant. The coefficient of the dummy variable 3 during the first ten days of initial public offerings (IPOs) is negative, which indicates that there was a reduction in value in the existing stocks with an amount of (-1.25E-05). although the results of the statistical analysis are inconclusive. It was difficult to determine whether or not the findings were reliable since the p-value was small (0.1873). To conclude, the offering days of D3 short-term negative effects were not sustained since there were no other factors remaining in the first ten days. We are trying to see whether it had an influence on the volatility of stock share prices and if its importance or not after ten days, whereas the E-GARCH demonstrated in the d2 decrease for the effect of the IPOs during the first five days in the market.

6. Conclusion

This analysis gives a more detailed and accurate view of the IPO price's influence on existing shares listed in the S&P500 index from the period 01, Jan 2020 to 30, Sep 2022. The price reaction to an IPO is mostly connected to the actual trading of IPO shares, and previous writers have shown that an IPO has a negative influence on existing equities, particularly its near substitutes, around the time of the IPO issue. We find a negative impact of IPOs after their announcements on the 1st day and up to the 5th day on the stock market share prices in the S&P500 index. Since this study was limited in its ability to assess all potential contributors to share price fluctuations, such as the impact of economic variables (inflation, foreign currency rates, interest rates) on share prices. The study recommends additional research that includes all external and internal factors that influence stock exchange market returns and share prices.

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