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The Volatility Asymmetry and Jump Effects: An Evidence for SPAC Exchange-Trade Funds (ETFs)

Chen, Jo-Hui[1], Hussain, Sabbor[2] and Chen, Fu-Ying[3]

1.Dept. of Finance, Chung Yuan Christian University
2.PhD. College of Business, Chung Yuan Christian University
3.College of Business, Chung Yuan Christian University

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ABSTRACT

Comparing the effects of volatility clustering for Special Purpose Acquisition Company (SPAC) and Initial Public Offering (IPO), this study uses the ARCH and GARCH models to exploit symmetric effects. Meanwhile, it applies the EGARCH and jump models to investigate the asymmetric effect. The results revealed an inverse leverage effect, reflecting that higher strikes may experience higher implied volatilities. In addition, this paper assesses whether the intensity of jumps is associated with significant news innovations and occurrences related to SPAC ETFs and IPO ETFs. The empirical results revealed that IPO ETFs have a higher frequency of jumps compared to SPAC ETFs due to the arrival of new information. This increase in M&A financing and its economic implications for SPAC stakeholders contributes to a better understanding of the expertise sought on risk in the literature.

Keywords: SPAC, Initial Public Offering, GARCH, Jump Model
JEL Classification: D22, F3, G11, G15

[1] Email: johui@cycu.edu.tw
[2] Email: sabborhussain9@gmail.com
[3] Email: ares.fy.chen@gmail.com

1. Introduction

Special Purpose Acquisition Company (SPAC) is a better alternative for applying an Initial Public Offering (IPO) to bring a private company public associated with an additional capital raise. To form a SPAC, the sponsor engages an underwriter to deal with the issue of shares through an IPO. Thus, a sponsor is a limited liability company and usually obtains a sponsor's promotion of 20% of post-IPO shares based on a nominal price. This paper compares some of the features of SPACs and traditional IPOs, as shown in Table 1. Key parameters included timing, cost, prices, regulations, timeline, volatility, valuation, management support, marketing, and compliance.

Klausner, Ohlrogge, and Ruan (2022) confirmed that a merger involving a SPAC is less expensive and quicks to go public than a traditional IPO. Lakicevic and Vulanovic (2013) demonstrated that the sponsors received significant returns following successful mergers. When seeking a high-quality target company in an acquisition, associated costs such as the cost of the IPO and operating expenses will be covered by the sponsor's investment proceeds. Shareholders will consider whether sufficient value can exceed the diluting effect of sponsor involvement. Jenkinson and Sousa (2015) reported that these rich rewards depended on a favorable vote for approval of the proposed acquisition.

Lakicevic et al. (2014) and Chaterjee, Chidambaran, and Goswami (2016) noted that the unique role of the warrants could dilute a sponsor's promotion. In the meantime, sponsors are encouraged to make an effort to select a low-risk target company and improve post-merger survivability. Using multinomial logistic regression, Vulanovic (2017) found that the involvement of SPAC stakeholders in the pre-merger stage, the decreased cost of the transaction, and the outperformed share price have a positive effect on the probability of survival after the merger. Blomkvist and Vulanovic (2020) reported that additional warrant shares held by sponsors were signaling SPAC's success in attracting more investors in an environment of high uncertainty and shareholder risk aversion. They also found that SPAC issues are negatively associated with the volatility index (VIX). Bai, Ma, and Zhang (2021) studied the impact of equity market sentiment, which is positively linked to SPAC market share. Dimitrova (2017) found that the continued involvement of SPAC sponsors designated as board members contributes to long-term performance.

Lewellen (2009) noted that a private company agrees to merge with a SPAC to have the chance to go public without the administrative costs and the hassle of a IPO process. There is no downside risk for IPO investors. SPAC liquidation will repay all trust funds and interest to investors if it does not end eighteen months mandated by the Securities and Exchange Commission (SEC) in the U.S. before announcing, completing, or withdrawing a proposed acquisition (Boyer and Baigent, 2008).

Table 1. The difference between SPACs and traditional IPOs

SPACs	Key Parameters	Traditional IPOs
Allows retail investors to enter earlier than a target business has been announced.	Timing	It may represent an opportunity to invest in a new public enterprise at its inception.
Underwriter fees: 2% and Completion fees: 3.5%.	Cost	Additional costs of 5-7% or greater, including legal, audit, registration, and administration fees.
Typically for $10 a share.	Prices	Usually cheap, so they "pop" the first day.
More regulatory flexibility, but more uncertainty in future regulations.	Regulations	Quite well known and steady.
It takes 4-6 months to complete.	Timeline	It may take between 12 and 18 months.
Private enterprise is generally evaluated through private	Volatility	The mood of the stock market may influence valuations at this time.

negotiations, which could help prevent fluctuations in the public market.		
The assessment can be determined based on prior negotiations between the SPAC sponsor and the target company.	Valuation	The price of shares depends to a large extent on market conditions and the trading period.
Companies have access to sponsors who have a long history and success with mergers and acquisitions.	Management Support	Enterprises should independently recruit experienced professionals after listing.
There is no marketing presentation from a privately held corporation.	Marketing	Marketing roadshows are held to attract the interest of investors.
Legal reporting requirements and financial reporting accommodations in the registration declaration.	Compliance	Financial disclosure obligations.

Source:
1. Hwang, Inyoung (2021), "SPAC IPO vs Traditional IPO: Pros and Cons of Investing in Each", SoFi Learn. (www.sofi.com/learn/content/spac-vs-ipo)
2. IG (2021), "SPACs vs IPOs: What Are the Differences? 2021.12.27. (www.ig.com/sg/trading-strategies/spacs-vs-ipos--what-are-the-differences--211221)

DealRoom (2021), "The Ultimate Guide to SPACs". (dealroom.net/faq/guide-to-spacs)

Sponsors will be damaged and lose their investment due to the liquidation. In addition, SPAC shareholders have the right to vote for the proposed acquisition prepared by the management team. They can redeem their shares against the preference of an acquisition by a majority vote. (Mason, 1993) In addition, the SPAC share price has increased to reflect the anticipation of added value through the proposed transaction. If shareholders do not support the proposed deal, they may sell at a profit. (Gose, 2006)

Concerning the difficulty of the IPO and the worrisome low price, SPAC plays a vital role in attracting individual and institutional investors to the capital market. In the meantime, SPAC supports the financing of growth companies or exits for venture capitalists and an alternative associated with the IPO and private equity. (O'Connor, 2006) Additionally, Boyer and Baigent (2008) found solid evidence that larger SPACs have higher share values.

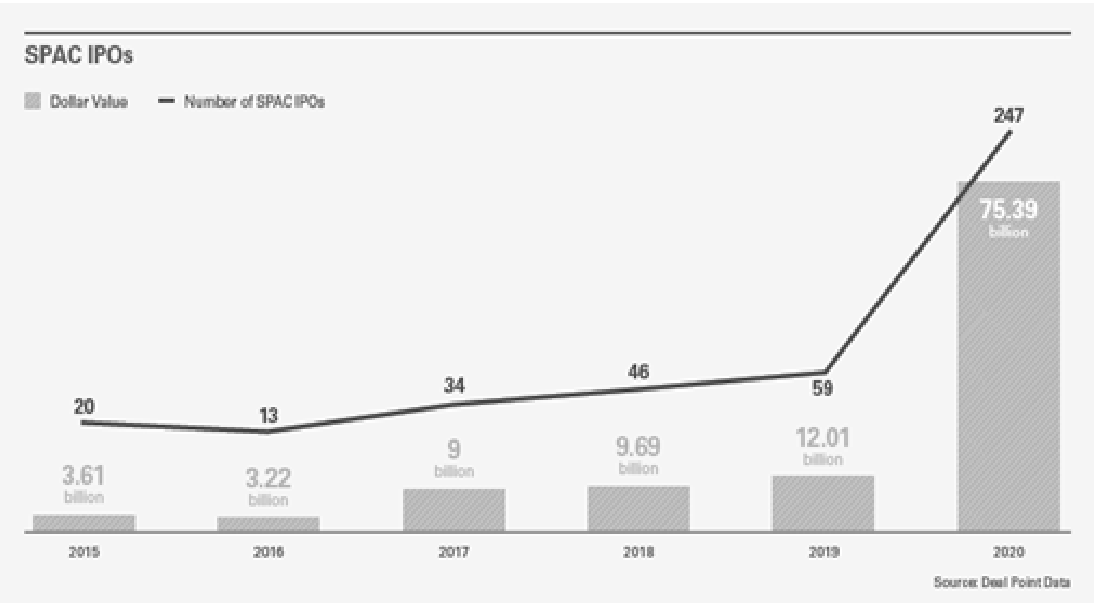
Lewellen (2009) stated that the value of SPAC shares had distinct characteristics, and the market volatility of a SPAC's return was relatively small. Another perspective is that SPACs have less undervalued prices than traditional IPOs. The share price must be greater than or equal to the value of trust on a pro-rata basis and before the shareholders' vote. Upon completion of the acquisition, the share should achieve positive excess returns if a positive market beta exists.

SPAC has less risk than IPOs when it comes to market volatility. Typically, traditional valuations of IPOs may be subject to the current mood of the stock market, which has affected stock price fluctuations. Underwriters attempt to ensure the first day of IPO pop, while shareholders may suffer due to market volatility or even lower stock prices for months after listing. Additionally, SPAC and the target company negotiated and agreed to the transaction on the price. It has offset IPO price volatility risk and reduced stock price uncertainty.

In addition, there are several noteworthy SPAC successes that demonstrate their potential. For example, DraftKings went public through a merger with Diamond Eagle Acquisition Corp., a SPAC that initially went public in May 2019. The combined entity's start trading on Nasdaq in 2020 led to its prominence in the online sports betting industry. Nikola's merger with VectoIQ Acquisition Corp. resulted in its public trading in 2020. The merger with Social Capital Hedosophia Holdings Corp. was concluded by Nikola. They remained a significant player in the electric vehicle and hydrogen fuel cell industries in 2019. The company is a prominent player in the space tourism industry. These examples show that, despite the challenges faced by the SPAC market, there are still substantial opportunities and successful outcomes that can be achieved.

By comparing the two asset groups, that is, SPAC Exchange-Traded Funds (ETFs) and IPO ETFs, it is possible to improve existing knowledge about SPACs and ETFs and assess the impact of volatility on SPACs. The de-SPAC transition process formally starts when the merger is announced, which can occur simultaneously or just after the due diligence. (Bai, Ma, and Zhang, 2021) In addition, Gahng, Ritter, and Zhang (2021) defined the SPAC period that began the following day with the consolidation of companies into a new company traded with a stock ticker. When a target company is found but insufficient funds, sponsors may invite more institutional investors to join SPAC through Private Investment in the Public Equity (PIPE) financing. PIPE provides many benefits, such as allowing SPACs to obtain additional cash for the initial business combination, providing the target shareholders with initial liquidity, and optimizing the cash and capital structure of the target as a new public company. A smaller SPAC IPO can be more attractive to a potential target and public shareholders if linked to a larger de-SPAC PIPE rather than a larger SPAC IPO connected with a smaller PIPE.

As SPACs embark on increasingly larger de-SPAC transactions, the importance and size of PIPE's complementary PIPE funding have increased. Figure 1 shows that 247 SPAC IPOs and $56 billion in de-SPAC transactions reached their record levels in 2020. They generated total gross proceeds of about $75 billion, capturing 53% of the total number of offers and 48% of the overall value of the IPO market.



Source: Christopher et al. (2021), "The Year of the SPAC", Skadden, 2021.1.26. (www.skadden.com/insights/publications/2021/01/2021-insights/corporate/the-year-of-the-spac)

Figure 1. History of SPAC IPOs

SPAC and traditional IPOs are vulnerable to price volatility due to new companies with no experience in establishing a business model and receiving the public contract. However, there is no relevant literature available to explore SPACs volatility empirically. As far as we know, this study is the first to empirically examine the symmetric and asymmetric volatility of SPAC ETFs and IPO ETFs. We study their jump clustering differences based on special events and news innovation announcements.

Unlike the previous work, this article is not intended to examine the impact of acquisition approvals of the SPAC process on returns and performance. Instead, it compares the effects of volatility clustering for SPAC ETFs and traditional IPO (i.e., non-SPAC IPO) ETFs. This article uses the Auto-Regressive Conditional Heteroskedasticity (ARCH) and Generalized Auto-Regressive Conditional Heteroskedasticity (GARCH) models to exploit symmetric effects while applying the

Exponential Generalized Auto-Regressive Conditional Heteroskedasticity (EGARCH) and jump models to examine the asymmetric effect. In addition, this paper evaluates the intensity of jumps associated with significant news innovations and occurrences for SPACs and IPOs.

Despite the growing popularity of SPACs, empirical research that examines the volatility of SPACs compared to traditional IPOs still needs to be completed. The motivation for this study is to focus on a deeper understanding of SPACs versus traditional IPOs, with a particular focus on volatility and investor behavior, as well as how special events and news innovations impact these securities, which can have significant implications for the market. This study aims to analyze the asymmetric effects of volatility using advanced models like EGARCH and jump models to comprehend how SPACs and IPOs respond to market shocks and significant news events. The research seeks to fill this gap by empirically analyzing the symmetric and asymmetric volatility of SPAC ETFs and IPO ETFs, thereby providing insights into how SPACs and IPOs react to market shocks and significant news events.

2. Literature Review

Studies that compared the performances of traditional IPOs and SPACs include Pastor and Veronesi (2005), Jog and Sun (2007), Boyer and Baigent (2008), and Floros and Sapp (2011). A study by Pastor and Veronesi (2005) found that demand for IPOs associated with the market's overall performance. Jog and Sun (2007) noted that SPCAs recorded stable returns after a target announcement and slightly significant negative returns after an acquisition. Boyer and Baigent (2008) analyzed the performance of SPACs and found that they followed the risk-return trade-off and were riskier than traditional IPOs. Four distinct occurrences are associated with SPACs, including the SPAC IPO, target announcement, merger completion, and withdrawal. Floros and Sapp (2011) used an event study and reviewed SPAC returns compared to shell Reverse Mergers (RM). They have found an adverse market reaction for SPACs RM agreement, while shell RM returns are strongly positive.

The study of Howe and O'Brien (2012) employed an empirical approach to measuring buy-and-hold returns concerning the effects of ownership of SPACs influencing the performance. They concluded that institutional ownership had a strong negative impact on the completion rate. It encouraged institutional investors to vote against the proposed acquisition and forced the dissolution of SPAC when the share price fell below the value of the trust per share. Cumming, Hab, and Schweizer (2014) used a logit model and examined the factors influencing the likelihood of a transaction being approved by a SPAC. The results showed that acquisition approvals decreased when block holdings held by active investors increased because they were looking for arbitrage strategies for SPAC liquidation instead of buying and holding strategies. They also highlighted a positive relationship between the management of SPAC and the likelihood of approval, which demonstrated an incentive to reduce the length of the SPAC process. Shachmurove and Vulanovic (2015) stated that the average "buy and hold" return on a SPAC shipping portfolio is a positive value that provides higher returns to their sponsors. Gigante and Guidotti (2021) implemented the event study and the logistics model for assessing positive feedback after the closing announcement. They demonstrated that by adopting a "buy and hold" analysis for SPAC, the performance of the Chinese portfolio was superior to that of the non-Chinese portfolio in the short and long term.

To address the issue of time pressure, Rodrigues and Stegemoller (2014) found that SPAC managers usually make worse choices when they are closed on the cutoff date, which reduces the returns of announcements. A further finding was that sound managerial ownership enhanced the performance of announcement returns. Dimitrova (2017) argued that perverse incentives from SPAC sponsors might discourage sponsors and underwriters from making good acquisitions for remuneration.

Lakicevic and Vulanovic (2012) found that specialized underwriters have positively impacted SPAC acquisitions. Likewise, Lakicevic, Shachmurove, and Vulanovic (2014) revealed that SPAC's success followed the countercyclical effect since the probability of acquisitions occurred in volatile markets. They suggested that the underwriters play an important role in mergers based on their appropriate choice and geographic selection.

The outstanding stock performance of a SPAC is evident between the announcement of the transaction and the shareholder's vote. However, the share price may be lower because of selecting an unreliable target company. Ignatyeva, Rauch, and Wahrenburg (2013) presented that European SPACs are connected with lower regulatory standards, flexibility, and tax considerations compared to U.S SPACs. Kolb and Tykvova (2016) showed that long-term investors of SPACs experienced consistently underperform after data about the market, non-SPAC firms, and IPO firms. They suffered from lower growth opportunities and higher leverage than IPO firms. Shachmurove and Vulanovic (2017) applied the event study. They revealed that China-focused SPCAs reduced their value as of the SEC's final decision date but outperformed other SPCAs overall in the United States.

Klausner et al. (2022) used 47 SPACs with Merge and Acquisition (M&A) implemented. The experience requirements for sponsors are USD 1 billion management funds or above and former Chief Executive Officer (CEO) or senior executives of Fortune 500 companies. They separate two groups: the high-quality group and the non-high-quality group. The empirical results revealed that the high-quality group had positive returns in the six months following the M&A, while the non-high-quality group had losses in the three months after the M&A. By buying and owning the SPAC shares for 48 days immediately following the announcement of the acquisition, Cohen and Qadan (2021) determined that investors obtained significant short-term returns.

Field and Hanka (2001) revealed that venture-backed IPO firms generally exhibited negative stock returns near the lockup expiration date limited by the regulation compared to non-venture-backed firms. Gibb and Hao (2018), who focused on the transaction around the expiry date of the IPO lockup, stated that there was an increase in short selling before the lockup expiry date and a decrease in the post-lockup period. For short sell, venture capital- and private equity-backed IPOs are higher than other IPOs.

As pointed out by Maheu and McCurdy (2004), the results obtained by the GARCH-Jump model showed that the dynamics of the time series of the clustering jumps could impact the 11 US stocks and indexes. They found asymmetric impacts of return innovations on volatility. Sidorov, Revutskiy, Faizliev, Korobov, and Balash (2014) used 10 UK shares under the FTSE100 Index and selected three years of survival for those shares. They found that the GARCH-Jumps model augmented with news analytics data has better performance than GARCH or GARCH-Jumps models.

Li, Li, and Zhou (2015) found that occasional large price changes due to the intensity of jumps have led to sharp fluctuations in equity markets that could significantly reduce economic growth. In this sense, Gupta, Lau, Liu, and Marfatia (2019) suggested that developed countries faced the dominant monetary role of the US Federal Reserve in the Monetary Policy Committee meetings to influence stock market shocks by the intensity of the jump. Khan, Khan, Mahmood, and Sheeraz (2019) used various GARCH models to measure volatility clustering and asymmetry in the stock markets of Religion Dominant Countries (RDCs). They found that the Glosten, Jagannathan and Runkle (GJR)-GARCH and EGARCH models were superior to the GARCH model in terms of the importance of accurately assessing volatility clustering.

Chen and Tung (2019) investigated the effects of the price volatility asymmetry on Financial Technology (FinTech), Financial, and Technology ETFs. They concluded that the impact of bad news exceeded the good news for the EGARCH and GJR-GARCH models. Technology ETFs have a more discreet effect in the Jump model than other ETFs. Xu, Bouri, Saeed, and Wen (2020) evaluated the impact of the intraday return predictability for crude oil, gold, and silver ETFs related to the Chicago Board Options Exchange (CBOE) crude oil, gold, and silver volatility index (VIX). The results revealed that the predictability of intraday performance on high-frequency data at half-hour intervals functioned well on days with greater volatility and higher jumps.

3. Data and Methodology

This article selects the daily data for SPAC ETFs and IPO ETFs extracted from the Yahoo Finance website. The ticker and inception date are shown in Table 2. The time frame for this study ranged from each creation date until 2021.12.31.

Choosing the correct model to capture different market behavior is essential for analyzing volatility. ARCH and GARCH models are effective because they can model changing variance over time based on past errors, which makes them symmetric volatility effect models. The EGARCH model addresses asymmetric volatility, offering insights into how different shocks impact volatility. Jump models account for sudden, significant changes due to discrete events. They complement the continuous volatility modeling provided by ARCH and GARCH models, allowing for comprehensive analysis of abrupt market shifts.

Table 2. SPAC ETFs and IPO ETFs data

Types	ETF	Ticker	Inception Date
SPAC	Definance Next Gen SPAC Derived	SPAK	2020-10-1
	SPAC and New Issue ETF	SPCX	2020-12-16
	Morgan Creek Exos SPAC Originated ETF	SPXZ	2021-2-9
	CrossingBridge Pre-Merger SPAC ETF	SPC	2021-9-21
	The De-SPAC ETF	DSPC	2021-5-20
Non-SPAC	First Trust U.S. Equity Opportunities ETF	FPX	2006.6.24
	First Trust International Equity Opportunities ETF	FPXI	2021-03-26
	Renaissance IPO ETF	RIPO	2013-10-16
	Goldman Sachs Access Inflation Protected USD Bond ETF	GTIP	2018-10-18
	First Trust IPOX Europe Equity Opportunities ETF	FPXE	2018-10-18

(1) Auto-Regressive and Moving Average Model (ARMA) model

The Auto-Regressive Moving Average (ARMA) model was created by Box and Jenkins (1976) to express the relationship between the current and the past variables. The AR model indicates that the variable y_t can be affected by the error term ε_t, and influenced by its own lagged variables.

This article estimates the generalized model of AR(p):

$$y_t = a_0 + \sum_{i=1}^{p} a_i y_{t-i} + \varepsilon_t \ , \tag{1}$$

where a_0 represents a constant intercept term; p is the number of lagged periods; a_i stands for the coefficient of y_{t-i}; and ε_t is error term.

The MA model is a function of implicit error correcting, where y_t correlated with the early stage of error term ($\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots$).

The generalized MA(q) model is set up as follows:

$$y_t = a_0 + \varepsilon_t + \sum_{i=1}^{q} b_i \varepsilon_{t-i}, \tag{2}$$

where a_0 represents a constant intercept term; p denotes the number of lagged periods; a_i is the coefficient of y_{t-i}; ε_t stands for white noise.

The ARMA(p,q) model is represented by:

$$y_t = a_0 + \sum_{i=1}^{p} a_i y_{t-i} + \varepsilon_t + \sum_{i=1}^{q} b_i \varepsilon_{t-i}. \tag{3}$$

This article divides the model for symmetric and asymmetric effects. The ARCH and GARCH models are part of the symmetric effect, while the asymmetric effect comprises EGARCH and Jumps

Models. These models measure asymmetry and volatility between SPAC ETFs and IPO ETFs.

(2) Symmetric Model

1) Auto-Regressive Conditional Heteroskedasticity (ARCH) model

Uncertain volatility influences conditional variability, which means the square of the residual term of the past q period. The ARCH model enables variation of the conditional variability at any time. Because residual variability was fixed in classical models, the ARCH model developed by Engle (1982) allowed residual variations over time and solved many econometric problems. The ARCH(q) model is given as follows:

$$y_t \mid \psi_{t-1} \sim N(x_t\beta, h_t) \tag{4}$$

$$h_t = h(\varepsilon_{t-1}, \varepsilon_{t-2}, \dots, \varepsilon_{t-q}, \alpha), \tag{5}$$

$$\varepsilon_t = y_t - x_t\beta.$$

where y_t stands for the time series data; ψ_{t-1} refers to all information in the period 1 to t-1; h_t represents the y_t conditional variation influenced by the residual term of the previous q; α, β are an unknown parameter; q is the order of the ARCH process; $x_t\beta$ means a linear set comprising of exogenous variables in the lagged period of the message set.

The conditional residual is parameterized to achieve a non-negative value. Rearrange the equation into the following form:

$$h_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \alpha_2\varepsilon_{t-2}^2 + \dots + \alpha_q\varepsilon_{t-q}^2 = Z_t'\alpha, \tag{6}$$

$$Z_t' = (1, \varepsilon_{t-1}^2, \varepsilon_{t-2}^2, \dots, \varepsilon_{t-q}^2),$$

$$\alpha = (\alpha_0, \alpha_1, \dots, \alpha_q),$$

$$\alpha_0 > 0, \alpha_i > 0, \quad i = 1,2, \dots, q.$$

where h_t represents the current condition change related to time-varying volatility and fluctuation clustering.

2) Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) model

By building on the ARCH model, the GARCH model proposed by Engle and Bollerslev (1986) is given the following form:

$$\begin{gathered} y_t = bx_t + \varepsilon_t, \\ \varepsilon_t = y_t - bx_t, \\ \varepsilon_t \mid \psi_{t-1} \sim N(0, h_t), \\ h_t = \omega + \sum_{j=1}^{q} \alpha_j\varepsilon_{t-1}^2 + \sum_{i=1}^{p} \beta_i h_{j-1}^2 = a_0 + A(L)\varepsilon_t^2 + B(L)h_t^2, \\ q \geq 0, p \geq 0, \\ \alpha_0 > 0, \alpha_j > 0, j = 1,2, \dots, q, \\ \beta_i > 0, i = 1,2, \dots, p, \end{gathered} \tag{7}$$

where y_t stands for the time series data, ψ_{t-1} provides all information from the period t to t-1, and h_t is the y connected with both the square of the residual q and the conditional variation from the previous period. The conditional variation number refers to the unknown parameter vector associated with the conditional average of y_t. q represents the order of the ARCH process, and p acts as the order of the GARCH process. Note that when p=0, GARCH (p, q) will be returned. Residual term is defined as a white noise process if p=q=0 for ARCH(q).

(3) Asymmetric Model

1) Exponential Generalized AutoRegressive Conditional Heteroskedasticity (EGARCH) Model

The EGARCH model proposed by Nelson (1991) was shown as follows:

$$ln(\sigma_t^2) = \omega + \beta ln(\sigma_{t-1}^2) + \alpha \left| \frac{\mu_{t-1}}{\sigma_{t-1}} - \sqrt{\frac{2}{\pi}} \right| + \gamma \frac{\mu_{t-1}}{\sigma_{t-1}}. \quad (8)$$

Let γ < 0 indicates the leverage effect, while $\gamma \neq 0$ represents an asymmetry effect.

2) Jumps Model

This study applied stochastic volatility models to solve the deficiency issue. The GARCH model was generally unable to explain well when it encountered excessive kurtosis in the time series data. Following Sebastien (2007), the jump-diffusion process can be evaluated by:

$$dp(t) = \mu(t)dt + \sigma(t)dW(t) + \kappa(t)dq(t), 0 \leq t \leq T, \quad (9)$$

where $\mu(t)$ represents a continuous locally restricted variation process, $\sigma(t)$ stands for a strictly positive stochastic volatility process, $W(t)$ acts as a standard Brownian motion, $dq(t)$ is a counting process equal to one when a jump happens at time t, and 0 if not. The jump intensity denotes the size of the jump for $\kappa(t)$.

Stock price jumps are supposed to follow a law of probability. The jumps represent a continuous-time discrete process linked to a Poisson distribution. Assumed that X_t is the number of times and a special event like an announcement during the period [0, t]. This study used a Poisson distribution followed by X_t if:

$$Pr\ Pr\ (X_t = m)\ = \frac{l^m t^m}{m!} exp\ exp\ (-lt)\ , l > 0. \quad (10)$$

Noted that l is parameter that rules the occurrence of the special event and let $E(X_t) = l$. It can be referred to as the rate or intensity of the process. A continuous- time GARCH diffusion processes with jumps can be stimulated as follows:

$$dp(t) = \sigma(t)dW_p(t) + \kappa(t)dq(t), \quad (11)$$

$$d\sigma^2(t) = \theta[\omega - \sigma^2(t)]dt + (2\lambda\theta)^{\frac{1}{2}}\sigma^2(t)dW_d(t), \quad (12)$$

$$\kappa(t) \sim N(0, \sigma_k^2),$$

$$dp(t) \sim Poisson(l).$$

This article provides a consistent nonparametric estimation of price variation to achieve discrete volatility. Andersen and Bollerslev (1998) used the realized volatility to convey the continuous time. The daily realized volatility is calculated as the sum of the squared intraday returns associated with a given trading day.

Let Δ-period return is $r_{t,\Delta} \equiv r(t,\Delta) \equiv p(t) - p(t-\Delta)$. This study normalizes the daily time interval to unity for $r_{t+1,1} = r_{t+1}$. Noted that $RV_{t+1}(\Delta)$can be calculated as the daily volatility at the end of day t, which is stated as:

$$RV_{t+1}(\Delta) \equiv \sum_{j=1}^{1/\Delta} \quad r_{t+j\Delta,\Delta}^2. \quad (13)$$

According to the theory of quadratic variation, when 0, the likelihood of no jumps can be defined as:

$$RV_{t+1}(\Delta) \to \int_t^{t+1} \quad \sigma^2(i)di. \quad (14)$$

Given quadratic variation, when Δ→ 0, the probability of jumps will be converged as follows:

$$RV_{t+1}(\Delta) \to \int_t^{t+1} \quad \sigma^2(i)di + \sum_{t<i\leq t+1} \quad k^2(i). \quad (15)$$

The realized volatility can be measured as a consistent estimator of the integrated volatility when there are no jumps, while the presence of jumps occurs. This study applies a bi-power variation measurement to split the two components of the quadratic variation process. This measurement consistently evaluates integral volatility at the time of the jump, based on the study by Barndorff-Nielsen and Shephard (2004, 2005). This paper defines the Bi-Power Variation (BV) as follows:

$$BV_{t+1}(\varDelta) \equiv \mu_1^{-2} \sum_{j=2}^{1/\varDelta} \quad |r_{t+j}\varDelta, \varDelta||r_{t+(j-1)}\varDelta, \varDelta| \quad , \tag{16}$$

where $\varDelta$ represent a small value in increments time and $\mu_1 \equiv \sqrt{\frac{2}{\pi}} \cong 0.79788$. The presence of jumps for $\Delta \rightarrow 0$ can be expressed as:

$$BV_{t+1}(\Delta) \rightarrow \int_t^{t+1} \quad \sigma^2(s)ds. \tag{17}$$

This study uses the product of the adjacent absolute returns and the probability of discontinuity that will disappear within the limit rather than selecting the sum of the squared returns. Following Barndorff-Nielsen and Shephard (2004), this paper consistently measures the discontinuities of the quadratic variation:

$$RV_{t+1}(\varDelta) - BV_{t+1}(\varDelta) \longrightarrow \sum_{t<i\leq t+1} \quad k^2(i), \tag{18}$$

where RV acts as realized variability. The study uses non-negativity on empirical measurement as follows:

$$J_{t+1}(\varDelta) \equiv max[RV_{t+1}(\varDelta) - BV_{t+1}(\varDelta), 0]. \tag{19}$$

4. Empirical Results

Table 3 shows descriptive statistics for SPAC ETFs and IPO ETFs daily returns, including sample means, standard deviations, skewness, kurtosis, the Jarque-Bera minimum, and maximum. Among SPAC ETFs returns, SPXZ (0.002) and SPAK (0.001) have the greatest mean returns, while SPCX and SPC have the lowest mean (-0.001). The returns on the SPAC ETFs prices are likewise larger than on the IPO ETFs. The standard deviation (Std. Dev.) measures how dispersed a set of values is. The smaller (greater) the value, the smaller (greater) the gap between the given sample. In the Table, DSPC (0.106) and SPC (0.019) have high volatility, as indicated by the standard deviation in SPAC ETFs.

The majority of the distribution's SPAC ETFs and IPO ETFs have positive skewness, such as SPAK, SPCX, SPXZ, FPX, RIPO, IPOS, and FPXE, showing right-biased distribution. When the kurtosis exceeds three, it indicates a leptokurtic distribution in SPAC ETFs and IPO ETFs for SPCX, SPC, DSPC, FPXI, IPOS, and FPXE. The Jarque-Bera statistic and corresponding p-value are used to test that the daily distribution of returns is normal distributed. The null hypothesis is rejected for all-time series and can be well estimated by the normal distribution if all p-values are significant at the 1% level.

For SPAC ETFs and IPO ETFs time series variables, Table 4 shows unit root, Lagrange Multiplier (LM), and ARMA-LM and GARCH-LM tests. The Augmented Dickey-Fuller (ADF) unit root is used for testing whether the time series is stationary or nonstationary. All the ADF results are significant, which means that the data set of SPAC ETFs and IPO ETFs are stationary. The Akaike Information Criterion (AIC) selected the best ARMA, GARCH, and EGARCH models with maximum (2,2) order based on the minimum AIC. Engle (1982) used the ARCH-LM test in time series data to test for the null hypothesis of no autoregressive conditional heteroscedasticity. The substantial results show that the null hypothesis for the time series is rejected. It indicates that ARCH effects are present in univariate samples. The post-test results for the ARCH-LM test are all insignificant, meaning that the ARCH effect has been eliminated after applying the GARCH model.

Table 3. Descriptive statistics of SPAC ETFs and IPO ETFs

SPAC ETFs					
	SPAK	SPCX	SPXZ	SPC	DSPC
Mean	0.001	-0.001	0.002	-0.001	-0.003
Std.Div	0.018	0.003	0.006	0.020	0.106
Minimum	-0.045	-0.032	-0.053	-0.024	-1.48 0
Maximum	0.070	0.019	0.066	0.093	0.112
Skewness	0.681	0.231	0.127	-2.189	-12.457
Kurtosis	0.917	4.424	0.337	47.696	170.510
J-Bera	14.719***	108.00***	0.973***	12522***	2.673***
IPO ETFs					
	FPX	FPXI	RIPO	GTIP	FPXE
Mean	-0.001	0.001	-0.001	-0.001	-0.001
Std.Div	0.014	0.014	0.017	0.004	0.015
Minimum	-0.126	-0.078	-0.088	-0.037	-0.092
Maximum	0.147	0.040	0.140	0.029	0.154
Skewness	0.324	-0.682	0.632	-0.156	0.157
Kurtosis	1.814	3.926	0.583	0.434	3.945
J-Bera	39.110	182.06	20.413	3.013	165.11

Note: *, **, and *** are significant at 10, 5, and 1% for p-value, respectively.

Table 4. ARCH, LM and ADF test for SPAC ETFs and IPO ETFs

SPAC ETFs					
	SPAK	SPCX	SPXZ	SPC	DSPC
ADF	-16.004*** (0.000)	-13.256*** (0.000)	-13.710*** (0.000)	-15.109*** (0.000)	-4.148*** (0.006)
ARMA	(1,0)	(2,1)	(2,1)	(2,1)	(0,1)
AIC	-5.229	-7.360	-5.045	-9.221	-1.621
LM	0.312 (0.855)	0.323 (0.850)	0.023 (0.988)	0.018 (0.990)	0.556 (0.757)
ARCH-LM	34.721*** (0.000)	76.157*** (0.000)	23.561*** (0.000)	0.011 (0.994)	0.472 (0.789)
GARCH	(2,2)	(2,1)	(1,2)	(1,1)	(2,2)
AIC	-5.294	-8.617	-5.115	-9.218	-3.443
ARCH-LM	1.619 (0.445)	0.198 (0.905)	1.787 (0.409)	0.010 (0.995)	0.159 (0.923)
IPO ETFs					
	FPX	FPXI	RIPO	GTIP	FPXE
ADF	-63.732*** (0.000)	-10.294*** (0.000)	-26.280*** (0.000)	-14.323*** (0.000)	-13.146*** (0.000)
ARMA	(2,2)	(1,0)	(2,0)	(2,2)	(2,2)
AIC	-5.683	-5.728	-5.371	-8.365	-5.559
LM	2.592 (0.628)	0.973 (0.379)	2.951 (0.228)	1.203 0.5480	0.083 (0.959)
ARCH-LM	919.903*** (0.000)	1.6016 (0.2037)	492.598*** (0.000)	120.874*** (0.000)	123.852*** (0.000)
GARCH	(2,2)	(2,1)	(2,1)	(1,1)	(2,1)
AIC	-6.116	-5.826	-5.813	-8.860	-5.959
ARCH-LM	0.479 (0.786)	1.300 (0.274)	0.261 (0.878)	0.592 (0.743)	4.424 (0.109)

Note: *, **, and *** are significant at 10, 5, and 1% for p-value, respectively.

Table 5 represents the ARMA-GARCH orders. It shows how GARCH variations interact with different order levels. To ensure the feasibility of the quasi-maximum likelihood estimator for the GARCH model, instant conditions represent the results for $\alpha+\beta < 1$. Some of $\alpha+\beta$ values in both SPAC ETFs and IPO ETFs are close to suggesting that each frequency's fluctuation rate is extremely persistent. It is suitable for prediction due to the clustering volatility. But the results in SPAC ETFs such as SPC and DSPC and in IPO ETFs like IPOs show higher than 1, which indicates that the volatility rate is not persistent. This paper use EGARCH and jump models to determine asymmetry in SPAC ETFs and IPO ETFs.

Table 5. ARMA-GARCH Of SPAC ETFs and IPO ETFs

SPAC ETFs					
ETF	SPAK	SPCX	SPXZ	SPC	DSPC
ARMA/ GARCH	(1,0)/ (2,2)	(2,1)/ (2,1)	(2,1)/ (1,2)	(2,1)/ (1,1)	(0,1)/ (2,2)
α+β	0.937	1.037	0.850	2.140	1.484
IPO ETFs					
ETF	FPX	FPXI	RIPO	GTIP	FPXE
ARMA/ GARCH	(2,2)/ (2,2)	(1,0)/ (2,1)	(2,0)/ (2,1)	(2,2)/ (1,1)	(2,2)/ (2,1)
α+β	0.969	0.881	0.834	0.828	1.031

The evidence of substantial volatility asymmetry can be shown in all variables at the 1% significant level. Table 6 presents the ARMA-EGARCH for Gama (γ) parameters. All the (γ) parameters are positive and significant effects, meaning that squared error terms correlate to conditional variance associated with an inverse leverage effect. Furthermore, asymmetry coefficients (γ) are negative and significant for DSPC in SPAC ETFs at the 1% level showing a leverage effect. The predictable results in return may be evidence of market inefficiency, with investors and traders potentially benefiting from excess returns. These findings are consistent with Tan and Khan (2010), Chen and Trang (2013), and Arouri et al. (2012) investigations of financial markets and precious metals.

A positive unilateral relationship in returns is exhibited for all SPAC ETFs and IPO ETFs in volatilities, except for DSPC in SPAC, which has a leverage effect. Furthermore, the findings give traders and speculators a solid sense of what to expect in terms of risks and returns when trading DSPC ETF. The positive effect has demonstrated that the return and risk obtained in SPAC ETFs and IPO ETFs may be derived from the rise (fall) of the others. The recognized inverse leverage effects of all SPAC ETFs and IPO ETFs may give investors, traders, speculators, and fund managers with a correct investing tool for decision making.

Table 6. ARMA-EGARCH of SPAC ETFs and IPO ETFs

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SPAC ETFs					
ETF	SPAK	SPCX	SPXZ	SPC	DSPC
ARMA/ EGARCH	(1,0)/ (1,2)	(2,1)/ (2,2)	(2,1)/ (1,2)	(2,1)/ (2,2)	(0,1)/ (2,2)
γ	0.279** (0.046)	0.313*** (0.000)	0.330* (0.057)	1.069* (0.056)	-0.493** (0.026)
IPO ETFs					
ETF	FPX	FPXI	RIPO	GTIP	FPXE
ARMA/ EGARCH	(2,2)/ (2,2)	(1,0)/ (1,2)	(2,0)/ (2,2)	(2,2)/ (2,2)	(2,2)/ (2,2)
γ	0.264*** (0.000)	0.253*** (0.000)	0.130*** (0.000)	0.060** (0.034)	0.301*** (0.000)

Note: *, **, and *** are significant at 10, 5, and 1% for p-value, respectively

This paper provides a new nonparametric test for detecting SPAC ETFs and IPO ETFs returns jump arrival times and realized jump frequency up to the intra-day level. Table 7 explains the different characteristics of jump dynamics and their distribution in the SPAC ETFs and IPO ETFs. Note that the realized bi-power variation is used in the denominator of the statistic for estimating instant volatility, which makes our method robust to the presence of jumps in previous periods. This paper investigated the distinction between Realized Volatility (RV) and Bi-Power Variation (BV). If a jump exists, there is an asymmetric effect on ETF. The results of Chen and Tung (2019) showed that the ETFs jumps are associated with earnings announcements, and other specific news events are scheduled in advance.

Table 7. Realize Jump (RJ) Dynamic of SPAC ETFs and IPO ETFs

ETFs Code	**SPAK**	**SPCX**	**SPXZ**	**SPC**	**DSPC**
Number of Detected Jumps	5	34	5	25	6
Expected Number of Spurious Detected Jumps (Under H0=No Jumps)	0.042	0.052	0.041	0.039	0.021
Proportion of Detected Jumps	0.119	0.653	0.122	0.641	0.286
Critical level:	0.001	0.001	0.001	0.001	0.001
Critical value:	3.090	3.090	3.090	3.090	3.090
Jump Ratio (%)	0.11	0.65	0.12	0.64	0.30
Jump Percentage (%)	11.90	65.38	12.19	64.10	28.57
Jump Average Percentage (%)	36.42				
IPO ETFs					
ETFs Code	**FPX**	**FPXI**	**RIPO**	**GTIP**	**FPXE**
Number of Detected Jumps	6	12	120	12	101
Expected Number of Spurious Detected Jumps (Under H0=No Jumps)	0.023	0.049	0.424	0.015	0.162
The Proportion of Detected Jumps	0.260	0.245	0.283	0.800	0.623
Critical level	0.001	0.001	0.001	0.001	0.001
Critical value	3.090	3.090	3.090	3.090	3.090
Jump Ratio (%)	0.26	0.24	0.28	0.80	0.62
Jump Percentage (%)	26.08	24.48	28.30	80	62.34
Jump Average Percentage (%)	44.24				

With the selected observation on SPAC ETFs, we have found that SPCX has a high number of detected jumps (34), which jump percentage becomes 65.38 %. Next is SPC (25), with a jump percentage of 64.10%, respectively. SPAK and SPXZ are found to be the minimum number of detected jumps. Moreover, in IPO ETFs, the highest number of detected jumps presence in RIPO (120), with a jump percentage of 28.3%, is the highest value among SPAC ETFs and IPO ETFs. Next, the number of the detected jump for FPXE (101) with a jump percentage of 62.34%. The results show that FPX has the minimum detected jumps on the selected data period.

The empirical results reveal that both SPAC ETFs and IPO ETFs have a jump effect, but IPO ETFs have the highest frequency of jumps, with an average percentage of 44.24%. The presence of jumps and their significant influence may give knowledge to the investors and fund managers with a correct investing tool for decision making, future trading planning, and investment.

SPACs often involve complex and high-profile merger transactions, attracting significant media coverage and investor attention. This constant attention can lead to more news-driven price volatility and jumps. The process of SPACs acquiring private companies typically involves high-profile announcements and negotiations, leading to frequent news updates.

In general, IPOs have a lower frequency and impact than SPAC transactions. The frequency of jumps is lower because IPOs are scheduled events, and their news is more predictable. The prospect of high returns from successful acquisitions drives investors and speculators to react to news about SPACs. Increasing investor sentiment can lead to more extensive market reactions and frequent market swings

5. Conclusion

This study uses ARMA-GARCH, ARMA- EGARCH, and Jump models to explore the leverage and asymmetric effect of SPAC ETFs and IPO ETFs returns and volatility. According to the findings, ARMA-GARCH models have demonstrated the majority of instant conditions, suggesting that the frequency of fluctuation rate expresses extremely persistent.

To determine volatility asymmetry, most of the Gama (γ) parameters of ARMA-EGARCH models are positively significant. The results showed high evidence of volatility asymmetry. This discovery might be useful for investors, fund managers, and academics when developing investment plans or strategies in response to SPAC market shocks. The results indicated that both SPAC ETFs and IPO ETFs have volatility asymmetry and inverse leverage effects.

This research offers a new nonparametric test for detecting SPAC ETFs and IPO ETFs jump arrival timings and realized jump frequency at the intra-day level. The distinct characteristics of jump dynamics and their distribution in the SPAC ETFs and IPO ETFs are investigated in this study. We discovered a significant presence number of jumps. The highest number of detected jumps present in IPO ETFs is in FPXE (120), which is considered the highest value.

Moreover, IPO ETFs have the largest frequency of jumps, with an average percentage of 44.24 percent across both ETFs. The presence of the jump effect gives information to benefit the investors by having the right decision making for SPAC investment based on the existence of jumps and their major effect.

The contribution in the finance literature related to SPACs is the model through which we can measure the symmetric and asymmetric volatility of daily SPAC ETFs and IPO ETFs. The jump effect can be linked to significant news innovation and announcements for specific events. For example, SPAC is heavily fashion driven as we have seen a collapse of this product in 2021.

The implications of the study underscore the growing importance of SPACs (Special Purpose Acquisition Companies) as an alternative to traditional IPOs. SPACs provide a faster and more cost-effective route to going public, potentially reducing valuation risks from market volatility. However, they also entail risks related to regulatory changes, which require investors to carefully balance their high return potential against these risks. This caution and informed decision-making are crucial in the SPAC market. Overall, the implications of the study reveal that SPACs offer new opportunities for companies and investors while also challenging existing regulatory frameworks.

In this study, several limitations need to be considered. Not all external factors, such as macroeconomic events, regulatory changes, or market sentiment, are included. This study should thoroughly describe the impact of these external elements on volatility and jump dynamics. Despite the study's findings that SPACs react more favorably to news than IPOs, quantifying the exact impact of specific news events on volatility and jump behavior remains challenging. Future research could examine how various news events impact market reactions. The analysis in the study is restricted to data from a particular period, which may only partially capture long-term trends or changes in market behavior. Future studies should consider longer time frames to validate and enhance their findings since market conditions change significantly over time.

Compliance with Ethical Standards:

Conflict of Interest: The authors declare that they have no conflict of interest.

Ethical Approval: This article does not contain any studies with human participants or animals performed by any of the authors.

Data Availability Statement: The datasets of current study are availabe in the Yahoo finance (www.finance.yahoo.com).

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