International Review of Accounting, Banking and Finance
Vol 16, No. 1, Spring, 2024, Pages 18-34

IRABF

Implications of Spillover and Asymmetric Volatility Effects of Leveraged and Inverse Leveraged Exchange Traded Funds (ETFs) in the Pre- and During COVID-19 Period

***John Francis Diaz*, PhD, RFP®, CRMC™[1*]**

1. *Associate Professor, Finance and Accounting, Asian Institute of Management, Makati, Philippines*

Accepted February 2024

A B S T R A C T

This research delves into the dynamics of leveraged and inverse leveraged Exchange-Traded Funds (ETFs), offering insights into their relationships with tracked indices. The study uncovers spillover and leverage effects, emphasizing the significance of such interactions. The research underscores the potential of these specialized financial instruments to amplify both positive and negative market news, serving as valuable tools for traders and risk management. Notably, the analysis reveals asymmetry in the response of stock market indices and ETFs to positive and negative news. These ETFs could be considered as hedges during market declines, given their demonstrated ability to move inversely to their respective indices. While the findings contribute valuable knowledge, the study acknowledges its reliance on historical data and a limited timeframe tied to the COVID-19 pandemic. Future research opportunities include exploring longer periods, incorporating diverse events, validating with alternative models, and extending analysis to diverse asset classes. This research lays a foundation for comprehending the complex interplay between leveraged ETFs and their indices, offering a roadmap for future studies to navigate the evolving financial landscape.

Keywords: Pre- and During COVID-19 Period, Spillover and Asymmetric Volatility Effects, Leveraged and Inverse ETFs
JEL Codes: G15, G23

[*] E-mail:jdiaz@aim.edu

1. Introduction

The COVID-19 pandemic has left an indelible mark on the world, triggering an unprecedented health and economic crisis that continues to reverberate across the globe. Since the World Health Organization (WHO) declared it a public health emergency on January 30, 2020, the pandemic's far-reaching effects have persisted, transforming the global landscape in profound ways. The declaration, while ultimately lifted on May 5, 2023, has cast a long shadow over both global health and the world economy, with financial markets being particularly susceptible to its disruptive influence. Within this context of global turmoil, one financial instrument that has garnered significant attention is the Exchange-Traded Fund (ETF) for its extreme form of hedging through leveraging and inverse leveraging.

ETFs, originally designed as vehicles for mirroring stock indices, have evolved into multifaceted investment tools spanning a diverse array of sectors, international markets, fixed income, commodities, and currencies. Among these, leveraged ETFs have emerged as a dynamic subset, seeking to provide amplified returns and a platform for investors and traders to capitalize on market dynamics.

This paper delves into the realm of leveraged and inverse leveraged ETFs in the equities market, these are financial instruments that aim to deliver double or triple the daily returns of their underlying indices, including inverse returns. The primary objective is to investigate the spillover and leverage effects exhibited by a specific group of twenty (20) ETFs, comprising ten (10) leveraged ETFs and ten (10) inverse leveraged ETFs, in relation to their corresponding stock indices. By employing the Exponential General Autoregressive Conditional Heteroskedasticity-in-Mean-Autoregressive Moving Average (EGARCH-M-ARMA) model, the study intends to uncover the impact of past ETF returns on current stock index returns, establishing intricate connections between these ETFs and their associated indices.

Furthermore, this research aims to explore the spillover, risk, and leverage effects of leveraged and inverse leveraged ETFs during the tumultuous period of the COVID-19 pandemic. The COVID-19 pandemic introduced heightened volatility into financial markets, as evidenced by research conducted by Van der Westhuizen et al. (2022) and Bhattacharjee and De (2022), which confirmed the escalation of market turbulence during this time. Given the unique characteristics of leveraged and inverse leveraged ETFs, they have become increasingly popular tools for traders and investors looking to leverage short-term market movements.

The study also addresses a noticeable gap in prior investigations. Most studies have predominantly focused on spillover and leverage effects within the domain of unleveraged ETFs (Chen and Huang, 2010; Chen, 2011) without assessing their performance during the pandemic. By expanding the inquiry to encompass both leveraged and inverse leveraged ETFs, this study aims to provide a comprehensive understanding of the distinct positive and negative impacts these specialized ETFs exert on their tracked indices, particularly during the turbulent period of the COVID-19 pandemic. Van der Westhuizen et al. (2022) conducted a study focusing on the interaction between stock market and foreign exchange market volatility in South Africa during the pandemic. Their findings highlighted the increased contagion between these markets, confirming the heightened volatility during crisis periods. This illustrates that the pandemic intensified market interdependencies and volatility, underscoring the importance of the study in investigating these effects on leveraged and inverse leveraged equity ETFs.

The findings from this research will refine the assessment of the feasibility of leveraged and inverse leveraged ETFs as potential alternative investments, catering to traders seeking amplified returns or robust portfolio hedging mechanisms. Additionally, the research aims to validate the efficacy of the EGARCH-M-ARMA model in capturing nuanced spillover and asymmetric-volatility effects, thereby contributing to the existing body of knowledge within the GARCH literature. This study holds significant implications for traders and fund managers, equipping them with vital insights to make more informed investment decisions.

The structure of this research paper is organized as follows. Section 2 contains the literature review, situating the research within the existing body of knowledge. Following this, Section 3 outlines the data and methodology employed, elucidating the analytical framework underpinning the investigation. Subsequently, Section 4 interprets the findings, unveiling the spillover and leverage effects observed in the study. Finally, in Section 5, the study concludes this research, encapsulating the implications of findings and suggesting avenues for further research.

2. Literature Review

This literature review aims to explore the increased volatility during the COVID-19 pandemic and its implications for the hedging capabilities of leveraged and inverse leveraged ETFs. To provide a comprehensive understanding of this topic, the study draws from a range of studies related to the impact of the pandemic on financial markets, ETFs and market volatility, and spillover effects of ETFs and financial instruments.

The COVID-19 pandemic had a profound impact on financial markets worldwide. Bhattacharjee and De (2022) conducted a broader study examining stock market volatility responses to shocks across various market segments, highlighting the impact of black swan events on market volatility in different regions. Davidescu et al. (2023) investigated changes in the volatility of biopharmaceutical companies during the pandemic, emphasizing the potential shift in the risk profiles of these companies. In the realm of ETFs, Tse et al. (2009) highlighted elevated overnight volatility in Asian ETFs and their susceptibility to local Asian stock market influences. Additional studies by Lin and Chiang (2005) and Madura and Ngo (2008) revealed positive and significant valuation effects on dominant component stocks upon the introduction of ETFs, leading to heightened trading volumes.

Leveraged and inverse leveraged ETFs have gained attention as potential hedging instruments during periods of heightened market volatility. March-Dallas et al. (2018) analyzed the differences in liquidity and volatility characteristics between leveraged and unleveraged ETFs. Their findings suggest that leveraged ETFs exhibit wider spreads and lower depth, particularly during high volatility periods. Liu (2009) showcased that dynamic rebalancing strategies enable leveraged ETFs to effectively replicate stock index returns. Leveraged ETFs offer investors the potential to amplify returns with a comparatively smaller capital outlay. Nevertheless, the allure of substantial gains must be weighed against the potential for substantial losses, given the inherent inverse relationship in leveraged positions. Giese (2009) expanded on this by revealing that the optimal level of leverage for maximizing returns is contingent upon market volatility and re-financing rates.

Trainor and Wampler (2022) delved into leveraged ETF option strategies, emphasizing the use of options and fixed-income assets. Their study provides insights into the performance of barbell strategies and their potential benefits in terms of risk and return. Furthermore, in the derivatives markets, Cheng and Madhavan (2009) explained that to establish leveraged positions, leveraged ETFs influence total return swaps and other financial instruments to amplify daily market movements. This process introduces heightened volatility as a result of daily re-leveraging at the close of trading. Primarily designed for short-term trading, leveraged ETFs offer tools for capitalizing on market volatility, regardless of the direction. This heightened volatility, however, comes hand in hand with increased risk. Lu et al. (2009) noted that leveraged ETFs can yield positive and negative returns over holding periods shorter than a month, yet their performance deviates from their tracked indices over longer periods. In specific areas of applicability, Curcio et al. (2014) explored the use of leveraged-inverse ETFs as risk management tools in real estate portfolios. Their study discussed the advantages and limitations of using these ETFs and provided evidence of their effectiveness in managing risk.

Market professionals assert that ETF activity, particularly leveraged ETFs, plays a significant role in market volatility and can extend its influence to stock indices as market participants engage in risk hedging. Ackert and Tian (2000), Elton et al. (2002), and Chen (2004) provided evidence of this claim by examining Standard & Poor's (S&P) Depositary Receipt ETFs (SPDRs). They demonstrated that changes in ETF prices can explain variations in asset allocation and underlying security volatility, and that SPDR returns have predictive power for stock prices. Chen and Edwards (2021) examined the spillover, risk, and leverage effects of different ETF management types, including active, passive, and smart beta ETFs. Their findings indicated significant relationships among these management types concerning spillover, with smart beta ETFs showing the highest positive effect. Additionally, they noted significant negative leverage effects. In a later study, Van Der Westhuizen et al. (2022) explored contagion effects and volatility spillovers between stock and foreign exchange markets in South Africa, shedding light on the interconnectedness of these markets during times of crisis. Chen and Huang (2010) conducted a global study showcasing the bilateral spillover effects on stock index and ETF volatilities.

The existing literature above has provided foundational insights into the operational dynamics of leveraged ETFs, their potential to impact underlying indices, and their role in market volatility. However, gaps in research persist, particularly concerning the potential for enhanced returns and volatility resulting from leveraged and inverse leveraged ETFs and the spillover effects on stock indices; and the unique investing strategy intrinsic to leveraged and inverse leveraged ETFs, wherein they generate double or triple effects on the gains and losses of their tracked indices. This study aims to address these gaps by examining the intricate relationships between leveraged ETFs and their tracked indices, shedding light on the nuanced dynamics that drive market interactions.

3. Data and Methodology

This study utilizes daily closing prices of leveraged equities ETFs and their underlying stock indices obtained from the Yahoo! Finance website. The sample period spans from October 20, 2016 up to May 5, 2023 with breaks during the duration of the COVID-19 Pandemic. The selected ETFs include those with higher trading activity compared to other leveraged and reverse leveraged ETFs, specifically tracking major stock market indices. The sample comprises of ten leveraged ETFs and ten inverse leveraged ETFs tracking major indices like the S&P 500, Dow Jones Industrial Average, and Russell 1000 indices. The leveraged ETFs consist of double-leveraged ETFs and triple-leveraged ETFs from some of the bigger investment houses like ProShares, Rydex, and Direxion.

This part of the study explains the proposed ARMA-EGARCH models to estimate the spillover and leverage effects of leveraged ETFs and inverse ETFs with their stock indices. The returns of both the stock indices and ETFs were calculated as the logarithm of closing prices, represented by:

$$R_{m,t} = ln\left(\frac{I_t}{I_{t-1}}\right) * 100, \quad (1)$$

$$R_{i,t} = ln\left(\frac{NAV_{i,t}}{NAV_{i,t-1}}\right) * 100, \quad (2)$$

where $R_{m,t}$ and $R_{i,t}$ denote the stock index returns and ETF returns (for both leveraged and inverse leveraged ETFs) at time *t*, respectively; *I* is the stock index; and NAV is the net asset value.

The spillover and leverage effects of stock indices and ETFs are the combination of both the EGARCH(p,q)-ARMA(g, s) models as shown by the conditional heteroscedasticity and asymmetric volatility.

The model for leveraged and inverse leveraged ETFs are represented as follows:

$$R_{i,t}^{e} = \alpha_0 + \sum_{i=1}^{g} \alpha_i R_{i,t-i}^{e} + \varepsilon_{i,t}^{e} + \sum_{i=1}^{s} \theta_i \varepsilon_{i,t-i}^{e}, \quad (3)$$

$$h_{i,t}^{e} = a_0 + \sum_{i=1}^{q} a_i \varepsilon_{i,t-1}^{e^2} + \sum_{i=1}^{p} \psi_i h_{i,t-i}^{e}, \text{ for GARCH}, \quad (4)$$

$$log\left(h_{i,t}^{e^2}\right) = a_0 + \sum_{i=1}^{q}\left(a_i \left|\frac{\varepsilon_{i,t-i}^{e}}{h_{i,t-i}^{e}}\right| + \delta_i \frac{\varepsilon_{i,t-i}^{e}}{h_{i,t-i}^{e}}\right) + \sum_{i=1}^{p} \psi_i \, log\left(h_{i,t-i}^{e^2}\right), \text{ for EGARCH}, \quad (5)$$

$$\varepsilon_{i,t}^{e} \mid \psi_{t-1} \sim N(0, h_{i,t}^{e}),$$

where $R_{i,t}^{e}$ denotes the ith ETF returns at time t; $\sum_{i=1}^{g} \alpha_i R_{i,t-i}^{e}$ represents the higher order of the autoregressive AR(g) for ETF returns; and $\varepsilon_{i,t}^{e}$ denotes for the ETF returns residual at time t. $\varepsilon_{i,t}^{e} + \sum_{i=1}^{s} \theta_i \varepsilon_{i,t-i}^{e}$ stands for the higher order moving average mean process MA (s) for $R_{i,t}^{e}$; $\sum_{i=1}^{p} \psi_i h_{i,t-i}^{e}$ denotes the p order conditional heteroscedasticity of the GARCH term for ETF returns at time t; $\sum_{i=1}^{q} a_i \varepsilon_{i,t-1}^{e^2}$ represents the q order of the ARCH term ETF returns at time t, while φ_{t-1} stands for all the information set at time t-1; δ_i is the leverage term; and θ_i captures the parameter that is not known.

The residual series equation is given below, to check if the residual possesses heteroscedasticity,

$$\varepsilon_t^2 = \alpha_0 + k_1 \varepsilon_{t-1}^2 + k_2 \varepsilon_{t-2}^2 + \cdots + k_p \varepsilon_{t-p}^2 + z_t. \quad (6)$$

One can reject the null hypothesis of the correlation among *p* = *n* periods, because the residual series will not move towards zero. This suggests that there's the existence of heteroscedasticity.

To examine the spillover and leverage effects for stock index returns, the subsequent equations are computed:

$$R_{i,t}^{m} = \beta_0 + \sum_{i=1}^{g} \beta_i R_{i,t-i}^{m} + \varepsilon_{i,t}^{m} + \sum_{i=1}^{s} \gamma_i \varepsilon_{i,t-i}^{m}, \quad (7)$$

$$h_{i,t}^{m} = b_0 + \sum_{i=1}^{q} b_i \varepsilon_{i,t-i}^{m^2} + \sum_{i=1}^{p} \zeta_i h_{i,t-i}^{m}, \text{ for GARCH}, \quad (8)$$

$$log\left(h_{i,t}^{m^2}\right) = b_0 + \sum_{i=1}^{q}\left(b_i \left|\frac{\varepsilon_{i,t-i}^{m}}{h_{i,t-i}^{m}}\right| + \delta_i \frac{\varepsilon_{i,t-i}^{m}}{h_{i,t-i}^{m}}\right) + \sum_{i=1}^{p} \zeta_i \, log\left(h_{i,t-i}^{m^2}\right), \text{ for EGARCH}, \quad (9)$$

$$\varepsilon_{i,t-j}^{m} \;\; \varphi_{t-1} \sim N\left(0, h_{i,t}^{m}\right),$$

where$R_{i,t}^{m}$ represents the *i*th stock index returns at time *t*; $\varepsilon_{i,t}^{m}$ denotes for the residual of stock index returns residual at time *t*; $h_{i,t}^{m}$ represents the conditional variance of stock index returns at time *t*; and φ_{t-1} represents all the information set at time *t-1*. In addition, δ_i denotes for the leverage term and γ_i is the unknown parameter. Noted that $h_{i,t}^{e^2}$ and $h_{i,t}^{m^2}$ are the conditional variance of leveraged (or inverse leveraged) ETFs and stock index returns, respectively.

The leverage effect test is also suggested in this research to give conclusions from the asymmetric volatility parameter (δ_i) in the EGARCH model. A negative value for δ, which is deemed to be statistically significant, means that there's leverage effect in ETF returns (or stock indices) for the entire sample period.

Multiple EGARCH(p,q)-ARMA(g, s) models are utilized to estimate the spillover effect of returns and volatilities for both stock indices and ETFs. The models will also try to determine positive or negative relationship that may arise from chosen leveraged and inverse leveraged ETFs and their stock indices.

3.1 The spillover effect of ETF and index returns

Spillover effects as illustrated below, explains the interdependence between ETF returns and stock index returns or the way they can be affected by market shocks:

$$R^e_{i,t} = \alpha_0 + \sum_{i=1}^{g} \alpha_i R^e_{i,t-i} + wR^m_{i,t-1} + \varepsilon^e_{i,t} + \sum_{i=1}^{s} \theta_i \varepsilon^e_{i,t-i} + zh^e_{i,t}, \quad (10)$$

$$h^e_{i,t} = a_0 + \sum_{i=1}^{q} a_i \varepsilon^{e^2}_{i,t-i} + \sum_{i=1}^{p} \psi_i h^e_{i,t-i}, \text{ for GARCH,} \quad (11)$$

$$log\left(h^{e^2}_{i,t}\right) = a_0 + \sum_{i=1}^{q}\left(a_i \left|\frac{\varepsilon^e_{i,t-i}}{h^e_{i,t-i}}\right| + \delta_i \frac{\varepsilon^e_{i,t-i}}{h^e_{i,t-i}}\right) + \sum_{i=1}^{p} \psi_i \, log\left(h^{e^2}_{i,t-i}\right), \text{for EGARCH,} \quad (12)$$

$\varepsilon^e_{i,t} \mid \psi_{t-1} \sim N(0, h^e_{i,t})$,

$$R^m_{i,t} = \beta_0 + \sum_{i=1}^{g} \beta_i R^m_{i,t-i} + dR^e_{i.t-1} + \varepsilon^m_{i,t} + \sum_{i=1}^{s} \gamma_i \varepsilon^m_{i,t-i} + kh^m_{i,t}, \quad (13)$$

$$h^m_{i,t} = b_0 + \sum_{i=1}^{q} b_1 \varepsilon^{m^2}_{i,t-1} + \sum_{i=1}^{q} \zeta_i h^m_{i,t-i}, \text{ for GARCH,} \quad (14)$$

$$log\left(h^{m^2}_{i,t}\right) = b_0 + \sum_{i=1}^{q}\left(b_i \left|\frac{\varepsilon^m_{i,t-i}}{h^m_{i,t-i}}\right| + \delta_i \frac{\varepsilon^m_{i,t-i}}{h^m_{i,t-i}}\right) + \sum_{i=1}^{p} \zeta_i \, log\left(h^{m^2}_{i,t-i}\right), \text{for EGARCH,} \quad (15)$$

$\varepsilon^m_{i,t} \mid \psi_{t-1} \sim N(0, h^m_{i,t})$,

where the spillover effects from stock index returns and leveraged (or inverse leveraged) ETF returns are represented by w and d, respectively. From the null hypothesis of no spillover effects of returns ($w = 0\,; d = 0$) the tests of spillover effects are applicable. The lagged stock index returns generally influence ETF returns if the w coefficient is significantly different from zero, and vice versa, and when the d coefficient is tested.

3.2 The spillover effect of ETF and index volatilities

In the following equation, this research expands the emphasis on possible spillover effects by checking how cross-market dynamics can influence stock index volatilities and ETF volatilities:

$$R^e_{i,t} = \alpha_0 + \sum_{i=1}^{g} \alpha_i R^e_{i,t-i} + \varepsilon^e_{i,t} + \sum_{i=1}^{s} \theta_i \varepsilon^e_{i,t-i} + zh^e_{i,t}, \quad (16)$$

$$h^e_{i,t} = a_0 + \sum_{i=1}^{q} a_i \varepsilon^{e^2}_{i,t-1} + \sum_{i=1}^{p} \psi_i h^e_{i,t-i} + v\varepsilon^{m^2}_{i,t-1}, \text{ for GARCH,} \quad (17)$$

$$log\left(h^{e^2}_{i,t}\right) = a_0 + \sum_{i=1}^{q}\left(a_i \left|\frac{\varepsilon^e_{i,t-i}}{h^e_{i,t-i}}\right| + \delta_i \frac{\varepsilon^e_{i,t-i}}{h^e_{i,t-i}}\right) + \sum_{i=1}^{p} \psi_i \, log\left(h^{e^2}_{i,t-i}\right) + v\varepsilon^{m^2}_{i,t-1}, \text{ for EGARCH,} \quad (18)$$

$\varepsilon^e_{i,t} \mid \psi_{t-1} \sim N(0, h^e_{i,t})$,

$$R^m_{i,t} = \beta_0 + \sum_{i=1}^{g} \beta_i R^m_{i,t-i} + \varepsilon^m_{i,t} + \sum_{i=1}^{s} \gamma_i \varepsilon^m_{i,t-i}, + kh^m_{i,t}, \quad (19)$$

$$h^m_{i,t} = b_0 + \sum_{i=1}^{q} b_i \varepsilon^{m^2}_{i,t-i} + \sum_{i=1}^{p} \zeta_i h^m_{i,t-i} + l\varepsilon^{e^2}_{i,t-1}, \text{ for GARCH,} \quad (20)$$

$$log\left(h_{i,t}^{m^2}\right) = b_0 + \sum_{i=1}^{q}\left(b_i\left|\frac{\varepsilon_{i,t-i}^{m}}{h_{i,t-i}^{m}}\right| + \delta_i\frac{\varepsilon_{i,t-i}^{m}}{h_{i,t-i}^{m}}\right) + \sum_{i=1}^{p}\zeta_i \cdot log\left(h_{i,t-i}^{m^2}\right) + l\varepsilon_{i,t-1}^{e^2}, \text{for EGARCH,(21)}$$

$\varepsilon_{i,t}^{m} \mid \psi_{t-1} \sim N(0, h_{i,t}^{m}),$

where the spillover effect from stock index volatilities and leveraged (or inverse leveraged) ETF volatilities are denoted by v and l, respectively. This research used the null hypothesis that the series has an absence of spillover effects of volatility (v =0; l =0) against alternative hypothesis that the series has the spillover effects of volatility (v ≠0; l ≠0). The lagged stock index (or ETF residual) affects the ETF volatility (or stock index volatility) if the alpha value is greater than the p-value of v (or l).

4. Empirical Results

Table 1.a and 1.b. provide summary statistics for a set of leveraged ETFs and the indices they track. Each row in the table represents a specific leveraged ETF along with its associated tracked index. The ETFs and Tracked Indices column lists the names of the leveraged ETFs and the respective stock market indices they track. For example, the first row ProShares UltraPro QQQ ETF (TQQQ) tracks the NASDAQ100 stock index (^NDX); while the ProShares Ultra S&P 500 ETF (SSO) tracks the S&P 500 stock index (^GSPC). The Ticker column provides the stock market symbols for each ETF and its tracked index. The Mean column displays the average or mean return for each ETF. For example, the TQQQ ETF has an average return of 0.103, while the tracked ^NDX has an average return of 0.061.

The Standard Deviation column represents the measure of the dispersion or volatility in the returns of the ETF and the tracked index. It shows how much the returns tend to deviate from their mean. For instance, the TQQQ ETF has a standard deviation of 4.506, while the tracked ^NDX stock index has a standard deviation of 1.524, this means that the ETF has a volatile return structure than its tracked stock index.

ETFs with higher standard deviations may present tactical opportunities for investors looking to capitalize on market volatility. During periods of heightened market uncertainty, these ETFs may exhibit more pronounced price movements, providing opportunities for short-term gains for those adept at tactical trading. The results also conclude that the Modern Portfolio Theory of Markowitz (1952), stating that a higher risk is compensated with higher returns is also consistent with the ETFs under study. Investors can employ a risk-return analysis using the provided mean and standard deviation values. ETFs with higher average returns and acceptable levels of volatility may be attractive for those seeking a balance between risk and reward. Conversely, risk-averse investors may prefer ETFs with lower volatility, even if they offer slightly lower average returns.

The Skewness measures the asymmetry of the return distribution. Positive skewness indicates a distribution with a longer right tail, while negative skewness suggests a longer left tail. In this table, positive and negative skewness values are provided. For example, the TQQQ ETF has a skewness of -0.982, indicating a negatively skewed distribution, while the tracked ^NDX Index has a skewness of -0.542, also negatively skewed.

The Kurtosis column measures the tail risk and thickness of the tails of the return distribution. High kurtosis indicates fat tails, meaning extreme events are more likely happening. In this table, positive and negative kurtosis values are observed. For example, the TQQQ ETF has a positive kurtosis of 11.528, indicating a leptokurtic distribution (fat-tailed), while the tracked ^NDX stock Index also has a positive kurtosis of 10.157.

The J-Bera column represents the Jarque-Bera statistic, which is used to test the normality of the return distribution. Large values indicate deviations from a normal distribution. The p-value (in parentheses) associated with the Jarque-Bera statistic is provided to assess the significance of the deviation. For example, the TQQQ ETF has a J-Bera statistic of 5,252.57 with a p-value of 0.000, indicating a significant departure from a normal distribution.

For Table 1.b., the Mean column displays that the average or mean return for each inverse leveraged ETFs are negative, indicating that inverse ETFs are designed to profit from the decline in the tracked index. For example, the SQQQ ETF has a mean return of -0.319, while it's tracked stock index ^NDX has a positive mean return of 0.061.

For the other information of the leveraged and inverse leveraged ETFs and the stock indices they track, including mean returns, standard deviations, skewness, kurtosis, and the Jarque-Bera statistic for normality testing, please refer to Tables 1.a. and 1.b. below.

Table 1.a. Summary Statistics of Leveraged ETFs

ETFs and Tracked Indices	Ticker	Mean	Standard Deviation	Skewness	Kurtosis	J-Bera
ProShares UltraPro QQQ	TQQQ	0.103	4.506	-0.982	11.528	5252.568*** (0.000)
NASDAQ-100 Index	^NDX	0.061	1.524	-0.542	10.157	3593.904*** (0.000)
ProShares Ultra QQQ	QLD	0.094	3.032	-0.789	11.130	4704.140*** (0.000)
NASDAQ-100 Index	^NDX	0.061	1.524	-0.542	10.157	3593.904*** (0.000)
ProShares Ultra S&P 500	SSO	0.065	2.491	-1.173	20.084	20394.98*** (0.000)
S&P 500	^GSPC	0.040	1.245	-0.848	18.601	16890.72*** (0.000)
Direxion Daily S&P 500 Bull 3X Shares	SPXL	0.069	3.740	-1.488	21.621	24391.27*** (0.000)
S&P 500	^GSPC	0.040	1.245	-0.848	18.601	16890.72*** (0.000)
ProShares UltraPro S&P500	UPRO	0.072	3.769	-1.560	23.024	28167.89*** (0.000)
S&P 500	^GSPC	0.040	1.245	-0.848	18.601	16890.72*** (0.000)
Direxion Daily Technology Bull 3X Shares	TECL	0.124	4.782	-0.858	12.565	6477.243*** (0.000)
Technology Select Sector Index	^IXTTR	0.075	1.615	-0.469	12.532	6292.787*** (0.000)
Direxion Daily Financial Bull 3X Shares	FAS	0.041	4.345	-1.513	21.988	25356.71*** (0.000)
Russell 1000 Financial Services Index	^RUI	0.039	1.258	-0.911	18.530	16770.07*** (0.000)
ProShares UltraPro	UDOW	0.068	3.689	-1.775	27.184	40976.49***

Dow30 Dow Jones Industrial	^DJI					(0.000)
ProShares Ultra Technology Technology Select Sector Index	ROM ^IXTTR	0.107 0.075	3.296 1.615	-0.597 -0.469	9.539 12.532	3030.828*** (0.000) 6292.787*** (0.000)
Direxion Daily S&P 500 Bull 2x Shares S&P 500	SPUU ^GSPC	0.048 0.040	2.511 1.245	-1.182 -0.848	18.346 18.601	16536.66*** (0.000) 16890.72*** (0.000)

*Note: * - significant at the 10% level.*
*** - significant at the 5% level.*
**** - significant at the 10% level.*

Table 1.b. Summary Statistics of Inverse Leveraged ETFs

ETFs and Tracked Indices	Ticker	Mean	Standard Deviation	Skewness	Kurtosis	J-Bera
ProShares UltraPro Short QQQ NASDAQ-100 Index	SQQQ ^NDX	- 0.319 0.061	4.460 1.524	-0.207 -0.542	9.068 10.157	2537.786*** (0.000) 3593.904*** (0.000)
ProShares UltraPro Short S&P500 S&P 500 Index	SPXU ^GSPC	- 0.217 0.070	3.668 1.245	-0.336 -0.848	16.846 18.601	13180.26*** (0.000) 16890.72*** (0.000)
ProShares UltraShort S&P500 S&P 500 Index	SDS ^GSPC	- 0.129 0.070	2.456 1.245	-0.026 -0.848	16.406 18.601	12327.71*** (0.000) 16890.72*** (0.000)
Direxion Daily S&P 500 Bear 3X Shares S&P 500 Index	SPXS ^GSPC	- 0.218 0.040	3.679 1.245	-0.301 -0.848	16.600 18.601	12710.94*** (0.000) 16890.72***
ProShares UltraPro Short Dow30 Dow Jones Industrial Average	SDOW ^DJI	- 0.211 0.036	3.646 1.237	-0.458 -1.013	22.237 24.878	25407.18*** (0.000) 33068.90*** (0.000)
ProShares UltraShort QQQ NASDAQ-100 Index	QID ^NDX	- 0.189 0.030	3.002 1.237	0.001 -1.013	9.141 24.878	2586.601*** (0.000) 33608.90*** (0.000)
Direxion Daily Financial Bear 3X Shares	FAZ ^RUI	- 0.246 0.039	4.354 1.258	-0.760 -0.911	19.544 18.530	18931.08*** (0.000) 16770.07*** (0.000)

Russell 1000 Financial Services Index						
Direxion Daily FTSE China Bear 3X Shares	YANG	-0.102	4.949	-0.336	6.452	848.2152*** (0.000)
FTSE China 50 Index	XIN0.FGI	-0.023	1.586	0.034	6.300	746.8493*** (0.000)
Direxion Daily Technology Bear 3X Shares	TECS	-0.371	4.750	-0.504	10.691	4127.016*** (0.000)
Technology Select Sector Index	^IXTTR	0.075	1.615	-0.469	12.532	6292.787*** (0.000)

*Note: * - significant at the 10% level.*
*** - significant at the 5% level.*
**** - significant at the 10% level.*

Tables 2.a. and 2.b. show that validity tests were done for both the leveraged and inverse leveraged ETFs, and their respective stock indices. The Augmented Dickey-Fuller (ADF) unit-root test results show that the alternative of no unit roots is not rejected for both samples, supporting a stationary time-series data. For example, TQQQ Leveraged ETF has significant -46.136*** coefficient; the same is true SQQQ Inverse Leveraged ETF is significant at -13.153***, and both their underlying stock index ^NDX (tech sector heavy NASDAQ100) is also significant at -47.694***. To further illustrate, SSO Leveraged ETF has significant -12.325*** coefficient; the same is true SPXU Inverse Leveraged ETF is significant at -12.598***, and both their underlying stock index ^GSPC (diversified S&P 500) is also significant at -12.351***.

This research used the basic combination of EGARCH (1,1) and ARMA (1,1) models to identify the ARCH effects using the Lagrange Multiplier Test (ARCH-LM) by Engle (1982). The ARCH-LM test is being done to check the hypothesis of ARCH errors in the residuals of the ARMA-EGARCH models. The results of the tests suggest that there’s no autoregressive conditional heteroscedasticity for all samples. For example, TQQQ leveraged ETF has 0.487, SQQQ inverse leveraged ETF has 0.398, and their underlying stock ^NDX has 0.587. To further illustrate, SSO leveraged ETF has 0.979, SPXU inverse leveraged ETF has 0.995, and their underlying stock ^GSPC has 0.746. For the details of these validity tests, please refer to Tables 2.a and 2.b. below.

Table 2.a. ARMA-EGARCH Validity Tests for Leveraged ETFs: ADF & ARCH-LM Tests

Code	ADF	ARMA	AIC	EGARCH	AIC	ARCH-LM
TQQQ	-46.139***	(1,1)	5.836	(1,1)	5.399	0.487
^NDX	-47.694***		3.358		3.221	0.587
QLD	-47.003***	(1,1)	5.038	(1,1)	4.567	0.318
^NDX	-47.694***		3.358		3.221	0.587
SSO	-12.325***	(1,1)	4.638	(1,1)	3.981	0.979
^GSPC	-12.351***		3.246		2.611	0.746
SPXL	-12.098***	(1,1)	5.453	(1,1)	4.803	0.911
^GSPC	-12.351***		3.246		2.611	0.746

UPRO ^GSPC	-12.153*** -12.351***	(1,1)	5.465 3.246	(1,1)	4.795 2.611	0.824 0.746
TECL ^IXTTR	-12.820*** -13.148***	(1,1)	5.951 3.768	(1,1)	5.508 3.311	0.673 0.609
FAS ^RUI	-11.939*** -12.481***	(1,1)	5.767 6.271	(1,1)	5.129 2.630	0.801 0.848
UDOW ^DJI	-12.084*** -12.460***	(1,1)	5.427 3.230	(1,1)	4.749 2.555	0.841 0.693
ROM ^IXTTR	-13.189*** -13.148***	(1,1)	5.210 3.768	(1,1)	3.311 4.823	0.609 0.656
SPUU ^GSPC	-12.416*** -12.351***	(1,1)	4.650 3.246	(1,1)	4.081 2.611	0.504 0.746

*Note: * - significant at the 10% level.*
*** - significant at the 5% level.*
**** - significant at the 10% level.*

Table 2.b. ARMA-EGARCH Validity Tests for Inverse Leveraged ETFs: ADF & ARCH-LM Tests

Code	ADF	ARMA	AIC	EGARCH	AIC	ARCH-LM
SQQQ ^NDX	-13.153*** -47.694***	(1,1)	5.813 3.358	(1,1)	5.372 3.221	0.398 0.587
SPXU ^GSPC	-12.598*** -12.351***	(1,1)	5.415 3.246	(1,1)	4.763 2.611	0.995 0.746
SDS ^GSPC	-12.562*** -12.351***	(1,1)	4.609 3.246	(1,1)	3.961 2.611	0.959 0.746
SPXS ^GSPC	-12.587*** -12.351***	(1,1)	5.419 3.246	(1,1)	4.762 2.611	0.857 0.746
SDOW ^DJI	-12.677*** -12.460***	(1,1)	5.400 3.230	(1,1)	4.715 2.555	0.641 0.693
QID ^NDX	-13.159*** -47.694***	(1,1)	5.018 3.358	(1,1)	4.572 3.221	0.378 0.587
FAZ ^RUI	-11.646*** -12.481***	(1,1)	5.767 6.271	(1,1)	5.127 2.630	0.824 0.848
YANG XIN0.FGI	-15.435*** -41.227***	(1,1)	6.035 3.764	(1,1)	5.842 3.553	0.040 0.539
TECS ^IXTTR	-13.272*** -13.148***	(1,1)	5.934 3.768	(1,1)	5.478 3.311	0.590 0.609

*Note: * - significant at the 10% level.*
*** - significant at the 5% level.*
**** - significant at the 10% level.*

Table 3 reveals the presence of asymmetric volatility effects in both the leverage and inverse leverage aspects of ETFs and stock indices, shedding light on their distinct reactions to market news. This information holds practical implications for investors and traders seeking to leverage these instruments in various ways. The results indicate that both leveraged ETFs and their corresponding stock indices tend to respond more vigorously to negative news than to positive news. For instance, the TQQQ ETF displays a significant negative result (-0.101***), and simultaneously, the ^NDX index exhibits a similar significant negative effect (-0.108***). This finding suggests that during times of adverse market conditions or negative news events, both leveraged ETFs and their underlying indices experience amplified reactions, potentially influencing trading strategies and investment decisions. Investors may consider implementing more robust risk management strategies, such as setting tighter stop-loss orders or diversifying their portfolios to mitigate the impact of adverse market movements. Market traders could also time their entries and exits more effectively by entering positions during periods of market optimism and exiting or adjusting positions when anticipating a potential downturn, based on the understanding that negative news could trigger more pronounced declines.

Conversely, the inverse leverage effects are predominantly observed in the stock indices. These indices tend to exhibit a stronger response to negative news, as evidenced by the ^GSPC index (-0.142***) and ^ICESEMI index (-0.108***). In contrast, inverse leveraged ETFs, by design, do not significantly react to news events, whether negative or positive, due to their structure designed to move inversely to their tracked index. For example, the SPXU ETF demonstrates a significant positive result (0.155***), and the SOXS ETF follows suit with a notable positive effect (0.112***). These results resemble the findings of Balaban and Bayar (2005), and Li (2007) in their study on asymmetric volatility effects and volatility clustering. This observation underscores the practical application of inverse leveraged ETFs as potential hedges or tools for investors seeking to maintain positions during market downturns, as their performance remains relatively stable in response to news. The observed asymmetry presents contrarian opportunities for investors who are comfortable going against the prevailing market sentiment. If negative news tends to provoke exaggerated responses, contrarian investors might seek buying opportunities during periods of unwarranted pessimism, anticipating a potential rebound.

Table 3 Asymmetric Volatility Effects of Leveraged and Inverse Leveraged ETFs

Leverage ETFs and Tracked Indices			**Inverse Leverage ETFs and Tracked Indices**		
Ticker	**Index**	**ETF**	**Ticker**	**Index**	**ETF**
TQQQ ^NDX	-0.108*** (0.000)	-0.101*** (0.000)	SQQQ ^NDX	-0.107*** (0.000)	0.112*** (0.000)
QLD ^NDX	-0.114*** (0.000)	-0.104*** (0.000)	SPXU ^GSPC	-0.142*** (0.000)	0.155*** (0.000)
SSO ^GSPC	-0.150*** (0.000)	-0.142*** (0.000)	SOXS ^ICESEMI	-0.108*** (0.000)	0.112*** (0.000)
SPXL ^GSPC	-0.141*** (0.000)	-0.144*** (0.000)	SDS ^GSPC	-0.142*** (0.000)	0.157*** (0.000)
UPRO ^GSPC	-0.142*** (0.000)	-0.146*** (0.000)	SPXS ^GSPC	-0.142*** (0.000)	0.163*** (0.000)
TECL ^IXTTR	-0.096*** (0.000)	-0.087*** (0.000)	SDOW ^DJI	-0.143*** (0.000)	0.150*** (0.000)
FAS ^RUI	-0.141*** (0.000)	-0.170*** (0.000)	QID ^NDX	-0.108*** (0.000)	0.115*** (0.000)
UDOW ^DJI	-0.253*** (0.000)	-0.149*** (0.000)	FAZ ^RUI	-0.141*** (0.000)	-0.170*** (0.000)

ROM ^IXTTR	-0.109*** (0.000)	-0.086*** (0.000)	YANG XIN0.FGI	-0.057*** (0.000)	0.054*** (0.000)
SPUU ^GSPC	-0.251*** (0.000)	-0.108*** (0.000)	TECS ^IXTTR	-0.096*** (0.000)	0.105*** (0.000)

*Note: * - significant at the 10% level.*
*** - significant at the 5% level.*
**** - significant at the 10% level.*

Table 4 shows valuable insights into the spillover effects of leveraged ETFs in the context of their tracked stock indices. This information not only contributes to our understanding of these financial instruments but also offers practical applications for investors and traders seeking to make informed decisions in dynamic market conditions. The Ticker column in Table 4 lists the symbols of leveraged ETFs alongside their respective stock market indices. The next two columns focusing on Spillover Effects of Returns provide essential data on how returns spillover from the stock index to the ETF (Index to ETF) and vice versa (ETF to Index). The numerical coefficients and accompanying p-values in parentheses denote the statistical significance of these relationships.

For instance, the SSO ETF demonstrates a significant positive effect (0.350***) on the ^GSPC index, indicating that during certain market conditions, the performance of this ETF positively influences the future performance of the tracked index. Conversely, the stock market index exerts no significant effect (-0.619) on the SSO ETF. A similar one-way relationship is observed in the case of the UPRO ETF (0.208***) to ^GSPC index, FAS ETF (0.017*) to ^RUI index, and ROM ETF (0.112**) to ^IXTTR index. These findings provide practical applications for investors who may use this information to make more informed trading decisions in knowing that certain leveraged ETFs can be used to predict future movements of their tracked. For example, recognizing that the SSO ETF has a significant impact on the ^GSPC index could guide investment strategies during periods when tracking the broader market index is of particular importance. Furthermore, investors could strategically allocate their assets based on the observed reactions. Allocating a smaller portion of the portfolio to leveraged ETFs and their corresponding indices during periods of anticipated negative news may help mitigate the impact on the overall portfolio. This significant spillover effect shows a consistently strong performance with exposures and supports the original design of leveraged ETFs from the studies of Avellaneda and Zhang (2009), and Cheng and Madhavan (2009).

Furthermore, it is noteworthy that the spillover effects of volatilities, as shown in the corresponding columns, do not exhibit statistical significance. This observation is crucial for investors and traders, indicating that while returns may be influenced by these relationships, volatility levels remain relatively unaffected. This practical insight can inform strategies that rely on the stability or volatility of these financial instruments.

Table 4 Spillover and Asymmetric Volatility Effects of Leveraged ETFs

Ticker	Spillover Effects of Returns		Spillover Effects of Volatilities	
	Index	ETF	Index	ETF
TQQQ ^NDX	-0.016 (0.782)	-0.245 (0.823)	0.000 (0.271)	0.001 (0.277)
QLD ^NDX	-0.033 (0.766)	-0.151 (0.849)	0.000 (0.273)	0.002 (0.237)
SSO	**0.350*** **	-0.619	0.000	0.001

^GSPC	**(0.000)**	(0.229)	(0.407)	(0.487)
SPXL ^GSPC	0.095 (0.613)	**-1.394***** **(0.008)**	0.450 (0.322)	0.001 (0.487)
UPRO ^GSPC	**0.208***** **(0.000)**	-0.924 (0.113)	0.000 (0.407)	0.000 (0.512)
TECL ^IXTTR	-0.010 (0.368)	0.786 (0.474)	0.000 (0.156)	0.001 (0.333)
FAS ^RUI	**0.017*** **(0.055)**	-0.072 (0.574)	0.000 (0.231)	0.002 (0.346)
UDOW ^DJI	-0.034 (0.507)	**-0.922*** **(0.065)**	0.000 (0.213)	0.002 (0.237)
ROM ^IXTTR	**0.112**** **(0.010)**	-0.338 (0.133)	0.000 (0.200)	0.001 (0.232)
SPUU ^GSPC	0.005 (0.863)	**1.017***** **(0.000)**	0.000 (0.431)	0.005 (0.112)

*Note: * - significant at the 10% level.*
*** - significant at the 5% level.*
**** - significant at the 10% level.*

Table 5 illustrates the spillover effects of inverse leveraged ETFs and their tracked stock indices. For instance, the SQQQ ETF exhibits a significant negative effect (-0.336***) on the ^NDX index, suggesting that during specific market conditions, the SQQQ ETF tends to exert a noticeable influence on the performance of the NASDAQ100 index. Conversely, the stock market index demonstrates no significant effect on the SQQQ ETF, highlighting a one-way relationship where the ETF impacts the index but not the other way around. This insight can inform investment strategies, helping traders understand how the SQQQ ETF may impact their portfolios during volatile market events or downturns. Investors may consider using ETFs like the SQQQ as a potential tool for downside protection during specific market conditions or downturns. One-way relationships in the market suggest that ETFs that tends to exert a noticeable influence on their stock indices make them a good basket for investors looking to hedge against declines in that particular industry, e.g., tech-heavy markets for NASDAQ100.

Likewise, the negative effects observed in the FAZ ETF (-0.016*) to ^RUI index and YANG ETF (-0.027***) to XIN0.FGI index provide practical applications for investors who may consider these ETFs as potential hedges during market declines. Understanding the asymmetric relationships between these ETFs and their tracked indices can guide risk management decisions and portfolio construction. These negative effects also confirm the results of Chen and Huang (2010), and Chen (2011) on their study of ETFs.

The analysis also reveals intriguing two-way relationships, such as the ^GSPC index (-0.422***) and SPXS ETF (-0.214***), which display a negative bilateral effect. These findings can guide investors in developing strategies that capitalize on these bidirectional relationships, potentially allowing them to take advantage of market fluctuations more effectively. For instance, during periods of heightened volatility, investors might consider using SPXS ETF as a tactical trading tool to benefit from declines in the S&P 500.

Regarding the spillover effects of volatilities, bilateral positive effects between the YANG ETF (0.002***) and XIN0.FGI index (0.004**) offer insights for investors looking to hedge against increased market volatility. By recognizing the mutual influence between these instruments, traders may adjust their portfolios to respond to changing market conditions. This mutual influence suggests that YANG and XIN0.FGI move in tandem during periods of heightened volatility. Investors could strategically allocate these instruments to manage risk and capture opportunities arising from volatile market conditions.

Table 5 Spillover and Asymmetric Volatility Effects of Inverse Leveraged ETFs

Ticker	Spillover Effects of Returns		Spillover Effects of Volatilities	
	Index	ETF	Index	ETF
SQQQ ^NDX	**-0.336*** (0.000)**	-0.445 (0.621)	0.000 (0.230)	0.003 (0.132)
SPXU ^GSPC	0.592 (0.444)	**-0.871*** (0.000)**	0.000 (0.360)	0.000 (0.252)
SDS ^GSPC	**0.735** (0.042)**	**-0.358*** (0.000)**	0.000 (0.376)	0.002 (0.394)
SPXS ^GSPC	**-0.214*** (0.000)**	**-0.422*** (0.000)**	0.000 (0.369)	0.122 (0.235)
SDOW ^DJI	**-0.184*** (0.000)**	**1.220** (0.012)**	0.000 (0.203)	**0.003* (0.082)**
QID ^NDX	**-0.270*** (0.000)**	**1.329*** (0.000)**	0.000 (0.242)	0.002 (0.179)
FAZ ^RUI	**-0.016* (0.063)**	0.093 (0.461)	0.000 (0.201)	0.002 (0.300)
YANG XIN0.FGI	**-0.027*** (0.000)**	-0.038 (0.642)	**0.002*** (0.000)**	**0.004** (0.028)**
TECS ^IXTTR	0.009 (0.440)	0.652 (0.401)	0.000 (0.164)	**0.324*** (0.000)**

*Note: * - significant at the 10% level.*
*** - significant at the 5% level.*
**** - significant at the 10% level.*

5. Conclusions and Limitations

This research has provided valuable insights into the dynamics of leveraged and inverse leveraged ETFs. The findings reveal the complex relationships between these specialized financial instruments and their tracked indices, shedding light on both spillover and leverage effects. The analysis demonstrates that spillover effects of returns and volatilities between leveraged ETFs and their corresponding stock indices are present, but their significance varies. This indicates that there is an interplay between these financial instruments and the broader market. The research also highlights the leverage effects of leveraged and inverse leveraged ETFs. It is evident that these ETFs have the potential to amplify both positive and negative news, making them valuable tools for traders looking to capitalize on short-term market movements or hedge against market downturns. The study reveals that stock market indices and ETFs tend to respond more strongly to negative news than to positive news, indicating a level of asymmetry in their reactions. This knowledge is crucial for understanding how these instruments behave in different market conditions. Maximizing the spillover effects observed in inverse leveraged and inverse leveraged ETFs and their tracked stock indices can guide investors in constructing robust portfolios. These strategies aim to enhance risk management, capitalize on bidirectional relationships, and adjust portfolios to navigate specific market conditions effectively. Leveraged and inverse leveraged

ETFs exhibit unique characteristics that set them apart from traditional ETFs. Investors and fund managers should consider these distinctions when incorporating these instruments into their portfolios.

Despite the valuable insights gained from this study, it is essential to acknowledge that this research is based on historical data, and the timeframe of analysis is limited to the COVID-19 pandemic. Future research could explore longer time periods and consider the impact of other significant events on these financial instruments. The results are specific to the set of leveraged ETFs and stock indices examined in this study. Further research could broaden the scope to encompass a more extensive range of financial instruments and indices. The EGARCH-M-ARMA model used in this study is just one of several possible approaches. Future research could explore alternative models to validate and enhance the findings.

To build upon the findings of this research and expand our understanding of leveraged and inverse leveraged ETFs, future studies can consider investigating the behavior of these ETFs across various market conditions and events to assess their adaptability and performance in different scenarios. Future studies can also explore risk management strategies and investment approaches that incorporate leveraged and inverse leveraged ETFs as tools for portfolio diversification and hedging. Furthermore, examine the regulatory implications and recommendations for the use of leveraged and inverse leveraged ETFs, considering the potential impact on market stability and investor protection. Lastly, extend the analysis to include leveraged and inverse leveraged ETFs in asset classes beyond equities, such as fixed income, commodities, and currencies.

This research serves as a foundation for understanding the complex interplay between leveraged and inverse leveraged ETFs and their tracked indices, particularly in the context of the COVID-19 pandemic. Future research in this area will further enrich our knowledge, providing investors, traders, and policymakers with the tools and insights necessary to navigate the evolving landscape of financial markets.

References

Ackert, L. F., & Tian, Y. S. (2000). Arbitrage and valuation in the market for Standard and Poor's depositary receipts. Financial Management, 29, 71-88.

Avellaneda, M. and Zhang, S.J. 2010. Path-dependence of leveraged ETF returns, SIAM Journal on Financial Mathematics, 1, 586-603.

Balaban, E. and Bayar, A. 2005. Stock returns and volatility: Empirical evidence from fourteen countries, Applied Economics Letter, 12(10), 603-611.

Bhattacharjee, N., & De, A. (2022). Black Swan Event and the Stock Market Volatility Response to Shocks in Developed, Emerging, Frontier and the BRIC Markets: Lessons from the COVID-19 Pandemic. Brazilian Business Review, 19(5), 492-507.

Chen, J. H. (2011). The spillover and leverage effects of ethical exchange-traded funds. Applied Economics Letter, 18(9), 983-987.

Chen, J. H., & Edwards, N. (2021). The Spillover, Risk, and Leverage Effects of Smart Beta Management Exchange-Traded Fund (ETF). Global Economy Journal, 21.

Chen, J. H., & Huang, C. Y. (2010). An analysis of the spillover effects of exchange traded funds.

Applied Economics, 42(9), 1155-1168.

Chen, T. (2004). Forecasting the information content derived from volatility of exchange traded funds. Dissertation, Tamkang University, Taiwan, R.O.C.

Cheng, M., & Madhavan, A. (2009). The dynamics of leveraged and inverse exchange-traded funds. SSRN Working Papers, 1539120.

Curcio, R. J., Anderson, R. I., & Guirguis, H. (2014). Managing risk in the real estate portfolio through the use of leveraged and inverse ETFs. Real Estate Finance, 31(2).

Davidescu, A. A., Manta, E. M., Vacaru (Boita), O. M., Gruiescu, M., Hapau, R. G., & Baranga, P. L. (2023). Has the COVID-19 Pandemic Led to a Switch in the Volatility of Biopharmaceutical Companies? Mathematics, 11(14).

Elton, E. J., Gruber, M. J., Comer, G., & Li, K. (2002). Spiders: where are the bugs. Journal of Business, 75(3), 453-472.

Giese, G. (2009). On the performance of leveraged and optimally leveraged investment funds. SSRN Working Papers, 1510344.

Li, M.C. 2007. Wealth, volume and stock market volatility: Case of Hong Kong (1993-2001), Applied Economics, 39, 1937-1953.

Lin, C., & Chiang, M. (2005). Volatility effect of ETFs on the constituents of the underlying Taiwan 50 index. Applied Financial Economics, 15(18), 1315-1322.

Liu, Q. (2009). Jump risk and the performance of leveraged exchange-traded funds. SSRN Working Papers, 1517290.

Lu, L., Wang, J. J., & Zhang, G. (2009). Long-term performance of leveraged ETFs. SSRN Working Papers, 1344133.

Madura, J., & Ngo, T. (2008). Impact of ETF inception on the valuation and trading of component stocks. Applied Financial Economics, 18(12), 995-1007.

March-Dallas, S., Daigler, R., Mishra, S., & Prakash, A. (2018). Exchange traded funds: leverage and liquidity. Applied Economics, 50(37), 4054-4073.

Markowitz, H. (1952) Portfolio selection, Journal of Finance, 7(1), 77-91.

Tse, Y., Gutierrez, J., & Martinez, V. (2009). Where does volatility and return come from? The case of Asian ETFs. University of Texas at San Antonio. Working Paper Series, 0063.

Trainor, W. J., & Wampler, E. B. (2022). Leveraged ETF Option Barbells. Journal of Beta Investment Strategies, 13(3), 66-75.

Van Der Westhuizen, C., Van Eyden, R., & Aye, G. C. (2022). Contagion across financial markets during COVID-19: A look at volatility spillovers between the stock and foreign exchange markets in South Africa. Annals of Financial Economics, 17(1), 1-46.