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COVID-19, Lockdowns and Implied Market Volatility: Evidence from Coronavirus Vaccine Stocks

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Article

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Abstract

This paper investigates the bilateral relationship (i.e., correlated and causal) between market returns of five coronavirus vaccine stocks, covering BioNTech, Pfizer, Moderna, Johnson&Johnson, and AstraZeneca, and the implied volatility index (IV), using weekly time series data from 3 May 2020 to 15 October 2023. In addition, the unique nature of this study is based on the empirical assessment of differential patterns, if any, across the selected vaccine stocks and bull and bear market cycles in each of these vaccine stocks by employing regression and causality models. The results indicate that market return and implied volatility movements are positively correlated, and the statistical association is asymmetric and non-linear in nature, based on correlation coefficients and pooled regression models, even after sorting out extreme outliers. The empirical findings also statistically validate strong evidence of unidirectional causal flow from market movements to IV, which supports the leverage effect holding for each market period (irrespective of bull and bear swings) and all selected vaccine stocks. In that vein, these outcomes support the idea that both effects (i.e., volatility feedback and leverage) are significant in different models. Thus, such an association challenges the premise that it holds in general equilibrium settings under restrictive assumptions.

JEL Classifications: C12, C21, G23

1. Introduction

Understanding the link between risk and return is fundamental to grasping why individuals make some investment decisions. In that vein, the essentials for the relationship between risk and return have been widely investigated over the past four decades for several reasons, such as the examination of rules in forming trading methods and strategies, managing potential risks, and forecasting economic conditions for the future (Blay & Markowitz, 2013). While the relationship between risk and return is directly proportional, volatility and returns are typically found to be negatively correlated in which the relation is asymmetric, especially for negative returns in nature (Black, 1976; French et al., 1987; Nelson, 1991; Bekaert & Wu, 2000; Ghysels et al., 2005; Lettau & Ludvigson, 2010; Chen et al., 2013; He, 2022). However, there needs to be more clarity about the empirical evidence of this relationship in financial literature. Some argue that assets with higher volatilities are expected to have higher returns (Guo & Whitelaw, 2006). Therefore, the nature of these inconsistent results differs in time of market cycles and across different markets along with changing maturity levels of assets.

Engle (2004) rightfully states that the advantage of being aware of risks is that individuals can alter their behavior to avoid them. However, many sophisticated methods of modeling volatility, including the autoregressive conditional heteroscedastic (ARCH) and generalized ARCH family models and forecasting-based stochastic volatility models, have recently been used to estimate market volatilities. Besides the fundamental methods in testing for the realized and conditional market volatilities in which, most of them are limited to fully gauging the investor sentiment or future expectations about price movements, using only historical data (Han et al., 2015), the alternative methods of volatility estimations are often initiated to analyze investors' behavior whether they are market bullish, bearish, or neutral on stocks. The theoretical fundamentals of these models are constructed on current market prices of tradable financial assets, assuming that they fully reflect all available information where the markets are efficiently functioning and the expectations are formed rationally. The volatilities estimated through the given models are known as "implied" and are represented by the implied volatility index (IV) in most stocks. IV is conducted as an index derived from real-time and is designed to measure the constant, 30-day expected volatility of selected stock market call and put options. On a global basis, it is one of the most distinguishing indices from the standard ones as a daily market indicator since it measures volatility, not price. Two significant purposes are initiated to build the theoretical foundations of VIX (Whaley, 2009).

On the one hand, the VIX was created to act as a benchmark for measuring future market volatility expectations considering short-term asset movements. Hence, minute-by-minute values are estimated using index option values to compare with historical levels. On the other hand, the IV is organized to provide a way to calculate the futures and options contracts on volatility. Thus, IV estimates are relatively more favored over historical volatilities associated with market conditions and forecasting future states (Giot & Laurent, 2007; Ryu, 2012).

The theoretical gap in this reasoning is that an entirely consistent foundation for the volatility-return nexus confronts some challenges that drove researchers to develop new methods, sophisticated models, and economic fundamentals. Looking ahead to the empirical literature leads us to realize that the changes in economic and financial conditions may acutely alter the direction of this nexus. Though the empirical studies reveal mixed results on the given relation, a relatively large part of them typically show that negative stock index returns are more associated than positive returns with more significant changes in VIX movements (Black, 1976; Christie, 1982; Schwert, 1989; Campbell & Hentschel, 1992; Bekaert & Wu, 2000; Kim et al., 2004; Bae et al., 2007; Qadan et al., 2019; Sharma et al., 2022). More specifically, the asymmetric relation between market volatility and investors' investment choices is associated with the magnitude of

forecasting the future market performance or of the trade-off between risk and return where the volatility shocks are much higher (lower) in a bear (bull) market. In addition, recent studies on volatility modeling have remarked on empirical regularities in the financial sector based on two popular hypotheses covering “leverage effect” and “volatility feedback effect” (Bekaert & Wu, 2000; Barucci et al., 2003; Bollerslev et al., 2006; Bollerslev et al., 2011; Pathak & Deb, 2020). First, the leverage ratio affects how risky the asset is from an investor’s standpoint, thus changing the stock’s volatility. According to this hypothesis, shareholders infer that down market cycles tend their future cash flow stream to become relatively riskier and cause an increase in its volatility because a fall in the value of a firm’s stock leads to a rise in the debt-to-equity ratio (Black, 1976; Christie, 1982). Second, the contradiction observations originated the concept of the volatility feedback effect. In that vein, this second hypothesis is based on the argument that the positive volatility shocks (i.e., an increase in the volatility) raise the required return on the underlying asset, which then causes an immediate decline in stock price (Poterba & Summers, 1986; Bekaert & Wu, 2000; Barucci et al., 2003). Thus, the positive cycles of volatility lead to an increase in expected future stock returns, and the future expectations are formed on one occasion allied to a simultaneous fall in current stock prices. In summary, thus, the leverage effect hypothesis specifies that negative shocks increase the volatility relatively more than positive shocks of equal size (Black, 1976; Christie, 1982), while the volatility feedback effect hypothesis asserts that anticipated increases in future volatility raise the required rate of return, thus leading to an immediate decline in stock price to allow for higher future returns (Söylemez, 2020).

Considering the importance and broad scope of the underlying study, the attempt to precisely figure out the implied volatility is central to stock market research. In that vein, a bulk of empirical studies are in place, investigating which of the two hypotheses comprehensively reflects the presence of a negative correlation between returns and volatility. However, the findings are primarily mixed in nature. For example, the leverage effect is examined at a firm (where the firm is encountered with idiosyncratic and market risks) and at a market level through the early studies of Black (1976), Christie (1982), Schwert (1989), Engle & Ng (1993), Duffee (1995), Bekaert & Wu (2000), and Figlewski & Wank (2000), which are indicated that financial leverage can explain the leverage effect. On the other side, the rest of the empirical findings asserted by Poterba & Summers (1986), French et al. (1987), Campbell & Hentschel (1992), Bakshi et al. (1997), and Bates (2000) imply that volatility asymmetry rests on a time-varying risk premium where the causality underlying the volatility feedback effect runs from volatility to prices. According to the latter studies, the magnitude of a change in stock prices on volatility can be altered to a considerable extent to be rendered by financial leverage fluctuations alone. In more recent studies, Wu (2001) reports that volatility in equity markets is asymmetric, in which contemporary and conditional returns volatility are negatively correlated. Bekaert & Wu (2000) state that the volatility feedback hypothesis is more likely to produce an asymmetric response than the leverage effect using Japanese stock market data. Bollerslev et al. (2006) and Dennis et al. (2006) carry forward that finding and classify the asymmetric relation's strong and weak forms. Though the strong form indicates the negative correlation between returns and volatility, the weak form dwells upon this negative link regarding expected volatility and return. Besides the two effects, there is also a third channel in which financial disruptions might exhibit a disconcerting pattern that worries both policymakers and financial managers: A significant negative financial shock often leads to an increase the possibility of more problems to follow and to occur. Ding et al. (2009)t-Sahalia et al. (2015), and Azizpour et al. (2018) label this phenomenon as self-exciting behavior, where the default of or sizeable negative shock to a firm increases the likelihood of default or large downward movements of other firms (Carr & Wu, 2017). Therefore, this cross-sectional spread in financial markets leads to an intertemporal self-exciting pattern: One market turmoil increases the likelihood of another to follow. In addition, some empirical studies shed light on risk-based effects in describing the observed return patterns, as traditional asset pricing models cannot explain the return divergence among the low- and high-risk stocks. This is rigid since low-volatility stocks, by and large, have low market betas, whereas high-volatility stocks exhibit high market betas (Saraf & Kayal, 2023). In that vein, it is expected to argue that high-beta stocks provide lower returns than equilibrium and that low-beta stocks are consistent with high-return earnings than expected. This tends to the fact that low-risk stocks should be assumed to be a unique asset class while allocating assets (Blitz & van Vliet, 2007). Therefore, the relevant literature also considers the correlation between realized volatilities and implied volatilities to diverge the effects of volatility feedback and leverage effects. According to Dufour & Taamouti (2010) and Dufour et al. (2012), when implied volatility is considered, volatility feedback becomes relatively more apparent than the leverage effect in which the latter substantially stays constant. That also means implied volatility is better explained with the volatility feedback effect, which provides solid information on future volatility through its non-linear correlation with prudential option prices.

Consistent with the latter view, Pathak & Deb (2020) draw attention to the behavioral finance explanation of the return-VIX asymmetric relation, which is theoretically informative for analyzing short-term movements of the variables. This draws primarily from the loss aversion concept of prospect theory, which is encapsulated in the expression “losses loom larger than gains” (Kahneman & Tversky, 1979). Pati et al. (2017) attempt to explain in behavioral pattern, in particular loss aversion, of negative asymmetric return-implied volatility relation, regardless of volatility returns, which is also empirically supported by Finucane et al. (2000), Low (2004), and Dennis et al. (2006). Bollen & Whaley (2004) explain this negative return-IV asymmetric relation in terms of buying pressure, which drives the volatility smile, while Shefrin (2005) provided behavioral explanations for the same nexus based on sentiment. The central proposition of

the latter study is that the common use of the heuristic approach can be widened to be implemented in analyzing the negative return versus VIX relation. In particular, the financial investors and dealers of options lead to a spot of increase in put prices during market downturns since there is distress about the emergence of a rise in potential future losses. Hibbert et al. (2008) imply that both the leverage and volatility feedback hypotheses are based on the core factors of any firm and, therefore, should signalize more on the longer-term lagged effect between return and volatility, or vice versa.

Besides the volatility issue in equity markets, the existing literature also indicates that there are other research fields in which the same problem is investigated like currency markets (Jebran & Iqbal, 2016; Cho et al., 2020; Drehmann & Sushko, 2022), energy markets (Efimova & Serletis, 2014; Serletis & Xu, 2016; Ha and Nham, 2022; Liu & Serletis, 2023), commodity markets (Prokopczuk et al., 2019; Alfeus & Nikitopoulos, 2022), and real estates (Hung & Glascock, 2010; Zhou, 2016; Liow & Huang, 2018; Abdullah et al., 2023). However, comparing those markets shows that commodities are typically more volatile than the others due to the lower liquidity or trading volume levels. In addition, the evidence in the real estate market indicates that leverage and volatility feedback effects are jointly effective on changing volatility, but the former (i.e., leverage) dominates the latter (i.e., volatility feedback) effect, where both are non-linear in nature (Zhou, 2016).

All in all, this study contributes to the relevant literature in three different ways. First, the data structure is constructed upon a weekly sample to analyze the short-term correlation between market returns and VIX. However, the VIX index is calculated based on the 30-day mean value of implied volatility for each selected coronavirus vaccine stock. It is the forecasted future volatility of the equity/stock over the time frame chosen, derived from the average of the put and call implied volatilities for options with the relevant expiration date. Given that the primary concern is the early determination of changes in data trends, weekly data is enough to be a fast-moving response to level shifts and trends. Second, most of the previous studies have been overwhelmingly concerned with the data from within, whether a specific stock or the stocks that are highly transacted in the market. However, it can be argued that the correlation between VIX and market movements is dynamic and changing cross-sectionally across various markets in line with their maturity levels. This study, therefore, carries out a newly popularized (especially within the COVID-19 outbreak) and comes up with an ultimate price surge in a very short time, which reflects that these stocks might much more relatively be exposed to volatility shocks than the rest of the others in the market and can be classified as follows: BioNTech, Pfizer, Johnson&Johnson, Moderna, and AstraZeneca. Third, the market swings (bull and bear) are explored in line with the dynamic correlation of VIX and market movements. Thus, the study is divided into two periods as bull and bear market cycles (by way of the following methodologies adopted by Fabozzi & Francis (1979) and Bhardwaj & Brooks (1993) over the COVID-19 pandemic and carries through the analysis of the bull market cycles and bear market cycles. The empirical findings show that the vaccine stocks' returns and VIX movements have a negative and statistically significant relationship. Irrespective of the bear and bull market cycles, this result prevails for most vaccine stocks over the whole sample period. It also needs to be mentioned that the change in VIX is much more substantial during market downturns than during market up-cycles, reflecting that the given relationship is asymmetric. In addition, the empirical results are much closer to the leverage effect hypothesis, where the causality is from market return to VIX movements for most vaccine stocks, even the market cycles present in the analysis.

In line with these contributions to the existing literature, these results imply that financial investors should follow some insights upcoming in VIX movements to grasp the possibilities that may occur in vaccine stocks, especially for the post-COVID-19 period. Therefore, the empirical findings of this study can provide significant signals and implications for stakeholders who are potential investors for selected vaccine stocks over the post-COVID-19 era, including financial investors, policymakers, suppliers, communities, portfolio managers, and trade associations.

The remaining part of the study is organized as follows: Section 2 explores the data and hypothetical formations; Section 3 discusses the methodological underpinnings; Section 4 presents the empirical results; and Section 5 concludes.

2. Data and Hypothetical Formations

2.1. Data

The study uses weekly time-series data from 3 May 2020 to 15 October 2023 for stock indices and the mean value of implied volatility index from 5 coronavirus vaccine stocks: BioNTech, Pfizer, Johnson&Johnson, Moderna, and AstraZeneca. The data is collected from the Alpha Query database. Implied volatility works as the market's forecast of a likely movement in a security's price. Investors use it to estimate future volatility/fluctuations of a security's price based on predictive factors. In that vein, implied volatility is used to quantify market sentiment and uncertainty, to help set options prices, and to determine trading strategy. It indicates how volatile the market may become and helps investors gauge future market volatility by forecasting potential movements of stock prices. For instance, if the implied

volatility is high, the actors in the market posit that the stock has the potential for significant price swings in either direction, just as low implied volatility refers to the stock not moving as much by option expiration. As with most sentiment indicators, the put/call ratio is used as a contrarian factor to gauge bullish and bearish extremes. Contrarians turn bearish when too many traders are bullish, or vice versa. A put/call ratio at its lower extremities indicates excessive bullishness because call volume will possibly be significantly higher than put volume. Thus, in contrarian terms, excessive bullishness argues for caution and the possibility of a stock market decline. The final sample consists of the intersection of data for all selected indices (both return and implied volatility). This leads to 180 observations for each vaccine stock. The respective stock indices and implied volatility in each sample, along with the time period, a proxy for the risk-free rate considered in each vaccine stock, are shown in Table 1 below.

This study uses the relative implied volatility (mean) changes (ΔIV) and stock returns, estimated by the following two methods. First, the changes in IV are measured by using log returns from the mean value of the IV on a specific moment in time (*t*), represented in Eq. (1).

$$IV_t = log\left(\frac{IV_t}{IV_{t-1}}\right)$$

1

Second, the stock market return (*r*) is estimated in Eq. (2) for a specific stock market index (*i*) at a given moment in time (*t*).

$$r_t = log\left(\frac{P_t}{P_{t-1}}\right)$$

2

Table 1
Data Description

Vaccine Stock	Stock Index	Risk Index	Risk-Free Index
BioNTech	BNTX	BNTX IV Index	3-Month Bond Yield
Pfizer	PFE	PFE IV Index	3-Month Bond Yield
Johnson&Johnson	JNJ	JNJ IV Index	3-Month Bond Yield
Moderna	MRNA	MRNA IV Index	3-Month Bond Yield
AstraZeneca	AZN	AZN IV Index	3-Month Bond Yield

2.2. Hypothetical Formation

The study's hypotheses are based on the relationship between IV and return and the identification of bull and bear market cycles in the vaccine stock market. First, as mentioned in the introduction, the IV is measured by taking the mean of the 30 days and shows the forecasted future volatility of the security over the selected time frame, derived from the average of the put and call implied volatilities for options with the relevant expiration date. In particular, IV options do not reflect the manner of historical volatility. While the historical volatility shows how volatile the stock has been in the past, IV tells you what is implied in the options prices and what will happen to those prices in the future. This implication in IV is gauged by the movements in the market price of options, which fairly reflects risk and volatility in a liquid and broad options market. For simplicity, if the stock prices tend to increase or decrease, the option is first seen in option prices. So, it impacts option implied volatility, expressing how IV gets predictive value for stock prices.

Additionally, IV is a dynamic metric that moves in real-time and depends on transactions in the options market. The option premium is higher when the IV is higher. Besides, IV can be assumed to be useful since it offers traders a range of prices that security is anticipated to oscillate between and assists in indicating good entry and exit points. Therefore, IV can configure investors' thinking about how a stock's price may change and how wide or narrow those changes might be. Ultimately, the calculation of IV utilizes several vital data points plugged into an options pricing model. Some of these metrics can be ranged as follows: (i) option price, (ii) price of the underlying stock, (iii) option's strike price, and (iv) expiration date of the options contract. Thus, it leads to understanding how much price movement investors can expect to see up until an options contract expires and helps those investors develop an effective options trading strategy.

Second, identifying bull and bear market cycles will be based on standard approaches in the relevant literature. The classification of markets into bull and bear market periods depends on either the comparison of the market index to a critical threshold value to divide "up" from "down" market periods or using the trend-based scheme to classify markets as bull or bear (Woodward & Anderson, 2009). This

study adopts three approaches initiated by Wiggins (1992) for classifying the sample period in each vaccine stock into bull and bear market cycles. According to Wiggins (1992), the excess return on the market portfolio becomes positive when the given period is considered to be in an increasing (up) movement, and thereby, the market is separated into periods when the market is substantially up, substantially down, or neither. Hence, weekly log returns are measured for each vaccine stock for the market and IV indexes. Table 2 represents the total number of observations and observations during bull and bear weeks.

As explained in the previous section a bulk of studies (Black, 1976; French et al., 1987; Nelson, 1991; Fleming et al., 1995; Bekaert & Wu, 2000; Kim et al., 2004; Bae et al., 2007; Qadan et al., 2019; Sharma & Malik, 2022) indicate a negative relation between realized stock market returns and volatility movements (i.e., when market is pressured downwardly, volatility rises or vice versa). As this study uses an extensive data set across coronavirus vaccine stocks, the hypothetical formations are ranged as follows:

Hypothesis 1

(*H1*): There is a positive correlation between market movement and implied volatility movement, which confirms the volatility feedback effect.

Hypothesis 2

(*H2*): The correlation between market movement and implied volatility movement is non-linear and asymmetric in nature.

Hypothesis 3

(*H3*): The causality between market movement and implied volatility movements is dynamic and flows from market to implied volatility.

Hypothesis 4

(*H4*): There are significant differences regarding *H1-H3* above for bull and bear markets.

Table 2
Total Number of Weeks During Bull and Bear Market Periods

Vaccine Stock	Stock Index	Start Time	End Time	Total Weekly Observations	No of Bull Weeks			No of Bear Weeks		
					Wiggins (1992)	Fabozzi & Francis (1979)	Bhardwaj & Brooks (1993)	Wiggins (1992)	Fabozzi & Francis (1979)	Bhardwaj & Brooks (1993)
BioNTech	BNTX	03-05-2020	15-10-2023	180	89	27	80	91	153	100
Pfizer	PFE	03-05-2020	15-10-2023	180	89	20	90	91	160	90
Johnson&Johnson	JNJ	03-05-2020	15-10-2023	180	90	27	90	90	153	90
Moderna	MRNA	03-05-2020	15-10-2023	180	91	23	90	89	157	90
AstraZeneca	AZN	03-05-2020	15-10-2023	180	91	24	90	89	156	90

Notes

The table shows the total number of observations and observations during the bull weeks taken together and during the bear weeks. Bull and bear weeks are measured and subjected to three alternative classification schemes defined in the study. The period chosen for each vaccine stock starts from 03-05-2020 and ends with 15-10-2023, which covers 181 weekly observations in total for each vaccine stock.

Additionally, the empirical framework is grounded on using the same lengths in terms of start and end periods to assess the impact of lockdowns in the same structure of selected trading processes during the COVID-19 outbreak and onwards.

3. Methodology

The empirical strategy of this study is conducted on six different methods as follows: As the preliminary test, the correlation analysis is used to assess the statistical significance of *H1* by looking at the correlation coefficients between weekly implied volatility percentage changes and weekly vaccine stock market returns for all selected samples. The presence of a negative correlation indicates that *H1* is statistically prevailing. Table 3 shows and discusses the results of the correlation analysis in the next section.

Table 3
Correlation Coefficients Between Return and IV

	Overall	**Bull**			**Bear**		
		Wiggins (1992)	**Fabozzi & Francis (1979)**	**Bhardwaj & Brooks (1993)**	**Wiggins (1992)**	**Fabozzi & Francis (1979)**	**Bhardwaj & Brooks (1993)**
All Vaccine Stocks	0.059***	0.257***	-0.060	0.206***	0.441***	0.612***	0.334***
BioNTech	-0.042	0.989***	0.775***	0.984***	0.986***	0.991***	0.986***
Pfizer	-0.043	0.932***	0.979***	0.954***	0.979***	0.990***	0.979***
Johnson&Johnson	-0.413***	0.953***	0.966***	0.991***	0.944***	0.972***	0.943***
Moderna	0.013	0.984***	0.960***	0.987***	0.987***	0.993***	0.987***
AstraZeneca	-0.159**	0.942***	0.982***	0.979***	0.991***	0.995***	0.991***

To further validate the above findings from correlation analysis and to test *H2* (i.e., asymmetric relation), this study adopts the following simple regression model represented in Eq. (3):

$$IV_t = {}_t + r_{m,t} + r^2_{m,t} + r_{m,t}DR + r^2_{m,t}DR + {}_t$$

3

where DR is a dummy variable, which takes the value DR = 1 if $RM_t \leq 0$, and 0 otherwise. RM_t and IV_t represent the market return and change in implied volatility at time *t*. R_t is the return for selected vaccine stock and ${}_t$ is the *i.i.d.* error term.

Theoretically, the negative *α* and *γ* values imply that higher IV values correspond to negative returns, indicating that *H2* is validated. The analysis continues with the sample selected vaccine stocks for bull and bear periods within these cross-sectional clusters. The results are depicted in Table 4.

Table 4
Pooled Regression Results

Overall	**β**	**γ**	**δ**	**θ**
	-0.534* **	**7.364*** **	**0.149**	**-9.306*** **
	(0.201)	**(2.03)**	**(0.347)**	**(2.658)**
Bear Period	-60.73***	7.611***	62.18***	0
	(11.77)	(1.395)	(11.80)	
Bull Period	1.355***	-10.03***	-3.294*	33.37
	(0.143)	(1.329)	(1.911)	(28.22)

Besides the pooled regression model, the empirical strategy also benefits from the T-GARCH (Zakoian, 1994) model to check whether there is an asymmetric relation between IV and returns. Eq. (4) and Eq. (5) describe the T-GARCH model for the same structure:

$$r_t = c_0 + \sum {}^{p}_{i=1} {}_i r_{t-i} + {}_t + {}_{1t-i}$$

4

$$^{2}_{t} = _{0} + \sum ^{p}_{i=1} i^{2}_{t-i} + \sum ^{q}_{j=1} j^{2}_{t-j} d_{t-1} + \sum ^{r}_{k=1} k^{2}_{t-k}$$

5

where d_{t-1} denotes the dummy variable at time *t-1* which is equal to 1 when $^{2}_{t-j}$ is less than 0, and 1 otherwise. In this model, it is expected that negative return shocks, $_{t} < 0$, have different effect on return asymmetry represented by conditional variance series than positive ones. In that vein, negative shocks would have an impact *α* + *γ* whereas positive shocks tend to have an effect equal to *γ*. If α ≠ 0, these shocks mark an asymmetric impact on return uncertainty. Therefore, if the regressand is positive and statistically significant, it implies that the asymmetric relation between return and IV is binding. Similar to that of pooled regression analysis, the investigation is repeated with the selected vaccine stocks for bull and bear periods within these cross-sectional clusters. The results are presented in Table 5.

Table 5
Estimates of T-GARCH Equations

Dependent Variable: r_t			
Method: ML - ARCH (Marquardt) - Normal Distribution			
Mean Equation			
	Overall	**Bear**	**Bull**
c	0.0001	-0.0019***	-0.0006
	(0.0003)	(0.0002)	(0.0005)
$_{-1}$	0.0786***	0.8508***	0.9112***
	(0.0378)	(0.0115)	(0.0002)
Variance Equation			
	Overall	**Bear**	**Bull**
ω	3.41E-06***	-6.48E-06***	3.53E-06***
	(1.10E-06)	(1.40E-0.6)	(1.31E-06)
γ	0.1236***	18.17***	0.1922***
	(0.0154)	(5.056)	(0.0237)
α	-0.0684***	-18.16***	-0.2162***
	(0.0281)	(5.071)	(0.0233)
β	0.9082***	0.3047***	0.8641***
	(0.0086)	(0.0542)	(0.0342)
Adj. R^2	0.0062	0.8314	0.7722
AIC	-4.854102	-7.743064	-7.757693
SIC	-4.822057	-7.688181	-7.702811
Durbin Watson stat.	1.982564	2.229785	2.236535

To test *H3* above, the empirical section also leans on employing a Granger (non) causality test between ΔIV and market movement across the vaccine stock market in bull and bear market cycles. The first issue is to check the stationary data of all the time series and reveal that the index values and the first differences of the IV series are non-stationary at the level. Following that statistical requisite, the next issue is to employ the standard Granger (non) causality test between ΔIV and market return (i.e., RM) series. The Granger causality test is based on a test for the causal relationship between two variables, and thereby, states that y is said to be Granger cause of *x* if past

values of a variable *y* are significant enough to forecast the future values of *x*, or vice versa (Granger, 1969). This method for the given study is conducted on the following models, represented in Eqs. (5) and (6):

$$IV_t = {}_0 + \sum {}_{k=1}^{M} {}_k IV_{t-k} + \sum {}_{l=1}^{N} {}_l RM_{t-l} + u_t$$

5

$$RM_t = {}_0 + \sum {}_{k=1}^{M} {}_k IV_{t-k} + \sum {}_{l=1}^{N} {}_l RM_{t-l} + {}_t$$

6

where IV_t and RM_t represent and change in implied volatility and the market return at time *t*, respectively. u_t and ${}_t$ are mutually uncorrelated error terms, and "k" and "l" are the number of lags. The null hypothesis is based on the following equational form: ${}_l = 0$ for all *l*'s and ${}_k = 0$ for all *k*'s. The rationale of this causality form indicates that RM causes IV when the coefficients ${}_l s$ are statistically significant but the coefficients ${}_k s$ are not. Conversely, IV causes RM when the coefficients ${}_k s$ are statistically significant but the coefficients ${}_l s$ are not. But if both coefficients, covering ${}_l$ and ${}_k$, are statistically significant, then causality runs both ways. This study conducts causality tests separately for the overall data and bull and bear market cycles to provide some crucial empirical insights for *H3* and *H4*. The results are represented in Table 6 and will be discussed in the next section.

Table 6
Granger Causality Test Results

Wiggins (1992)			
	Overall	***Bear***	***Bull***
Return on IV	1.309**	3.462**	3.683**
	(0.027)	(0.032)	(0.026)
IV on Return	0.931	1.552	0.445
	(0.673)	(0.213)	(0.641)

Next to the Granger causality test, the empirical strategy will use winsorizing or winsorization, which is the process of replacing the extreme values in the statistical data to limit the effect of the spurious outliers on the results obtained by using that data (Tukey, 1962). Since the distribution of many statistics can be heavily affected by outliers, the winsorization method provides more reliable statistical findings. Using our data, we are likely to obtain results driven by a few extreme changes. Thus, the extreme values that we observe could be originated not from the large outliers but from the historical trends. To address such issues, the models will be tested by eliminating all sample points with market returns in the top 1% or bottom 1% of the entire range (Pathak & Deb, 2020) for 1% winsorized sample.

Table 7
Robustness Test 1: Regression Models on Alternate Bull-Bear Classification Schemes

		β	γ	δ	θ
Overall		-0.534***	7.364***	0.149	-9.306***
		(0.201)	(2.03)	(0.347)	(2.658)
Bear Period	Fabozzi & Francis (1979**)**	4.617***	-133.9***	-3.129***	140.1***
		(0.385)	(11.92)	(0.463)	(11.64)
	Bhardwaj & Brooks (1993**)**	-83.19***	21.97***	83.74***	-21.72***
		(15.48)	(59.30)	(15.51)	(59.19)
Bull Period	Fabozzi & Francis (1979**)**	-0.137	0.699	0	0
		(0.209)	(1.557)		
	Bhardwaj & Brooks (1993**)**	0.224	0.493	-371.4	0
		(0.142)	(1.323)	(261.1)	

In the final phase of empirical process, the robustness tests will be performed from the main analysis within the context of two techniques as follows: First, the alternative classification schemes of bull and bear market cycles will be used to assess the relationship between market movement and IV movement for each vaccine stock. This alternative classification scheme will differ from the method proposed by Wiggins (1992) since the results are likely to be biased about the market cycles, covering both bull and bear periods. Therefore, as a robustness check, the empirical study will carry out two more approaches when the market cycles are explained.

Table 8
Robustness Test 2: Regression Models on 1% Winsorized Sample

Regression Models on 1% Winsorized Sample				
	β	**γ**	**δ**	**θ**
Overall	-1.125***	17.15***	0.416	-27.87***
	(0.307)	(4.473)	(0.541)	(5.922)
Bear Period	-61.57***	9.505***	63.12***	0
	(11.18)	(3.334)	(11.23)	
Bull Period	2.349***	-23.06***	-3.399**	35.82
	(0.207)	(2.771)	(1.645)	(24.30)

Table 9
Robustness Test 1: Granger Causality Test Results Based on Alternate Bull-Bear Classification Schemes

Fabozzi & Francis (1979)			
	Overall	**Bear**	**Bull**
Return on IV	1.309**	3.402***	1.743*
	(0.027)	(0.000)	(0.067)
IV on Return	0.931	22.57***	0.842
	(0.673)	(0.000)	(0.679)
Bhardwaj & Brooks (1993)			
	Overall	**Bear**	**Bull**
Return on IV	1.309**	0.043	3.112**
	(0.027)	(0.957)	(0.045)
IV on Return	0.931	2.497*	0.066
	(0.673)	(0.083)	(0.936)

Those approaches will cover the methods produced by Fabozzi & Francis (1977, 1979) and Bhardwaj & Brooks (1993). According to Fabozzi & Francis (1977, 1979), the up (down) months are defined as months when the market return is higher (lower) than 1.5 times its standard deviation. Besides, Bhardwaj & Brooks (1993) adopt the median return on the market portfolio as the demarcating value. Further, the robustness check will also extend the significance of empirical results using 1% winsorized sample to eliminate more extreme outliers from the sample without significantly increasing the chances of information loss. So, the robustness test results will be discussed in the following section.

Table 10
Robustness Test 2: Granger Causality Test Results Based on 1% Winsorized Sample

Wiggins (1992)			
	Overall	**Bear**	**Bull**
Return on IV	0.974	33.59***	1.859
	(0.559)	(0.000)	(0.173)
IV on Return	1.141	2.954*	4.179**
	(0.174)	(0.053)	(0.041)
Fabozzi & Francis (1979**)**			
	Overall	**Bear**	**Bull**
Return on IV	0.974	5.981***	0.661
	(0.559)	(0.000)	(0.783)
IV on Return	1.141	15.29***	0.896
	(0.174)	(0.000)	(0.554)
Bhardwaj & Brooks (1993**)**			
	Overall	**Bear**	**Bull**
Return on IV	0.974	0.016	3.967**
	(0.559)	(0.984)	(0.019)
IV on Return	1.141	3.909**	0.143
	(0.174)	(0.021)	(0.866)

Table 11
T-GARCH Analysis for Asymmetry Winsorized

Dependent Variable: r_t			
Method: ML - ARCH (Marquardt) - Normal Distribution			
Mean Equation			
	Overall	**Bear**	**Bull**
c	0.0007	-0.0010	0.0005***
	(0.0005)	(0.0009)	(1.89E-05)
$_{-1}$	0.0832**	0.9299***	0.9576***
	(0.0371)	(0.0271)	(0.0007)
Variance Equation			
	Overall	**Bear**	**Bull**
ω	2.67E-06***	1.13E-05	2.05E-08***
	(9.61E-07)	(2.55E-05)	(2.63E-09)
γ	0.0884***	0.0667	1.5303***
	(0.0160)	(0.5396)	(0.0295)
α	-0.0634***	-0.0696	-1.5352***
	(0.0209)	(0.5401)	(0.0294)
β	0.9352***	0.5383	0.5506***
	(0.0121)	(1.0412)	(0.0116)
Adj. R^2	0.0126	0.9050	0.8683
AIC	-5.049917	-7.763867	-10.98800
SIC	-5.017356	-7.708138	-10.93139
Durbin Watson stat.	1.913626	1.987404	2.009714

4. Empirical Findings and Discussions

This section captures the empirical findings by employing different estimation schemes between the market return and implied volatility index for selected coronavirus vaccine stocks. First, Table 3 represents the correlation coefficients between IV changes (ΔIV_t) and market returns ($r_{m,t}$). The empirical results indicate a highly significant and positive correlation between ΔIV_t and $r_{m,t}$. The coefficients are statistically robust during bull and bear periods but almost robust for the whole sample period. The only exception for this given positive correlation among those indicators is captured for Johnson&Johnson and AstraZeneca for the overall period. However, the overall correlation results for all vaccine stocks are still robust and positive on average, barring a few exceptions (Johnson&Johnson and AstraZeneca). All correlation coefficients are statistically significant at 1%. These findings give us the preliminary tips that lead us to approve hypothesis 1, which supports the negative association between ΔIV_t and $r_{m,t}$.

Table 4 reports the regression results from the model 3 above. In particular, the following patterns are obtained here: (i) the association between ΔIV_t and $r_{m,t}$ is negative for bear and overall periods but positive for the bull period, as well as the γ's have reverse signs and statistically significant coefficients; (ii) The δ's and θ's follow the same pattern thus validates the asymmetric and non-linear relations between IV and market returns, i.e., IV scales down during market downturns are much effective compared to IV rises during market upswings and in the future period. This implies that the volatility during market upswings is much stronger than that of the downturns. Therefore, given the empirical findings represented in Table 4, hypothesis 2 is empirically validated, which is in line with the findings of Kumar & Dhankar (2011), Pati et al. (2017), Fousekis (2020), Echaust (2021) and Ghorbel et al. (2022). These patterns are also individually consistent across the selected vaccine stocks, including bull and bear markets.

Moreover, the threshold GARCH (T-GARCH) model proposed by Glosten et al. (1993) and Zakoian (1994) is used to define the conditional variance among the selected vaccine stock series as a linear piecewise function. T-GARCH model is also applied to relax the linear restriction on the conditional variance dynamics among the series. The asymmetric impact is incorporated into the GARCH framework using a dummy variable for both return and squared return series. The T-GARCH γ coefficient is positive and statistically significant for all groups, which reflects that the results are in coherence with the estimates of pooled regression models for asymmetry and non-linearity.

Table 6 summarizes the results of Granger causality tests using Wiggins's (1992) approach for classification schemes of bull and bear markets in each vaccine stock. For the sake of brevity, the results are reported only for the aggregate group-wise results, not for each vaccine stock individually. The findings indicate a unidirectional causal flow from return to IV changes for all vaccine stocks, irrespective of bull and bear periods. Therefore, besides the other results supporting the volatility feedback effect, the Granger causality test results support the leverage effect hypothesis holding for all vaccine stocks.

Finally, Tables 7–11 present the results of the robustness checks of initial empirical findings. On the one hand, Tables 7 and 8 summarize the results of the pooled regression models to empirically assess positive and asymmetric links between market returns and implied volatility along with alternate schemes of bull-bear classification and 1% winsorized sample, respectively. The results are only different for the bull market and almost similar to initial findings from the core analysis, i.e., market and IV changes are positively and asymmetrically correlated, and they are non-linear in nature. The asymmetric and non-linear relations for vaccine stock series are much stronger for both samples and during both periods within the 1% winsorized sample. Tables 9 and 10 report the results for Granger causality tests based on alternate schemes for both periods and 1% winsorized sample, respectively. Similar to the initial findings in Table 6, the alternate schemes and 1% winsorized sample analysis show the same pattern of results. The leverage effect hypothesis is validated based on all vaccine stocks' overall period and bull-bear classification schemes. In addition, Table 11 shows the results of T-GARCH analysis for asymmetry winsorized. The findings imply that the conditional variance among the selected vaccine stock series as a linear piecewise function is also statistically significant and robust for each period, holding also for bull-bear markets, in which the coefficients get enhanced for all periods and during market downturns and upswings.

The benchmark results of the empirical models strongly support the hypotheses 1 and 2 above. In that vein, correlation coefficients and pooled regression models, even after the sorting out of extreme outliers, indicate that market return and implied volatility movements are positively correlated to each other, and the statistical association is asymmetric and non-linear in nature, i.e., volatility rises during positive market periods are higher rather than peaks during negative market movements. This is statistically valid at the initial period of market movement, but the long-run period validates that the reverse case holds in the series, based on implying the squared term of market return (except for the bull period). The T-GARCH analysis also substantiates this asymmetry and non-linearity among the results. The results of the T-GARCH models indicate that all market periods (covering both bear-bull periods) comprise a positive association between market return and implied volatility. While these two hypotheses support the means of volatility feedback effect, the Granger causality test results provide evidence of unidirectional causal flow from market movements to IV, which confirms the leverage effect holding for each market period. To test whether the benchmark results are significant over the whole sample and market cycles, hypotheses (1)-(3) are revisited within the case of the same model structures. This is also done to determine whether there are significant differences regarding *H1-H3* above for bull and bear markets based on alternate classification schemes. The robustness checks are statistically validated that there are no significant differences in either associative or causal relation between returns and volatility across bull and bear market swings (hypothesis 4). However, the marginal differences in robustness tests across the selected vaccine stock series are much more substantial.

In line with the benchmark models and robustness tests, the empirical findings reveal that the two effects (leverage versus volatility feedback) are still statistically approved as being active for explaining the asymmetric and non-linear nature of the return-volatility nexus but remain controversial of which are much effective on grasping this relation in the financial context. As pointed out by Bekaert & Wu (2000) for the volatility feedback effect to hold, the persistence of volatility should thoroughly be determined, i.e., the extreme price movements, rises or decreases, affecting both current and future volatility. In addition, besides that primary condition, the volatility feedback effect is a crucial component of the intertemporal risk-return relation, inducing time variation in the expected risk premium (Chelikani et al., 2023). Thus, along with time variation, such changes in conditional variance simultaneously lead to variations in expected returns and stock prices, which holds under restrictive assumptions of general equilibrium settings (Backus and Gregory, 1993). However, this context is sometimes relaxed within different conditions and contradicts the general equilibrium settings (Turner et al., 1989; Glosten et al., 1993). Compared with the leverage effect, the empirical evidence of regression analysis and T-GARCH models strongly support volatility feedback theory to statistically prove the positive intertemporal relationship between expected return and conditional variance.

5. Concluding Remarks

This paper investigates the correlation of implied volatility indices on stock market returns with data from 5 coronavirus vaccine stocks. The sample is collected using weekly time series data from 3 May 2020 to 15 October 2023 for stock indices and a mean value of implied volatility index from the following coronavirus vaccine stocks: BioNTech, Pfizer, Johnson&Johnson, Moderna, and AstraZeneca, which is obtained from Alpha Query database. This leads to 180 weekly observations for each vaccine stock for each index. On the one hand, regression analysis and causality models are employed to address this data statistically and also address the nature of the relationship between IV and stock market movements. On the other hand, the differential patterns are explored, if any, across the selected vaccine stocks and bull and bear market cycles in each of these vaccine stocks.

The results indicate that market return and implied volatility movements are positively correlated to each other, and the statistical association is asymmetric and non-linear in nature, based on correlation coefficients and pooled regression models, even after the sorting out of extreme outliers, which contradicts with some of the previous studies employing traditional models and approaches (e.g., Li et al., 2005; Bae et al., 2007; Antonakakis et al., 2013; Atilgan et al., 2015; Just & Echaust, 2020; Pathak & Deb, 2020). As pointed out, this positive relation exhibits non-linearity, i.e., volatility rises during positive market periods and is higher than peaks during negative market movements. The empirical findings also statistically validate strong evidence of unidirectional causal flow from market movements to IV, which supports the leverage effect holding for each market period (irrespective of bull and bear swings) and all selected vaccine stocks. This is in coherence with previous studies represented in Black (1976), Christie (1982), Schwert (1989), Malliaris & Urrutia (1992), Engle & Ng (1993), Duffee (1995), Bekaert & Wu (2000), Figlewski & Wank (2000), Princ (2010), Jebran & Iqbal (2016), Dungore and Patel (2021). The causality test results also imply weak evidence of reverse causality (i.e., IV changes to market movements) for selected vaccine stocks, particularly during bear periods, irrespective of alternate classification schemes. As Bekaert & Wu (2000) specify, holding must consistently persist in volatility and a positive relationship between implied volatility and stock return for the volatility feedback effect to have. However, the empirical findings support that both effects (i.e., volatility feedback and leverage) are found to be significant in different models. Thus, such an association challenges the premise that it holds in general equilibrium settings under restrictive assumptions.

Based on these findings, the changes in VIX movements can provide effective signals for financial investors regarding the perils of market downturns. They can use those signals to decide whether to invest in a stock or to guide decisions about their earnings potential. Following the arguments of Sarwar (2012), some part of financial investors, especially speculators, may gauge negative signals from VIX movements to realize gains on their portfolio before the market returns to its equilibrium. It can be assumed that there are signal points when the VIX reaches the resistance level, which is considered high for purchasing stock, which provides potential timing opportunities for speculators and risk managers. This tells us that the market participants are too bearish, and implied volatility has figured out at capacity. Therefore, these results indicate that VIX can be pointed out as an effective indicator for risk management. In summary, the empirical outputs of this study can have significant investment opportunities for the stakeholders in coronavirus stock markets, including financial investors, portfolio and risk managers, informed traders, and policymakers.

Declarations

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The author declares no competing interests.

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All data generated or analyzed during this study are included in this published article and its supplementary information files.

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