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Stock Market Volatility in the Covid-19 Era: Insights from a GARCH family and VECM in Tunisia

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Abstract
This paper examines the effects of the COVID-19 pandemic on the volatility of the TUNINDEX stock market. Our main goal is to decipher how this worldwide health epidemic has influenced Tunisia's financial stability. A thorough empirical approach was employed, leveraging sophisticated econometric techniques such as GARCH and VECM to scrutinize daily market data. The analysis uncovers a notable escalation in TUNINDEX volatility during the pandemic, emphasizing the critical role of investors' sentiment, economic, and monetary interventions in mitigating the crisis. These insights shed light on the dilemmas and prospects facing investors, portfolio managers, and policymakers in navigating market volatility amidst pandemic uncertainty.

Keywords: Stock market volatility, TUNINDEX, COVID-19, GARCH, VECM

JEL codes: C22, E31, E44

1. Introduction

The outbreak of the COVID-19 pandemic has had an unprecedented impact on global financial markets, leading to increased volatility and uncertainty (see Yousef, 2020; Baek et al., 2020; Albulescu, 2021; Bora &Basistha, 2021; Endri et al., 2021; Izzeldin et al., 2021; Megaritis et al., 2021; Akinlaso et al., 2022; Chowdhury et al., 2022; Gao et al., 2022; Asgharian et al., 2023). In Tunisia, as in many countries, the stock market has faced significant challenges, with the TUNINDEX index experiencing notable fluctuations.

Spikes in the closing prices of TUNINDEX are frequent when the stock market encounters exogenous shocks. While Rachdi et al. (2013) argued that the drastic change in the volatility is not totally attributed to the international financial crisis, Hammami & Boujelbene (2022) underlined a change in investors' sentiments due to the occurrence of stock market crises. Assaf (2016) further evidenced efficient use of information, risk management, financial liberalization, etc. to understand the onset of the crisis in terms of structural change. Improved corporate governance helps stabilize stock price volatility (Aloui & Jarboui, 2018). A surge in the volatility of the stock market might follow political turmoil (see Kaddour & Zmami, 2014; Jeribi et al., 2015; Moussa & Talbi, 2019; Talbi et al., 2022). Indeed, political distress during the 2011 revolution and terrorist attacks perturbed the financial market (Soltani et al., 2017;

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Zaiane, 2018; Souffargi et Boubaker, 2022) but the volatility diminishes in the long-run (Mnif, 2017). How investors perceive political events is also of utmost matter (Trichilli et al., 2020).

We record very few studies that relate the Tunisian stock market to the pandemic. Jeribi & Manzli (2020) used specific metrics of Covid-19 and showed that infected and dead people have led to an increase in the Tunisian volatility. Announcing the recovery rate, has somewhat refreshed investors, pushing returns upward in the first wave of the pandemic (Ben Ayed & Lamouchi, 2020). Ben Ayed (2022) found out that government intervention did not alter the stock performance, while Fakhfekh et al. (2023) cheered the role of hedge strategies to dispatch persistent volatility, especially amid COVID-19.

This study aims to explore the determinants of stock return volatility in Tunisia during the COVID-19 era. By analyzing the Tunisian stock market's response to the pandemic, this research seeks to identify the key factors driving volatility in stock returns, providing insights into the complexities of financial markets under stress and the effectiveness of policy responses to mitigate such volatility (Binder & Merges, 2001; Mazzucato & Semmler, 2002; Nikmanesh et al., 2016; Dhingra et al., 2023).

The structure of the paper is as follows. In Section 2, we survey papers that relate stock market volatility to the cyclical factors and to the pandemic. Section 3 presents materials and method. Section 4 exposes and discusses the main findings and Section 5 concludes.

2. Literature review

2.1 The macroeconomic determinants of stock market volatility in theory and practice

Litzenberger & Ramaswamy (1979) presented a capital asset pricing model and found that stock returns on the NYSE are positively related to dividends. These empirical observations challenge prior results, particularly those suggesting dividends have no impact on stock prices. Conversely, Miller & Modigliani (1961), in their simple analytical framework under the assumptions of perfect capital markets, rational behavior, and perfect certainty, posited that dividends are irrelevant in perfect markets. They argued that the share price is not sensitive to the distribution of dividends. This theory was later contrasted by Kumaraswamy et al. (2019), who used a panel regression technique on data from 116 textile companies in India spanning 10 years. They found that dividend policy causes upward stock price fluctuations in India, consistent with the theoretical argument that dividends matter for imperfect markets.

In terms of the relationship between stock prices and economic news, Chen et al. (1986) developed a simple theoretical model of stock prices, demonstrating that stock prices systematically react to economic news in accordance with efficient market theory (Fama, 1981) and rational expectations (Cox et al., 1985). Schwert (1981) applied time series regressions on daily data of the S&P and observed that returns react instantaneously to unexpected inflation. However, Schwert (1989) later found that macroeconomic variables explain only a small part of unusual jumps in stock market volatility, especially during the Great Depression (1929-1939).

The negative relationship between inflation and stock returns was explored by Fama (1981) in his model of bond equity equilibrium, attributing it to the adverse effect of inflation on real activity. This idea was supported by Fama & Gibbons (1982), who applied the Mundell-Tobin model and found that expected returns are negatively related to expected inflation. Contrary to this, Davis & Kutan (2003) used GARCH family models and data from 13 developed and developing countries to find no empirical support for Schwert's (1989) argument. They concluded that inflation and output have a limited impact on stock market volatility and returns. Aliyu (2012) used a quadratic GARCH model and monthly time series data from

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Nigeria and Ghana to show that establishing a low inflation rate has favorable effects on stock market volatility in both countries. Similarly, Saryal (2007) found support for the Fisher effect using a quadratic GARCH model and monthly data from Turkey and Canada, showing that the inflation rate has strong predictive power for stock market volatility and that knowledge about the state of the economy shapes investors' behavior.

Barakat et al. (2016), employing a VAR model on monthly data from Egypt and Tunisia, found that inflation and interest rates exert a long-run effect on stock market volatility in both countries. This view is shared by Amata et al. (2016), who used a questionnaire distributed to investors and VECM on monthly data in Kenya, demonstrating that both inflation and interest rates cause movements in stock market volatility, especially in the short run. Their results are corroborated by the investors' perception of the contributing role of both variables. El Ouni et al. (2014) used a VAR model on annual data in Tunisia, suggesting that Tunisian investors could gain insights from monetary and economic information portrayed by interest rates and inflation.

Lastly, Koutmos (2012) analyzed time series data from G-7 countries and found that the price-to-earnings (P/E) ratio has an adverse effect on stock market volatility whenever agents are risk-averse. Alajekwu & Ezeabasili (2020) used panel regression and data from 60 firms spanning 11 years in Nigeria to show that investors in the financial sector should pay attention to the distribution policy of dividends to shape volatility patterns and decrease uncertainty surrounding the stock market, while the latter is not sensitive to dividends in the non-financial sector. Touny et al. (2021) used FGLS and panel data from MENA countries spanning 11 years to conclude that stabilizing inflation at reasonable rates could alter jumps in stock market volatility.

2.2 Stock market volatility and COVID-19

The broad empirical literature on the impact of COVID-19 on the volatility of financial markets encompasses numerous studies, including those by Khan et al. (2023), Fakhfekh et al. (2023), and Toumi & Lafi (2023). These investigations collectively demonstrate that the pandemic has induced substantial alterations in the global economy, as evidenced by the work of Maital & Barzani (2020), McKibbin & Fernando (2020), Ozili & Arun (2020), and Mazur et al. (2021). Severe measures such as quarantines and the cancellation of public events have led to restrictions on international travel, disrupting economic activities worldwide.

The long-term ramifications of COVID-19 are emerging with bleak forecasts, including an increase in company bankruptcies and rising unemployment rates, as highlighted by Amankwah-Amoah et al. (2021), Holder et al. (2021), and Montenovo et al. (2022). This scenario is aggravated by the heightened volatility and the interconnected nature of financial markets, as examined by Aslam et al. (2020), Chaudhary et al. (2020), Corbet et al. (2021), Khan et al. (2021), and Sadiq et al. (2021). These dynamics have prompted international investors to ramp up their speculative investments, leading to a speculative bubble with ensuing market crashes and fluctuations (Biu & Kusuma, 2023). These developments have had a significant negative impact on global financial investors, as detailed by Zhang & Hamori (2021), Budiarso et al. (2020), and Ortmann et al. (2020).

A thorough analysis of volatility is crucial during exceptional periods like the COVID-19 pandemic. This analysis, serving the interests of investors and policymakers, takes into account the complex and dynamic asymmetric dependency of financial markets, highlighted by Baruník et al. (2016). The stronger correlation between returns during downtrends leads to asymmetric volatility, diminishing the benefits of diversification, as observed by Amonlirdviman & Carvalho (2010).

Empirical evidence shows that COVID-19 has had dramatic consequences on global financial markets. The studies by Baker et al. (2020) and Umar et al. (2021) point out significant losses in stock markets, while Al-Awadhi et al. (2020), Alfaro et al. (2020), and Onali (2020) highlight negative reactions to infected cases and deaths from the virus. The use of GARCH models by Adenomon et al. (2022), Liu et al. (2022), and He et al. (2020) confirms the negative impact of COVID-19 on stock market returns. In crisis times, investors feel insecurity highlighted by an increase in risk-aversion (Papadamou et al., 2020; Li et al., 2022). Erdem (2020) argues that the adverse effects of the epidemic are less pronounced in countries with high degree of freedom while Uddin et al. (2021) cheer the role of macroprudential policies such as corporate governance, capitalism, financial development, economic resilience to grapple with future exogenous shocks.

In the context of the pandemic, the World Health Organization (WHO) officially declared COVID-19 a pandemic, leading to the implementation of crucial measures to prevent the overwhelming of intensive care services. This global health crisis had significant repercussions, including the cancellation of events, the imposition of lockdown measures, border closures, and the collapse of stock markets due to economic uncertainties.

The economic situation induced significant changes in consumer behavior, favoring online shopping and creating growth opportunities for some industries, while others experienced major disruptions. These dynamics have been analyzed by several researchers, such as Ibn-Mohammed et al. (2021), Choi (2020), Gunay & Kurtulmus (2020), and Baek et al. (2020), highlighting specific sectoral trends.

In Tunisia, government measures have had a significant impact on the TUNINDEX index, particularly in the banking sector. The crisis period has drawn parallels to the situation during the Tunisian revolution in 2011, marked by economic restrictions and a decline in the stock market. Future research can delve deeper into analyzing the impact of COVID-19 on the Tunisian economy, just as studies have been conducted on the consequences of the Tunisian revolution.

The use of GARCH models to assess the volatility of the Tunisian stock market during the pandemic offers interesting insights. The findings can contribute to a better understanding of the relationship between economic uncertainty and market volatility, highlighting the crucial importance of volatility analysis in investment decisions (Trabelsi, 2024). The asymmetric effects, as demonstrated by the GARCH analysis, can have significant implications for market participants, underscoring the need for dynamic models to comprehend the complex behaviors of financial markets during a crisis.

To sum up, the impact of COVID-19 on the volatility of financial markets is a complex and constantly evolving research area. The multiple dimensions of this crisis, from economic consequences to changes in consumer behavior, require a multidisciplinary approach. Current work provides a solid foundation, but future research is needed to deepen our understanding of these dynamics and to inform the strategic decisions of investors and policymakers in an increasingly complex and uncertain financial environment. Kusumahadi & Permana (2021) recommend the focus on in-depth factors of volatility's movements besides the COVID-19 incident. We try to fill this gap in the Tunisian context.

3. Data and Methods

3.1 Data

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Our study will focus on the analysis of daily data from 2017 to 2020 related to TUNINDEX, the inflation rate, the interest rate, the P/E ratio, and dividend, making a complete set of 992 data points for each variable (see Table 1):

Table 1 Description of variables

Variable	Definition	Source	Expected Sign
TUNINDEX	The official stock market index	Tunis Stock Exchange	
PER	The Price-Earnings Ratio (P/E Ratio)	Tunis Stock Exchange	+
Inflation	The inflation rate	National Institute of Statistics	+
Interest rate	The interest rate of a loan or borrowing	Central Bank of Tunisia	+
Dividend	The distribution of profits made by a company to its shareholders.	Tunis Stock Exchange	-

Table 2 summarizes the key characteristics of the variables. The skewness indicates that the distributions of the Dividend and PER variables lean towards the right. This suggests a predominance of values on the higher end of the scale, with a notable concentration of data points towards the lower end. Conversely, the distributions of inflation, interest rate, and TUNINDEX exhibit a leftward skewness. A significant observation is the higher standard deviation (Std. Dev) for the TUNINDEX, indicating a wider spread of data around the mean compared to the other variables. This highlights greater data variability.

Table 2 Descriptive statistics

	TUNINDEX	PER	Inflation	Interest Rate	Dividend
Mean	6758.971	12.21771	6.270013	6.345766	3.781028
Median	6856.010	12.13000	6.284334	6.750000	3.760000
Maximum	8431.640	16.26000	7.803139	7.750000	5.180000
Minimum	2385.490	9.260000	4.569085	4.250000	3.090000
Std. Dev.	673.4937	1.836685	0.962492	1.164953	0.391638
Skewness	-0.215833	0.096223	-0.149453	-0.340852	0.897080
Kurtosis	4.443095	2.220182	1.861444	1.841084	5.065345
Jarque-Bera	93.77944	26.66626	57.27378	74.72267	309.3660
Probability	0.000000	0.000002	0.000000	0.000000	0.000000
Sum	6704899.	12119.97	6219.852	6295.000	3750.780
Sum Sq. Dev.	4.50E+08	3343.049	918.0526	1344.902	152.0000
Observations	992	992	992	992	992

From Table 3, we derive the following:

- The positive correlation between the PER and inflation indicates a moderate relationship. A positive correlation suggests that as inflation rises, PER tends to increase, and similarly, a negative correlation (-0.54885) between PER and interest rate, as well as between PER and dividend, indicates a moderate inverse relationship, suggesting that an increase in interest rates leads to a decrease in PER.
- Positive correlations between inflation and PER, as well as interest rate, imply that rising inflation could be linked to an increase in PER, possibly due to expectations of economic growth. Similarly, the positive correlation with interest rates might reflect specific economic conditions. However, the negative correlation between inflation and dividends indicates a trend where dividends decrease as inflation rises, and vice versa

- The findings indicate a positive correlation between Dividend and Interest rate, while a negative correlation appears between Dividend and inflation and between Dividend and PER.

Table 3 Correlation Matrix

	PER	Inflation	Interest Rate	Dividend
PER	1	0.3545086042442187	-0.5488497404566407	-0.6210999027690834
Inflation	0.3545086042442187	1	0.4417184097935406	-0.4310353895875806
Interest Rate	-0.5488497404566407	0.4417184097935406	1	0.2067467060620082
Dividend	-0.6210999027690834	-0.4310353895875806	0.2067467060620082	1

3.2 Methods

The assessment of volatility has mandated the application of models within the Autoregressive Conditional Heteroskedasticity (ARCH) framework in the realm of financial literature. Originating with the seminal ARCH model introduced by Engle (1982), subsequent advancements have been made.

Our econometric modelling follows Fakhfekh et al. (2023). However, we distinguish from their study by including specific economic factors.

3.2.1 ARCH

An ARCH model characterizes the variance of a time series, particularly in situations involving dynamic and potentially volatile variance. While ARCH models can potentially depict a slowly escalating variance trend over time, their primary application lies in scenarios featuring brief episodes of heightened variation. It is worth noting that situations involving a gradual increase in both variance and mean level may be more effectively addressed by transforming the variable.

The stock return is calculated using this formula:

$$R_t = Ln\left(\frac{P_t}{P_{t-1}}\right) \quad (1)$$

where P_t and $P_{t-1}$are the stock market indices of the Tunisian Stock Exchange at times t and t-1, respectively. Ln is the natural logarithm.

The mean equation is given by:

$$R_t = \alpha + \sum_{i=1}^{p} \beta_i R_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t \quad (2)$$

The autoregressive (AR) (p) or autoregressive moving average (ARMA) (p, q) structures are commonly integrated as explanatory elements within the conditional mean equation. The choice between AR(1), MA(1) and ARMA(1,1) is based on Akaike (AIC) and Schwarz (SC) information criteria for which the value is minimized.

The conditional variance equation is defined as:

$$\sigma_t^2 = a_0 + \sum_{i=1}^{p} a_i \varepsilon_{t-i}^2 \quad (3)$$

where $a_0 > 0, a_i > 0$. This model is known as the linear ARCH(p). In financial data analysis, the model captures the phenomenon of volatility clustering, wherein significant (insignificant) price changes tend to be succeeded by other substantial (moderate) price changes, but with an unpredictable direction. To streamline the model and guarantee a consistently diminishing impact of more distant shocks, a makeshift linearly declining lag structure was frequently enforced in many early applications of the model (see Bollerslev et al., 1992).

3.2.2 GARCH

Bollerslev's Generalized ARCH model (1986) is the most widely used model for estimating volatility. GARCH models have had great success in the literature due to their simple specification and ease of interpretation.

The conditional variance equation is defined as:

$$\sigma_t^2 = a_0 + \sum_{i=1}^{p} a_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} b_j \sigma_{t-j}^2 \tag{4}$$

where $a_0 > 0, a_i > 0, b_j > 0$. For a GARCH(1,1), the constraint $a_1 + b_1 < 1$ implies that the unconditional variance of the ε yield series is finite and that the conditional variance σ_t^2 evolves over time. It also provides the necessary and sufficient for the stochastic process σ_t; $t \in Z$ to be a unique process strictly stationary with $E(\sigma_t^2) < \infty$.

Two key properties can be noted from the above equation. First, a high value of ε_{t-1}^2 or σ_{t-1}^2 gives rise to a high value of σ_t^2 and this generates the volatility clustering that is common in time series. Second, the tail distribution is thicker than that of a normal distribution (see Mestiri, 2022).

3.2.3 EGARCH

This model is suggested by Nelson (1991) to account for leverage effects. It is an asymmetric Exponential GARCH specification that distinguishes between "good" and "bad" news on volatility.

The conditional volatility equation is given by:

$$Ln\sigma_t^2 = a_0 + \sum_{i=1}^{p} a_i \frac{|\varepsilon_{t-i}| + \delta_i \varepsilon_{t-i}}{\sigma_{t-i}} + \sum_{j=1}^{q} b_j Ln\sigma_{t-j}^2 \tag{5}$$

If there are "good" news, $\varepsilon_{t-i} > 0$ and the total effect is given by $(1 + \delta_i)\varepsilon_{t-i}$. If there are "bad" news, $\varepsilon_{t-i} < 0$ and the total effect is given by $(1 - \delta_i)\varepsilon_{t-i}$. "Bad" news are likely to give a more pronounced impact on volatility and $\delta_i < 0$.

3.2.4 TGARCH

The Threshold GARCH specification portrays another asymmetric GARCH model with leverage effects is. The conditional volatility is given by:

$$\sigma_t^2 = a_0 + \sum_{i=1}^{p} a_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \gamma_i S_{t-i} \varepsilon_{t-i}^2 + \sum_{j=1}^{q} b_j \sigma_{t-j}^2 \tag{6}$$

With

$$S_{t-i} = \begin{cases} 1 \text{ if} \varepsilon_{t-i} < 0 \\ 0 \text{ if} \varepsilon_{t-i} > 0 \end{cases}$$

when $\varepsilon_{t-i} > 0$, the full effect pertains to $a_i \varepsilon_{t-i}^2$. If $\varepsilon_{t-i} < 0$, the full effect alludes to $(a_i + \gamma_i)\varepsilon_{t-i}^2$. The coefficient $\gamma_i > 0$ so that "bad" news exhibit more moves in volatility.

According to Bera & Higgins (1993), the most applied financial work shows that GARCH (1,1) provides a flexible and parsimonious approximation of the conditional variance dynamics and is capable of representing the majority financial series. Therefore, p=1, q=1 are applied for all GARCH family models to be estimated.

3.2.5 FIGARCH

The ARMA representation of a GARCH(p,q) model is given by:

$$\sigma_t^2 = a_0 + \sum_{i=1}^{p} a_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} b_j \sigma_{t-j}^2 \quad (7)$$

Eq. (7) can be rewritten as

$$\varphi(L)\varepsilon_t^2 = a_0 + b(L)\mu_t$$

where $\mu_t = \varepsilon_t^2 - \sigma_t^2$, $m = \max(p,q)$ and $\varphi_i = a_i + b_i$

$$\varphi(L) = 1 - \varphi_1 L - \varphi_2 L^2 - \cdots - \varphi_m L^m$$

$$b(L) = 1 - b_1 L - b_2 L^2 - \cdots - b_q L^q$$

ARMA(p.q) representation becomes a FARIMA(m,d,q) process to accommodate high persistence and long memory properties:

$$\varphi(L)(1-L)^d \varepsilon_t^2 = a_0 + [1 - b(L)]\mu_t \quad (8)$$

Eq. (8) can be rewritten in terms of the conditional variance σ_t^2 as follows:

$$b(L)\sigma_t^2 = a + [b(L) - \varphi(L) - (1-L)^d \varepsilon_t^2]$$

Baillie et al. (1996) identify that model as the Fractionally Integrated GARCH (FIGARCH(m,d,q)) model. The coefficients in $\varphi(L)$ and $b(L)$ describe the short-term fluctuations in volatility, whereas d, which denotes the fractional difference represents the long-term features of volatility when $0 < d < 1$.

3.2.6 FIEGARCH

The Fractionally Integrated EGARCH is suggested by Bollerslev & Mikkelsen (1996). This specification makes the FIGARCH stationary and the conditional variance σ_t^2always positive by allowing for some restrictions. Eq.(8) becomes:

$$\varphi(L)(1-L)^d Ln\sigma_t^2 = a + \sum_{j=1}^{q}\left(b_j |x_{t-j}| + \gamma_j x_{t-j}\right),\ \gamma_j \neq 0 \quad (9)$$

where x_t is the standardized residual given by $x_t = \frac{\varepsilon_t}{\sigma_t}$. The FIGARCH is stationary if $0 < d < 1$ (see Bollerslev & Mikkelsen, 1996).

4. Results and discussion

4.1 Results

4.1.1 ARCH effect

The probability observed falls beneath the 5% significance level (F-statistic=80.00399, Prob=0.0000; Obs*R-squared=74.12217, Prob=0.0000), rejecting the null hypothesis of no ARCH effect.

4.1.2 GARCH Family estimation

We suggest estimating various variants of the GARCH model to identify the model that best reflects volatility's behavior. According to Table 4, the optimal model based on AIC and SC is the FIEGARCH(1,1) model with a constant and AR(1) before the crisis and FIEGARCH(1,1) model with both a constant and a MA(1) term during the COVID-19.

Table 4 GARCH Estimation results

Before the crisis				
Model	GARCH (1,1) with constant	GARCH (1,1) with constant , AR(1)	GARCH (1,1) with constant, MA(1)	GARCH (1,1) with constant, AR(1) MA(1)
AIC	-3.559130	-3.558696	-3.055413	-3.554728
SC	-3.535164	-3.528708	-3.025455	-3.518742
Model	EGARCH (1,1) with constant	EGARCH (1,1) with constant, AR(1)	EGARCH (1,1) with constant, MA(1)	EGARCH (1,1) with constant, AR(1) MA(1)
AIC	-6.833878	-6.830606	-6.831366	-6.669408
SC	-6.803920	-6.794620	-6.795417	-6.627425
Model	FIGARCH (1,1) with constant	FIGARCH (1,1) with constant, AR(1)	FIGARCH (1,1) with constant, MA(1)	FIGARCH (1,1) with constant, AR(1) MA(1)
AIC	-3.422932	-3.409494	-3.416563	-3.405550
SC	-3.392975	-3.373508	-3.402734	-3.389399
Model	FIEGARCH (1,1) with constant	FIEGARCH (1,1) with constant, AR(1)	FIEGARCH (1,1) with constant, MA(1)	FIEGARCH (1,1) with constant, AR(1) MA(1)
AIC	-4.159200	-6.957826	-4.772775	-4.354319
SC	-4.117259	-6.909845	-4.724843	-4.300340
Model	TGARCH (1,1) with constant	TGARCH (1,1) with constant, AR(1)	TGARCH (1.1) with constant, MA(1)	TGARCH (1,1) with constant, AR(1) MA(1)
AIC	-3.549925	-3.559317	-3.545499	-3.549215
SC	-3.519967	-3.523331	-3.509550	-3.533064
During the crisis				
Model	GARCH (1,1) with constant	GARCH (1,1) with constant, AR(1)	GARCH (1,1) with constant, MA(1)	GARCH (1,1) with constant, AR(1) MA(1)
AIC	-7.666841	-7.713002	-7.727698	-7.720541
SC	-7.603298	-7.633574	-7.648270	-7.625227
Model	EGARCH (1,1) with constant	EGARCH (1,1) with constant, AR(1)	EGARCH (1,1) with constant, MA(1)	EGARCH (1,1) with constant, AR(1) MA(1)
AIC	-7.649055	-7.706309	-7.718663	-7.710391
SC	-7.569627	-7.610996	-7.623349	-7.599192
Model	FIGARCH (1,1) with constant	FIGARCH (1,1) with constant, AR(1)	FIGARCH (1,1) with constant, MA(1)	FIGARCH (1,1) with constant, AR(1) MA(1)
AIC	-7.705866	-7.735988	-7.749264	-7.744535
SC	-7.626438	-7.640674	-7.653951	-7.633336
Model	FIEGARCH (1,1) with constant	FIEGARCH (1,1) with constant, AR(1)	FIEGARCH (1,1) with constant, MA(1)	FIEGARCH (1,1) with constant, AR(1) MA(1)
AIC	-7.678729	-7.716050	-7.734716	-7.727123
SC	-7.567530	-7.588965	-7.607631	-7.584153
Model	TGARCH (1,1) with constant	TGARCH (1,1) with constant, AR(1)	TGARCH (1,1) with constant, MA(1)	TGARCH (1,1) with constant, AR(1) MA(1)
AIC	-7.659213	-7.708752	-7.721295	-7.712225
SC	-7.579785	-7.613439	-7.625981	-7.601025

The selected model from the GARCH model family aligns with previous studies such as Jeribi et al. (2015), Fakhfekh et al. (2015), and Fakhfekh et al. (2016), suggesting long-memory properties. Indeed, the modified R/S (Range over Standard Deviation) statistic proposed by Lo (1991) falls within the intervals at the 90%, 95%, and 99% thresholds, before the crisis (statistic=1.15) and during the COVID-19 crisis (statistic=1.42).

According to Figure 1, the volatility is characterized by three significant spikes: It increases during January (M1) and February (M2), corresponding to the first phase of the COVID-19 crisis. This is followed by a period of stagnation from February (M2) to July (M7), indicating a period of relative stability. Between July and August (M7 and M8), a rapid rise is observed, followed by a stagnation that persists from August (M8) until the end of the observed period.

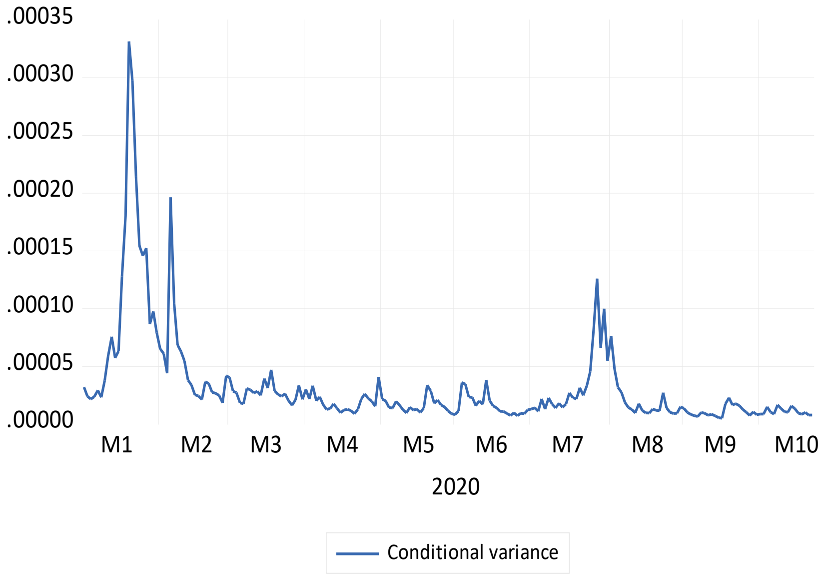

Figure 1 Evolution of volatility during the COVID-19

4.1.3 Steps of VECM

4.1.2.1 Unit Root Test

The findings in Table 5 reveal that the volatility maintains stationarity at both its level and its first difference, meaning that it is integrated of both order 0 (I(0)) and order 1 (I(1)) while the remaining variables are stationary at the first difference (I(1)).

Table 5 Unit Root Test

In level						
Before the crisis	Augmented Dickey _Fuller (ADF)			Phillips _ Perron (PP)		
	With Constant	With Constant and Trend	None	With Constant	With Constant and Trend	None
Inflation	-1.903267 (0.3309)	-0.509169 (0.9830)	0.640286 (0.8543	-1.903858 (0.3306)	-0.475852 (0.9845	0.640623 (0.8544)
PER	-1.241783 (0.6579)	-2.090439 (0.5498)	-0.627992 (0.4452)	-1.246054 (0.6560)	-2.101377 (0.5437)	-0.627992 (0.4452)
Interest Rate	-0.986993 (0.7595)	-2.371925 (0.3940)	1.741143 (0.9806)	-0.984215 (0.7605)	-2.382195 (0.3886)	1.755691 (0.9813)
Dividend	0.883242 (0.7936)	-1.125739 (0.9228)	0.293894 (0.7707)	-0.884477 (0.7932)	-1.125739 (0.9228)	0.293894 (0.7707)
Volatility	-27.83882 (0.0000)	-27.82507 (0.0000)	-27.82086 (0.0000)	-27.83882 (0.0000)	-27.82507 (0.0000)	-27.82086 (0.0000)
During the crisis	With Constant	With Constant and Trend	None	With Constant	With Constant and Trend	None
Inflation	-0.279618 (0.9245)	-2.090399 (0.5481)	-1.140092 (0.2323	-0.276900 (0.9249)	-2.090399 (0.5481)	-1.142390 (0.2305)
PER	-1.903955 (0.3302)	-1.424479 (0.8516)	-1.254716 (0.1926)	-1.903658 (0.3303)	-1.424479 (0.8516)	-1.257875 (0.1916)
Interest Rate	-1.756733 (0.4015)	-2.267082 (0.4499)	-1.463347 (0.1338)	-1.755748 (0.4020)	-2.276909 (0.4445)	-1.473711 (0.1313
Dividend	-1.322997 (0.6192)	-2.003683 (0.5960)	-0.464186 (0.5135)	-1.338266 (0.6120)	-2.018921 (0.5877)	-0.464186 (0.5135)
Volatility	-3.678852 (0.0051)	-4.268807 (0.0042	-2.737134 (0.0063)	-3.836665 (0.0030)	-4.425110 (0.0025)	-2.949354 (0.0033)
In first difference						
Before the crisis	Augmented Dickey _Fuller (ADF)			Phillips _ Perron (PP)		
	With constant	With constant and trend	None	With constant	With constant and trend	None
Inflation	-27.20786 (0.0000)	-27.24725 (0.0000)	-27.22132 (0.0000)	-27.20786 (0.0000)	-27.24726 (0.0000)	-27.22132 (0.0000)
PER	-27.21206 (0.0000)	-27.20468 (0.0000)	-27.22132 (0.0000)	-27.21206 (0.0000)	-27.20468 (0.0000)	-27.22132 (0.0000)
Interest rate	-27.34780 (0.0000)	-27.33487 (0.0000)	-27.22132 (0.0000)	-27.34847 (0.0000)	-27.33552 (0.0000)	-27.22132 (0.0000)
Dividend	-27.20786 (0.0000)	-27.24725 (0.0000)	-27.22132 (0.0000)	-27.20786 (0.0000)	-27.24726 (0.0000)	-27.22132 (0.0000)
Volatility	-15.87451 (0.0000)	-15.86403 (0.0000)	-15.88500 (0.0000)	-778.0390 (0.0001)	-778.8881 (0.0001)	-778.7105 (0.0001)
During the crisis	With constant	With constant and trend	None	With constant	With constant and trend	None
Inflation	-15.60504 (0.0000)	-15.64987 (0.0000)	-15.55635 (0.0000)	-15.60504 (0.0000)	-15.65019 (0.0000)	-15.55635 (0.0000)
PER	-15.60429 (0.0000)	-15.68367 (0.0000)	-15.55635 (0.0000)	-15.60429 (0.0000)	-15.68428 (0.0000)	-15.55635 (0.0000
Interest rate	-15.64046 (0.0000)	-15.63506 (0.0000)	-15.55635 (0.0000)	-15.64046 (0.0000)	-15.63530 (0.0000)	-15.55635 (0.0000
Dividend	-15.53073 (0.0000)	-15.53294 (0.0000)	15.55635 (0.0000)	-15.53073 (0.0000)	-15.53294 (0.0000	15.55635 (0.0000)
Volatility	-5.461549 (0.0000)	-5.447670 (0.0000)	-5.442109 (0.000)	-16.53108 (0.0000)	-16.48454 (0.0000)	-16.58027 (0.0000)

4.1.2.2 Optimal Lag

Based on Table 6, the selection of the optimal lag is set to 1, as indicated by the conventional criteria (AIC, SC).

Table 6 Optimal lag selection

Lag	Before the COVID-19 Crisis		During the COVID-19 Crisis	
	AIC	**SC**	**AIC**	**SC**
0	45.26365	45.29494	-16.32095	-16.23934
1	**27.19451***	**27.38226***	**−29.50534***	**29.01571***
2	27.26146	27.60566	-29.31045	-28.41278
3	27.32836	27.82902	-29.16228	-27.85658
4	27.39521	28.05233	-29.15431	-27.44059
5	27.46200	28.27558	-28.96665	-26.84490
6	27.52874	28.49878	-28.81733	-26.28754
7	27.59541	28.72191	-29.01409	-26.07627
8	27.66201	28.94497	-28.92322	-25.57737

4.1.2.3 Johansen Cointegration Test

The Johansen cointegration test outcomes distinctly affirm a cointegration linkage among the series under review, indicating a consistent long-term association between them prior to the COVID-19 crisis and during the pandemic (see Table 7). The Trace and Max-Eigenvalue tests validate at least one meaningful cointegration relationship at the 0.05 level of significance before the crisis, decisively refuting the hypothesis of no cointegration.

Table 7 Cointegration Test

Unrestricted Cointegration Rank Test (Trace)

Before the crisis: Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**	During the crisis: Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.255527	255.1526	69.81889	0.0000	None *	0.154358	71.72400	69.81889	0.0350
At most 1	0.023719	36.79478	47.85613	0.3573	At most 1	0.105912	36.85096	47.85613	0.3546
At most 2	0.014987	19.03116	29.79707	0.4907	At most 2	0.035411	13.56514	29.79707	0.8641
At most 3	0.006906	7.857052	15.49471	0.4808	At most 3	0.026355	6.066118	15.49471	0.6877
At most 4	0.003681	2.729023	3.841465	0.0985	At most 4	0.002453	0.510766	3.841465	0.4748

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**	Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.255527	218.3578	33.87687	0.0000	None *	0.154358	34.87304	33.87687	0.0379
At most 1	0.023719	17.76362	27.58434	0.5149	At most 1	0.105912	23.28582	27.58434	0.1616
At most 2	0.014987	11.17410	21.13162	0.6299	At most 2	0.035411	7.499022	21.13162	0.9316
At most 3	0.006906	5.128030	14.26460	0.7256	At most 3	0.026355	5.555352	14.26460	0.6707
At most 4	0.003681	2.729023	3.841465	0.0985	At most 4	0.002453	0.510766	3.841465	0.4748

* denotes rejection of the hypothesis at the 0.05 level

**MacKinnon-Haug-Michelis (1999) p-values

4.1.2.4 Estimation of the VECM

Prior to the COVID-19 crisis, the results in Table 8 (left-hand sided) highlighted significant relationships between the Tunisian market's volatility (Vol_tun) and essential economic variables such as interest rate, PER, inflation, and dividend. The cointegration coefficients illustrate that fluctuations in interest rate (with a coefficient of 9809050) and in inflation (-9767229) significantly influenced the conditional volatility, showcasing the market's acute sensitivity to these macroeconomic factors. Furthermore, the error correction mechanism, demonstrated by a coefficient of -1.021214 emphasizes the market's capability to efficiently and swiftly correct itself to revert to long-term equilibrium following any short-term imbalances.

Table 8 VECM cointegrating equation

Before the crisis		During the crisis
DIVIDEND(-1)	6764202.	8.84E-05
	[0.40890]	[1.16733]
INFLATION(-1)	-9767229.	6.34E-05
	[-1.47351]	[0.97571]
PER(-1)	8684128.	-0.000197
	[1.90985]	[-3.51311]
INTEREST RATE(-1)	9809050.	-0.000292
	[1.65976]	[-2.91394]
C	-1.38E+08	0.003051
COINTEQ(-1)	-1.021214	-0.027518

t-statistics in [ ]

During the epidemic (Table 7, right-hand sided), the error correction coefficient stands at -0.027518, indicating a negative adjustment towards long-term equilibrium and the market's tendency to recalibrate following imbalances. Furthermore, the t-statistics of the interest rate and PER illuminate the most significant effects on volatility. However, dividend and inflation remain statistically insignificant in both periods. These results indicate that moves in volatility are more dictated by investors' sentiment than fundamentals before attention to economic fundamentals, mainly the interest rate, prevails when the COVID-19 occurs.

Economic linkages during periods of stability and uncertainty highlight the imperative for investors to grasp these dynamics in order to effectively foresee market shifts and tailor their decisions accordingly.

4.2 Discussion

We find that all variables' coefficients have their expected signs except Inflation and Dividend before the crisis. However, the first variable turns to be positive during the crisis. In either case, both variables are not relevant to explain volatility patterns while interest rate shows up with a negative and statistically significant coefficient during the crisis. This might be explained by investors' comfort to the central bank policy rate and announcement of eases in credit payments. Good news has somewhat led to a decrease in stock market volatility. The price earnings ratio portrays investors' sentiment. The positive sign of the coefficient indicates irrational enthusiasm about the future of an asset they buy, leading to a rise in volatility while

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it is negative during the epidemic, meaning that investors take this crisis as a learning point and start to adopt mature behavior.

Overall, the Tunisian financial market has demonstrated a capacity for a relative adaptation and response to economic fluctuations across both periods. However, there is still a void of vulnerability to shocks necessitating flexible and proactive approaches in strategic management and planning during increased economic unpredictability.

5. Conclusions

We have mapped the response of the Tunisian financial market before and during the COVID-19 crisis through the GARCH and VECM models. The increased volatility underlines the sensitivity of markets to sudden shocks and how they align according to investor sentiment, economic fundamentals, and response to news and information. We contend that the stock market volatility changes are more likely the result of irrational emotions than fundamentals before the crisis while investors become more attentive to fundamentals during the epidemic.

The observations shed light on the necessity for policymakers and investors to perpetually assess the evolving landscape of risks and opportunities within an ever-changing economic framework, ensuring preparedness and agility in response to shifts in market conditions.

The institutional framework of the financial market is paramount. Upcoming research should focus on how investors' behavior changes according to information transparency under exogenous shocks.

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Declaration of interests

The authors have no competing interests to declare.

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