

Financial technology and financial inclusion in remote areas of Algeria. Analytical study using data mining

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Abstract. *This study aimed to demonstrate how financial technology tools can be used to achieve financial inclusion by shedding light on the reality of financial technology and financial inclusion in Algeria, specifically in the remote areas of Algeria, as financial inclusion represents one of the main areas that economists and governments are trying to focus on to eliminate poverty. To reach the goal of the study, a statistical analysis method was adopted for the various questions asked to 200 participants in the survey during the period 2022–2023. A set of quantitative and qualitative data was used. The study population represents 200 individuals to whom the questionnaire was distributed. A data mining tool was used to analyze the study data, and the survey participants' K algorithm was later used to predict the behavior patterns of people from a similarly contextualized community regarding financial activities. The study concluded that financial technology, through its multiple tools, changes the structure of comprehensive financial services, in addition to the diversity and style of financial services provided to individuals, which has enhanced and increased their availability to a broader social group that did not have access to them. It was also shown that there is a significant impact of financial technology tools on enhancing financial inclusion indicators. It is recommended to adopt effective and modern financial and technological strategies that provide marginalized social groups with reasonable access to financial services and products that meet their needs, including transactions, payments, savings, credit, and insurance. Therefore, obtaining the added value of data and investing it will increase financial inclusion indicators.*

Keywords: technology, financial technology, financial inclusion, data mining, remote areas.

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Introduction. Technology has formed and will continue to constitute a revolution in the field of global and Arab financial systems, as it now meets many needs and provides services related to various operations. Technology-accredited institutions have succeeded in providing a variety of services, especially those financial institutions (Baptiste.V, 2019, p. 5), which include, among other things, payment services and digital currencies. Money transfer, as well as lending, crowd funding, and wealth management, in addition to insurance services, also succeeded in creating demand for those products. While in some countries and regions the formal financial sector (GPMI, 2016, p.5), which mainly consists of the banking system, serves most of the population, other countries, and regions, with which we highlight remote or rural areas and specifically Algeria, do not enjoy a large segment of their society, particularly the low-income group, with limited access to financial services, whether formal or semi-formal. As a result, many people necessarily must rely either on their own sources or informal sources of financing, which generally come at a high cost. Poverty is not just insufficient income; rather, it is the absence of a wide range of capabilities, including security and the ability to participate in economic and political systems. Hence, the importance of financial inclusion arises from the problem of the financial exclusion of nearly 3 billion people from formal financial services around the world.

Therefore, the following problem can be formulated:

What is the reality of using financial technology in remote Algerian regions and its role in achieving financial inclusion?

To answer the above problem, the following main hypothesis is proposed: There is a role for financial technology in achieving financial inclusion in remote areas. The following sub-hypotheses were proposed:

- There is no relationship between parents' educational level and financial inclusion.
- There is no relationship between the type of bank and financial inclusion.
- There is no relationship between the distance to the bank and financial inclusion.
- There is no relationship between monthly income and banking inclusion.

I. Academic literature

Financial Inclusion

The definitions of financial inclusion (Chen XH, You XY, 2021, p.7) differed according to the source of the definition. We find: The World Bank defines it as having access to useful financial products and services at affordable prices that meet their needs. (Mirjana Pejić, 2019, p. 2)

The 1990s saw the introduction of the FI idea. Researchers who found that impoverished people in developed countries' periphery were denied formal credit due to racial or geographic prejudices, even though they had regular income streams and collateral, raised the issue of people being excluded from the formal financial system. (Thereza, 2021, p. 1)

The procedure that guarantees accessibility and availability to the formal financial sector is known as financial inclusion. (Sarma, 2012, p.3)

From the above, we can say that financial inclusion is the process of ensuring access to appropriate and formal financial products and services needed by all sectors of society in general, and vulnerable groups such as low-income people in particular, at a reasonable cost and in a fair and transparent manner by formal financial service providers. (Saliha Falaq, 2019, p.3). Therefore, the establishment of financial inclusion entails many development benefits, especially through the exploitation of information and communication technology and the use of digital financial services. There is also a close relationship between financial inclusion, financial stability, and economic growth, as financial inclusion aims to provide segments of society with official financial services at reasonable costs.

Through the legality of some unofficial channels, the diversity of their product offerings, attention to quality to draw in the greatest number of consumers and transactions, and other means, financial inclusion also increases competition amongst financial institutions. (Qasim, 2023, p. 5)

Financial inclusion is a key factor for achieving the goals of sustainable development, as the generalization of financial services contributes to improving the standard of living. (Tamara Firas, 2020, p. 180) Financial inclusion is concerned with the social aspect, and this is in terms of caring for the poor and low-income people, through their fair access to financial products at low prices, thus developing their social and economic conditions.

Data mining

The term data mining (Nihat, A., 2014, p.11) appeared in the mid-nineties in the United States of America, but data mining itself is a development for a sector with a long history. Interest in data mining began in 1989 during a workshop on discovering knowledge in databases, and since then it has been held. This workshop continued annually until 1995. The Knowledge Discovery and Data Mining International Conference. (Sanghamitra, 2005, p.04) became one of the most important events. Its development and modifications continued to the present day. Data mining (Dzeroski, S. 2002, p. 348) refers to extracting information and knowledge from a large amount of data using a set of statistical methods. And smart technologies and others, as a combination of multiple disciplines. (Margaret H., 2009, p. 2).

Researchers in the field of data mining proposed several approaches to increase the chances of success in implementing data mining projects, and among the most common processes is the six-step GRISP-DM process for data mining, which can be explained as follows: (Jiawei Han, 2012, p. 02)

- Understanding the business is necessary in order to identify the field of work and define the objectives of the application.
- Data understanding: selecting and creating a target data set. (Nemiche Mohamed, 2015, p. 13)
- Data processing: It includes selecting expected variables and sample size (Rasha Odeh Lafta, 2019, p. 10), formulating new variables to build effective models, and rearranging data fields as required in the data mining model. (Jiawei Han, 2012, p. 357)
- Building the model: This process needs the help of specialists in data mining (Cheng Che, 2019, p. 13) in order to investigate the options and choose which model is best for handling the study's challenge. (Dimitrios, 2022, p. 10-13)

Applied study

To reveal the extent of financial inclusion and exclusion in the region and to identify the factors that support financial inclusion, respondents were carefully selected to ensure that all groups of society in the region are subject to the survey. In the first step of the analysis, we come up with the statistical results of the survey, which present the facts and figures. In the second step, we apply data mining techniques to the data set collected through the survey process.

Statistical results from the survey

A statistical analysis of various questions asked to 200 survey participants over the period 2022–2023 has been found, and the main areas of analysis are presented below.

A. Awareness of the banking service and its use

People's awareness about the various facilities available with modern banking services such as ATMs, money transfers, etc. was also found to be 12% of the percentage of people who actually use this type of facility.

B. bank account

This analysis shows the current state of banking inclusion. This information is very important for understanding the state of financial inclusion in the region. The percentage of people with a bank account is 65.23%, and the percentage of people without a bank account is 34.77%.

C. Bank account details

This is the division of the respondents according to their choice of banking institution. Mostly, we have banks that are subject to government banking groups and private banks, but their availability in remote areas is very limited, and therefore 25% resort to government banks only.

D. Having a bank account

35% of the respondents do not have accounts with any of the financial institutions. Lack of awareness and accessibility are the main reasons for not having accounts at banks. Until now, many public-sector banks did not exist in remote villages.

E. The type and source of credit available

Among the respondents, 40% did not benefit from any loans from formal financial institutions, and 60% had loans from formal banking institutions. These loans are mainly for agricultural purposes.

Data mining approach to financial inclusion

The data mining approach to financial inclusion is to discover hidden patterns and valuable knowledge from data collection. These patterns are highlighted by factors affecting financial inclusion and exclusion. The specific patterns from data mining analysis in this area will be a set of rules that reveal socioeconomic and educational conditions that lead to either financial inclusion or exclusion. The survey respondents' K-algorithm was subsequently used to predict the behavior patterns of people in a similar context with regard to

financial activities.(Ching TM, 2020, p.8).

The K-algorithm and its variants are the most well-known partitioning methods. The value "k" indicates the number of data points initially submitted to the algorithm. This algorithm takes the input parameter "k" and divides a set of m data points into k groups. The technique works by calculating the distance between a data point and the center of a variable to add an element to a set so that the similarity within the element is high but the similarity between sets is low. A common way to find the distance is to calculate the sum of the squared differences.(Chongda. L, 2014, p. 215)

To divide users according to their participation in different banking operations, we chose fields from the database that directly represent different banking operations. The specific fields are having a bank account, credit loan, insurance awareness money transfer, using an ATM, using basic banking services, having deposits. These fields are of the boolean type, and their values are converted to 0 and 1, and the sum of these fields is found for each respondent. In the next step, the sum of the deposited fuses is divided into segments of field levels called low, medium, and high, as shown in Table1.

Table 1. Levels of financial inclusion variable field

financial inclusion variable										
have an	field of variablestatements							field levels		
	Credit loan	money	Insurance	machine	Use of	Having	Su	low	Me dium	Hig
1	1	1	1	1	1	1	4	0.5	0.50	0.50
0	0	0	0	1	1	0	3	0.3	0.50	1.00
1	1	0	1	1	0	0	5	0.2	0.50	1.00
1	0	1	0	0	0	0	5	0.3	0.50	0.5
0	0	1	0	0	1	0	2	0.2	0.50	0.25
0	1	1	0	0	1	1	2	1.0	0.50	0.25
1	0	1	1	0	1	0	1	0.2	0.50	0.50
1	1	0	0	1	0	0	1	0.5	0.50	0.22
0	0	0	1	0	0	0	5	0.5	0.50	0.33
1	1	1	1	0	1	1	3	0.2	0.50	1.00
1	1	1	1	0	1	1	4	0.1	0.50	0.50
1	1	1	0	1	0	0	3	0.2	0.50	1.00
0	0	0	1	0	0	0	3	0.1	0.50	0.25
1	1	0	0	0	1	0	5	0.5	0.50	0.33
1	0	1	1	1	1	0	5	0.2	0.50	1.00
1	0	1	1	0	0	0	6	1.0	0.50	0.20
0	0	0	0	0	0	1	1	0.2	0.50	0.20
0	0	1	0	0	0	0	6	0.5	0.50	0.20
1	1	0	1	1	1	1	5	0.2	0.50	0.50
0	1	0	1	0	1	1	1	0.3	0.50	0.25
0	0	0	1	0	0	0	3	1.0	0.50	0.33
1	1	1	0	1	1	0	5	1.0	0.50	0.50

Source: Kneam data mining technology outputs.

In a similar fashion, we also grouped fields such as owning a bank account, borrowing, saving, informed insurance, and financial advice to represent their financial inclusion status. The sum obtained from these fields is then mapped into low, medium, and high language segments.

In the data mining technique using Kneam software, quantitative attribute values can be converted into boolean values using time intervals to apply traditional association rule mining algorithms to find relationships between items, and fuzzy clustering is used, which is an efficient modeling technique that can be used to divide quantitative values into meaningful groups rather than fixed, weighted periods of time.

It measures how dependent a particular element is on another. The intuitive meaning of such a rule is that a database transaction containing X tends to contain, given the set of transactions, T. The problem with data mining rules is to find all the rules that have support and confidence greater than or equal to the minimum support defined by the user and minimum trust, respectively.

Fuzzy association rules use fuzzy logic to convert numerical attributes into linguistic attributes, such as "income = high", thus preserving the integrity of the information conveyed by these numerical attributes. On the other hand, explicit association rules use sharp division to convert numeric attributes into binary attributes, such as "income = [-500020000]".

To find associations between novel linguistic features derived from the survey database, we used weighted fuzzy association grammar mining techniques using Kneam software. The association rules generated from the survey database can be later converted into classification rules so that we can extrapolate facts about financial inclusion and its relationship to fintech. To find the associations of technology and financial inclusion, we take the maximum value from the groups in a record for each attribute and assign this group that has the maximum membership for an attribute with that attribute (for example, in the first, if we consider the Have a bank account field, the associated groups are low, medium, and high with values, respectively, so we set the Money Transfer field with a high value for that record). This is done for all records and attributes. If we take the first five records from the derived database, we get the following correlations in Table 2 and the results of the study in Table 3.

Table 2. Rules for the first level association between the variables of financial inclusion and financial technology

No	First level rules	Support
1	Education level = high => banking	0.72
2	include = high	0.65
3	Monthly Income =High => Banking Inclusion = Low	0.32
4	The distance to thebank = near => Banking	0.65
5	include = high	0.63
6	Newness of the bank =high	0.72
7	Mobile phone use =high	0.72
8	=> Access to credits	0.72
9	= average	0.72
10	Computer use = high	0.72

Source: Kneam data mining technology outputs.

Table 3. The results of the study of the relationship between financial technology and financial inclusion

The first variable	The second variable		field	The distance
Financial inclusion	high		FinTech	-
Financial inclusion	high		FinTech	close
Financial inclusion		middle	FinTech	-
Financial inclusion		low	FinTech	far
Financial inclusion	high		FinTech	-
Financial inclusion	high		FinTech	close
Financial inclusion	low		FinTech	-
Financial inclusion	low		FinTech	-
Financial inclusion	low		FinTech	-
Financial inclusion		middle	FinTech	close

Source: Kneam data mining technology outputs.

Conclusion

In this work, we started with a database that was collected for statistical analysis on the situation of financial inclusion in a remote area of Algeria. The results of the analysis gave a clear picture of the statistics of the current situation in this area in the field of financial inclusion and exclusion, upon careful analysis of the rules and patterns that were created. We can easily reach the conclusion that modern information technology and modern banking systems in remote areas are the main factors affecting financial inclusion, and through data mining techniques, we have concluded that there is a relative use of technology in these remote areas, and we have found fields. It clearly indicates that awareness of modern technology plays a vital role in financial inclusion in these regions, and this is within the framework of the efforts made by Algeria in the field of technology by providing multiple digital services, including ATMs, smart cards, etc., as we have come to and based on the results in Table 2:

- there is a positive relationship between the educational level of parents and banking inclusion, which means that there is a relationship between the educational level of parents and banking inclusion, and this denies the validity of the first sub-hypothesis;
- there is a positive relationship between the type of bank and financial inclusion, which means that there is a relationship between the type of bank and financial inclusion, which negates the validity of the second sub-hypothesis;
- there is a positive relationship between the distance to the bank and financial inclusion, which means that there is a relationship between the distance to the bank and financial inclusion, which negates the validity of the third sub-hypothesis;
- there is a negative relationship between monthly income and financial inclusion, which means that there is no relationship between monthly income and banking inclusion, which confirms the validity of the fourth sub-hypothesis;
- therefore, despite the efforts made by Algeria in the field of technology, it has provided various digital services, including ATMs, smart cards, and so on.

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Impact of COVID-19 Pandemic and Russo-Ukrainian War on Tunisian Stock Exchange Performance and Volatility

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Abstract. *The purpose of our study was to investigate the impact of COVID-19 pandemic and the Russo-Ukraine (RU) war on the return volatility and value of the Tunisian Stock Exchange proxied by TUNINDEX. We applied GARCH (1,1) to assess the impact on the index return volatility, using daily observations from January 2019 to December 2022, and a multiple linear regression to determine the effect on the index value, based on monthly observations for January 2018 to December 2022. GARCH output revealed that both exogenous shocks led to higher stock market return volatility. The regression results disclosed statistically significant though opposite impacts on the index price. The pandemic exerted a positive, though extremely mild impact on the Index value, while the war had a negative effect on its performance. As for the control variables, both inflation rate and industrial production index exhibited positive effects on the TUNINDEX values, while trade balance had a negative impact. GDP growth rate and interest rate however, showed no significant influence on the index performance during the study period. We faced some difficulty accessing data, in addition to the scarcity of data on other potentially relevant factors, along with a short study period. Incorporating new variables i.e. mortality rates, unemployment due to the lockdown, travel bans effect, trade dependence with Ukraine and Russia, and using Time-Varying Vector Auto Regressive model may add additional value to our work. The paper contributes to the literature on external shocks impacts on stock markets, specifically on the Tunisian stock exchange. In addition, it offers insights on the potential expected economic effects of unpredicted events, and may help identify appropriate strategies to mitigate their dramatic effects. Finally, this research presents the first investigation on the impact of the Russian invasion on Ukraine on the Tunisian stock exchange by probing into the impact on both volatility and performance of the market's index.*

Keywords: Exogenous Shocks, COVID-19 Pandemic, RU war, TUNINDEX, Return, Volatility, Performance, OLS, GARCH.

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Introduction

Exogenous shocks, such as policy changes, new products and technologies, geopolitical events, natural disasters, natural resources/critical inputs, and financial crises, are unpredictable and can have a dramatic structural impact on a country's economic landscape, with a ripple effect on the financial markets. The oil

embargo in 1973, the 9/11 attack on US soil in 2001, the Iraq war in 2003, the 2008 financial crisis, the Arab spring in 2011, the Australian drought in 2018, the COVID-19 pandemic from 2020, and the Russian invasion of Ukraine in 2022 are few examples of exogenous shocks, some with long-lasting devastating effects, severe recessions or widespread social and economic instability, either domestically, regionally or globally.

The Covid-19 pandemic caused a world-wide economic slowdown, and financial markets disruptions. The ongoing Russian invasion on Ukraine caused a shock wave across the globe and drove food and gas prices up, and shortage of essential commodities, directly impacting economic stability not limited to the epicenter of the conflict. Our focus will be on the COVID-19 pandemic and the RU war, and their impact on the Tunisian Stock market index value and return volatility.

The impact of COVID-19 pandemic and the RU war on the stock markets' performance and volatility in different regions have been the main subject of several recent studies, such as Gherghina Et Al. (2021), O'Donnell Et Al. (2021), Ftiti Et Al. (2021), and Greta and Julius (2021), who focused on the COVID-19 effects, and others, such as, Ahmed and Mariya (2022), Boubaker Et Al. (2022), and Reza and Hassan (2023), worked on the impact of the recent Russian invasion of Ukraine and its global financial repercussions.

In the Tunisian context, very few investigations have been done on the impact of external shocks. Kaddour and Zmami (2014) worked on the impact of the 2011 Tunisian revolution on stock market index, the financial sector and the exchange rate. Jeribi Et Al (2015) studied the impact of the political unrest, following the uprising on the volatility of the major sectors indices in the stock exchange. Jeribi and Manzli (2020), Ben Ayed and Lamouchi (2020), Fakhfekh Et Al. (2021), and Ben Ayed (2022) evaluated the impact of COVID-19 on Tunisian Stock Exchange.

However, to the best of our knowledge, there are no academic studies so far, on the impact of the recent RU war on the Tunisian Stock Exchange. In addition, the focus was either on the impact on the Tunisian stock market performance or volatility, not on both. The Tunisian financial markets were directly hit by both shocks and by the fluctuations in international financial markets. That is why, we're offering an investigation on the impact of both events on the Tunisian Stock markets' performance and volatility.

The rest of the paper is structured as follow: We will be offering some context through relevant literature review, followed by the description of our methodology, and the sample period and data. Next, we will share our empirical findings and analysis. Finally, we will offer our concluding remarks, limitations and recommendations.

1. Literature Review

Stock markets were hit due to both COVID-19 outbreak and the RU war onset, at various degrees. Uncertainty in the financial world spiked and market participants' confidence and expectations were compromised. Some consequences were severe to a point that they have been compared to those of the financial crisis of 2007-2008.

Several studies investigated the severe effects of the COVID-19 health crisis on different stock markets, sectors and indies. Rashmi Et Al. (2020) looked into the pandemic's impact on the performance and volatility of the stock market indices of the top 10 countries based on GDP using the GARCH (1,1) model. The results revealed that the COVID-19 health crisis did have a significant impact and increased the stock market volatility during the pandemic period for all market indices. On the other hand, Gherghina Et Al. (2021) studied the Romanian stock market and investigated the volatility of the BET (Bucharest Exchange Trading) index on the BSE (Bucharest Stock Exchange) traded shares between January 2020 and April 2021 using the GARCH (1,1) model. The findings revealed that the Romanian equity volatility increased due to the Covid-19 pandemic.

Surprisingly, Sansa (2020) found a positive impact of the COVID-19 confirmed cases on both the US Dow Jones and the Chinese Shanghai stock exchange indices values, from March 1st to March 25th, 2020. Al-Awadhi Et Al. (2020) on the other hand, documented in his research of COVID-19 impact on The Chinese stock exchange, form January 10 to March 16, 2020, that overall, growth in total confirmed cases and in total cases of death caused by COVID-19 have significant negative effects on stock performances, across all firms. Ftiti Et Al. (2021) worked on the Shanghai stock exchange volatility, from December 31st, 2019 to April 7, 2020. They documented that the pandemic crisis led to higher stock market volatility and a decrease in the level of liquidity.

Erdem (2020) worked on 75 countries stock market indices, ranked by degree of Freedom, and looked into the impact of COVID-19 on their performances and volatility, from January to April, 2020. Overall, the pandemic led to higher volatility and lower return, especially in countries with more transparency in terms of COVID-19 cases and higher freedom score. The effects of the growth in number of cases were 3 times higher than those of the growth in death cases, overall. Czech Et Al. (2020) noticed an increased volatility overall in their study of the effect of COVID-19 confirmed cases on exchange rates and stock market volatility of VISEGRAD Group nations, from January 14 to May 7, 2020, using the TGARCH model.

Nieto and Rubio (2020), working on the Spanish stock market, from January 3rd to April 29, 2020, showed that the COVID-19 pandemic significantly decreased the IBEX 35 stock index price performance and increased volatility. Greta and Julius (2021) worked on the COVID-19 health crisis effect on Italy and Spain stock markets, two of the most severely affected European nations, from March to August 2020. The findings showed that the stock market response to the pandemic depended on the nation and the period under study: While GARCH models (in the case of Spain) confirmed that the Covid-19 pandemic increased stock market return volatility, OLS regression models did not show any statistically significant impact of the pandemic's spread on both stock market indices prices. O'Donnell Et Al. (2021) looked into the sensitivity of the equity index prices in China, Italy, Spain, UK, and USA to the growth in total COVID-19 cases, from January 10 to end of June, 2020. Overall, all but Chinese Index experienced a significant negative shock. Implied volatility, proxied by investors' sentiment also had a huge impact on the price changes overall.

Khan Et Al (2020) studied the impact of COVID-19 on different stock market indices i.e. USA, China, UK, South Korea and others, from 09 April 2019 to 03 April, 2020. Overall, all major indices were negatively affected by the Pandemic. However, there were no reactions in the early stage of the pandemic. Interestingly, Shanghai composite index recovered very quick, in the longer event window, mostly due to the prompt government measures to contain the virus spread. Ramelli and Wagner (2020) probed the effect of the virus spread on most of Russell 3000 composite constituents, from December 31, 2018 through April 3, 2020. Overall, the pandemic had a significant positive impact on stock market prices. Specifically, International firms directly exposed to Chinese economy, underperformed at first, then regained positive momentum once the pandemic was relatively contained in China.

Shehzad Et Al. (2020) investigated the impact of both the 2007 Financial crisis and the Covid-19 pandemic on the returns and volatilities of China, Japan, USA, Italy and Germany stock markets, from 30 June 2007 to 07 April, 2020. Findings showed higher volatility during the COVID-19 period, mostly noticeable in US and EU markets, while mean returns were shown to be negative overall. However, US and Japan were hit the most. Baek Et Al (2020) documented, in their study of US stock markets, from January to April, 2020, a more sensitive return volatility to COVID-19 related news, both positive and negative, vs. economic indicators. However, the impact of the negative news i.e. death cases, was more prominent. In addition, during the same period, defensive industries incurred higher systematic risk vs. lower systematic risk for the aggressive industries.

Endri Et Al. (2021) investigated volatility and abnormal returns in Indonesian stock market through the study of both JCI (Jakarta Composite index) and LQ-45 index prices changes sensitivity to COVID-19, from January 06 to March 16, 2020, using GARCH (1,2) model. Results showed overall higher volatility, causing negative abnormal performance. Vera-Valdés (2021) studied volatility measures (VIX) of 21 international markets over the period of January 1st, 2018 to January 15, 2021, before and during the COVID-19 pandemic. Results suggested high and persistent levels of volatility overall, turning into non-stationary following the WHO's declaration of COVID-19 as pandemic, suggesting a long-term effect of the outbreak on financial markets.

Jan Et Al (2022) conducted an event Study of 5000 investors in Shandong Stock market in China, during a period of 8 months, 4 months before and after December 20, 2019, the date of the outbreak in China. They documented that the pandemic had a positive impact on the investors' decision making in some of the industries i.e. cosmetic, electronic, consumer household, textile; and negative effect on others i.e. sporting and appliances. Ganie Et Al. (2022) performed an event study on 6 most affected countries: US, India, Brazil, Russia, Mexico and Spain, -150/+172 days from event day, till September 24, 2020. Results showed higher volatility, and negative returns overall. Brazilian market index fell the hardest, by 50%, while the Mexican index price registered the lowest fall of 30%.

Fewer studies focused on the impact of the RU war. Boungou and Yatie (2022) studied the responses of the stock market indices of 94 countries to the ongoing aggression on Ukraine, from January 22 to March 24, 2022. They documented a negative impact of the RU war on the selected stock market performances. These effects were more noticeable in the neighboring countries sharing borders with both nations. Ahmed and Mariya (2022) worked on the asymmetric impact of ongoing RU war, proxied by the Geopolitical Risk (GPR), on both the top 7 emerging and developed stock markets, from February 24 to July 25, 2022. The impacts were market specific: a mix of favorable and adverse effects on stock markets. The impacts were asymmetric and most countries showed resilience to GPR in bearish markets.

Ahmed Et Al. (2022) conducted an event study and discovered that, following Russia's invasion on Ukrainian territories, different European stocks in the STOXX EU 600 experienced a significant negative cumulative abnormal returns (CAR) 25 days prior and after the event day on February 21st, 2022. They noticed that the severity of the stock market's reactions to this crisis varied greatly across industries, nations and company sizes. Similarly, Boubaker Et Al. (2022) performed an event study on the impact of the RU war on global stock markets: 23 developed and 24 emerging countries, listed in the MSCI market classification, with -7/+7-day window from the event day, February 24, 2022. Overall, they found negative significant cumulative abnormal returns (CAR) across global market indices, though with heterogenous effects.

Mahrn (2023) looked into the impact of the RU war on 10 Egyptian stock market sectors' return volatility and connectedness, from February 1, 2019 to May 31, 2022. He found higher volatility and higher dynamic connectedness among sectors during the invasion period, with the transportation sector as the highest volatility transmitter overall. Reza and Hassan (2023) studied the impact of the RU war in 83 countries, from February 23 to March 23, 2022. Results revealed that the decline in the value of stock market indices in response to the war was sharper in countries that have stronger trade connection (exports and imports) with the two countries. However, the impact was mitigated in countries with more trade openness.

Marwan Et Al. (2023) worked on the impact of both RU war and COVID-19 on 25 counties (G7 + rest of EU + rest of the world) on stock markets prices volatility. They used a 6-month window data, 3 months prior and after specific due dates, March 9, 2020 for COVID-19, and February 24, 2022 for the war. Results showed higher volatility from both events, though the pandemic impact was more pronounced, though. However, the response to COVID-19 was lagging, while it was instantaneous with the invasion. Najaf Et Al. (2023) worked on the RU war impact on both Russia and Ukraine stock markets' volatilities and performance, from January 1st to February 24, 2022. Findings indicated, as expected, that the war sparked higher volatility and stock market indices underperformance in both markets. However, Russian market seemed to have inflicted steeper decline mainly due to the fear of actual economic sanctions imposed by US and its allies.

Tunisian context. Most of the findings we shared confirmed the great impact caused by either COVID-19 or the ongoing RU dispute on the stock markets of different countries around the world. The purpose of our research is to assess the impact of both shocks on the Tunisian market. There are few interesting studies on the direct impact of the pandemic on the Tunisian Economy and stock markets. Jeribi and Manzli (2020) investigated the behavior of the Tunisian stock market performance during the COVID-19 outbreak from March 2nd to April 30, 2020. Findings indicated that TUNINDEX return was clearly negatively affected by the growth rate of the COVID-19 confirmed cases and deaths.

Ben Ayed and Lamouchi (2020) worked on the Tunisian Stock exchange sensitivity to the COVID-19 pandemic from January 20 to April 20, 2020. Results showed that confirmed cases growth had a negative impact, while confirmed death cases growth showed a positive impact. Recovery cases growth was not significant however. Fakhfekh Et Al. (2021) worked on the Tunisian sectorial indices return volatility, from January 2016 to April 2020, before and during the pandemic. Overall, volatility was high, asymmetric and persistent after COVID-19 outbreak, mostly in consumer service, financials & distribution, industrials, basic materials and banks sector. Ben Ayed (2022) found that the COVID-19 related Tunisian government actions and measures had a negative impact on the stock market performance, from March 2, 2020, to July 23, 2021.

These studies were focused either on the performance or on the volatility of the Tunisian stock market, not on both. In addition, we were not able to identify so far, any research on the impact of the current RU war on the Tunisian stock exchange. We're offering a comprehensive investigation on the effect of both shocks on the Tunisian equity market index performance and volatility, all in one single work. In the next section, we present

our methodology, followed by our major findings, analysis, concluding remarks, limitations and recommendations.

2. Research Statement, Data, and Methodology

We are attempting to determine the impact of the exogenous shocks, COVID-19 and the RU conflict, on the Tunis Stock Exchange index TUNINDEX return volatility and performance. Based on the literature review and expectations, we are testing the following hypothesis:

- H1: COVID-19 and RU war increase TUNINDEX volatility.
- H2: COVID-19 and RU war reduce TUNINDEX performance.

We will test the first hypothesis on the index volatility using the Generalized Autoregressive Conditional Heteroscedasticity GARCH (1,1) as in Engle (2001). Hansen and Lunde (2005) evidenced that the simple GARCH (1,1) outperforms all other volatility models. The GARCH (1,1) model can be considered as the de facto volatility model of choice for daily returns, with the most consistent predictive ability.

We're extending the model by adding two dummy variables for exogenous shocks: One for the COVID-19 pandemic and one for the ongoing RU dispute. The study period ranges from 2019 to end of 2022. We will use daily TUNINDEX returns, based on daily closing values, from January 2nd, 2019, to December 30th, 2022, that are determined as follow:

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

Where:

- R: TUNINDEX daily return;
- P_{t-1} and P_t : Daily closing prices of TUNINDEX at t-1 and t.

The dummy variable COVID (COVID-19 pandemic) takes the value of 0 for the pre-pandemic period from January 2nd, 2019, till March 1st, 2020, then 1 from March 2nd, 2020 (at which Tunisian authority registered the very first case of COVID-19), to October 22nd, 2021 (after the majority of the population had their shots, and signs of relief became obvious), then back to 0 from October 23rd, 2022 until December 30th, 2022.

As for the RUW (Russo-Ukrainian War) dummy variable, it takes the value of 0 for the pre-invasion period from January 2nd, 2019, till February 23rd, 2022, and 1 for the rest of the period, February 24th, 2022, to December 30th, 2022.

Our model can be described as follow:

Conditional mean equation:

$$y_t = \mu + \lambda_1 RUW_t + \lambda_2 COVID_t + \varepsilon_t \quad (2)$$

Conditional variance equation:

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \delta_1 RUW_t + \delta_2 COVID_t \quad (3)$$

Where:

- y_t : Conditional mean at t;
- σ_t^2 : Conditional variance at t;
- σ_{t-1}^2 : Variance at t-1;
- μ : Mean intercept;
- ω : Variance intercept;
- RUW_t : Russo-Ukraine War, Dummy variable for the ongoing dispute period;
- $COVID_t$: COVID-19, Dummy variable for the pandemic period;

- λ_1 & λ_2 : Sensitivity coefficients of conditional mean to RUV & COVID respectively;
- δ_1 & δ_2 : Sensitivity coefficients of conditional variance to RUV & COVID respectively;
- α_1 : ARCH (Autoregressive Conditionally Heteroscedastic) effect;
- β_1 : GARCH (Generalized Autoregressive Conditionally Heteroscedastic) effect;
- ε_t : Residual term in conditional mean equation;
- ε_{t-1} : Residual return at t-1 in conditional variance equation.

A High ARCH α_i implies a significant volatility reaction to market movements, while a high GARCH β_j is a sign of persistence of the shocks.

Our second hypothesis on index price performance will be examined with an OLS model. We are measuring the impact on TUNINDEX by regressing the index values with factors representing the COVID-19 pandemic and the RU war. We're applying the Monthly number of COVID-19 cases for the pandemic and the Geopolitical Risk Index for the conflict. We're also controlling for a series of macroeconomic factors commonly used in similar studies. We're using monthly data overall, from January 2018 to December 2022. We're applying Natural Logarithm on the TUNINDEX values, similar to Greta and Julius (2021). The model is presented as follow:

$$\text{Ln (TUNDX)} = \beta_0 + \beta_1 \text{GPR} + \beta_2 \text{NCT} + \beta_3 \text{GDPg} + \beta_4 \text{INFL} + \beta_5 \text{IPI} + \beta_6 \text{TB} + \beta_7 \text{INT} + \varepsilon_t \quad (4)$$

Where:

- Ln (TUNDX): Natural Logarithm of TUNINDEX values (source: Tunisian Stock Market);
- GPR: Geopolitical Risk Index, proxy for the RU war impact (source: Matteo Iacoviello Database);
- NCT: Number of COVID-19 cases, proxy for the pandemic (source: Statista database);
- GDPg: Economic Growth Rate (source: Institut National de Statistiques database);
- INFL: Inflation Rate (source: Institut National de Statistiques database);
- IPI: Industrial Production Index (source: Tunisian Central Bank database);
- TB: Trade Balance (source: Tunisian Central Bank database);
- INT: Interest Rate (source: Tunisian Central Bank database);
- β_0 : Intercept;
- β from 1 to 7: Sensitivity coefficients to changes in the independent variables;
- ε_t : Residual term.

3. Empirical Findings

3.1- External Shocks Impact on TUNINDEX Volatility

Figure 1 presents TUNINDEX prices from 2018 to 2022. We notice a sharp drop in the 4th quarter of 2019, mostly due to the controversial parliamentary and presidential election results. The graph also clearly shows a price fluctuation from the first quarter in 2020, when the COVID-19 became an official and public concern, all the way to the last quarter of 2021, after apparent signs of relief on the ground, followed by an upward movement with more stable price volatility, all the way to mid-first quarter of 2022, right when the Russian launched their first offensive attack on Ukrainian soil. The fluctuation continued all the way till end of 2022.

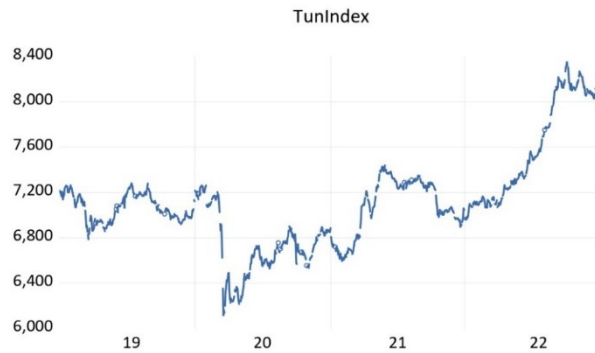


Figure 1. TUNINDEX Daily Price Movements

Source: BVMT then compiled by authors.

Figure 2 shows a positive but low mean return (0.000109), indicating a slight price increase over the given period. Returns are negatively skewed (-1.94495), with mean return lower than the median, indicating small possible gains, but possibly few larger losses.

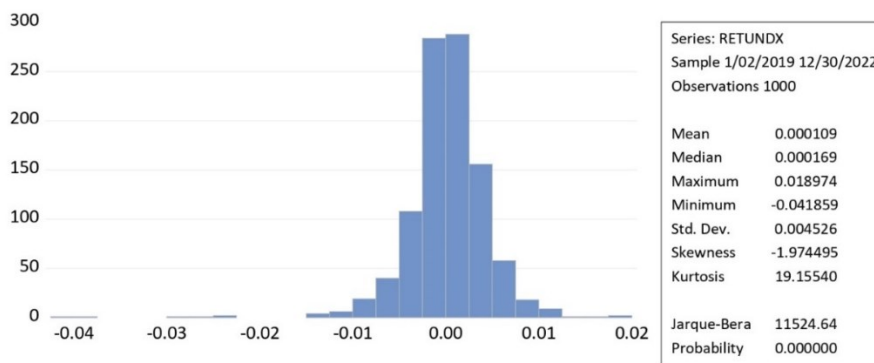


Figure 2. Summary Statistics of TUNINDEX Daily Returns

Source: Compiled by authors.

A high kurtosis (19.1554), indicating a leptokurtic series with fat tails. It is a sign of high price fluctuations over the period. Our series then isn't normally distributed and that is further confirmed by Jarque-Bera test statistics, which is significant at 1% level. The null hypothesis of normality is therefore rejected.

Table 1. Augmented Dickey-Fuller Test Results

Variables	ADF Statistics	Critical Values		
		1%	5%	10%
Intercept	-23.7328	-3.4364	-2.8641	-2.5682
With Trend & Intercept	-23.7603	-3.9668	-3.4141	-3.1292
Without Trend & Intercept	-23.7338	-2.5672	-1.9411	-1.6165

Source: Compiled by authors.

Table 1 shows the different Augmented Dickey-Fuller (ADF) test results for the three levels of significance. We notice that all the ADF statistics for the TUNINDEX returns are less than the critical values. Thus, we reject the null hypothesis of the non-stationarity, and we can conclude that our data is stationary during the study period.

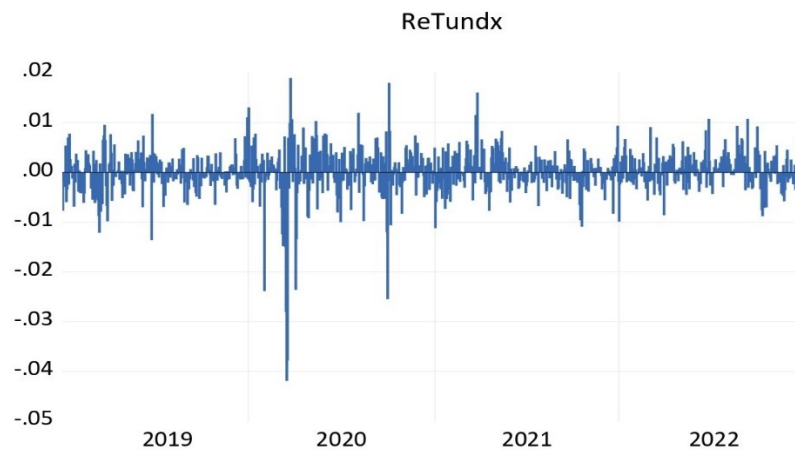


Figure 3. TUNINDEX Daily Returns

Source: Compiled by authors.

Based on figure 3 that illustrates the daily index returns from 2018 to 2022, we notice signs of index return volatility clustering. Our series showed high volatility in the last quarter of 2019, following the country's controversial parliament and presidential election. Volatility spiked up again in the 1st quarter of 2020 to early 2021 due to COVID-19 pandemic. A less potent volatility level however, caused by the RU war, was registered in early 2022.

Table 2. Test for Heteroscedasticity: ARCH Effect

Tests	Values	Probabilities	Values
F-Statistic	432.7568	Prob. F (1.833)	0.0000
Obs*R-squared	385.7233	Prob. Chi-Squared (1)	0.0000

Source: Compiled by authors.

Table 2 shows a significant Chi-square test at 5%, indicating the presence of an ARCH effect. Now that we are certain that all the requirements are met, presence of ARCH effect, data stationarity, and volatility clustering, it is time to run our GARCH model.

Table 3. GARCH (1,1) Estimation Results

Parameters	Estimates	Standard Errors	P-values
Conditional Mean Equation			
μ	-0.000327	0.000146	0.0481**
λ_1 (RUW)	0.000091	0.000584	0.0879*
λ_2 (COVID)	0.000247	0.000249	0.0269**
Conditional Variance Equation			
ω	1.69e-6	2.74e-7	0.0000***
α (ARCH Effect)	0.348724	0.028592	0.0000***
β (GARCH Effect)	0.542998	0.026152	0.0000***
δ_1 (RUW)	0.000358	0.007052	0.0091***
δ_2 (COVID)	0.057912	0.001456	0.0957*
Log Likelihood	4324.033		
AIC	-8.287971		
BIC	-8.259475		

Significant at 0.1 *, Significant at 0.05 **, Significant at 0.01 ***.

AIC: Akaike Information Criterion / BIC: Bayesian Information Criterion.

Source: Compiled by authors.

Based on the results in table 3, the index mean return was impacted by both RUV and COVID events at 10% and 5% respectively. The return variance endured both ARCH and GARCH effects as evidenced by statistically significant α and β coefficients at 1% respectively. This means that previous days' return

information and volatility did affect today’s return volatility. The findings confirmed our first hypothesis on the effect of both exogenous shocks on the index volatility.

The sum of α and β is less than 1 (0.891722). This is a sign of a mean reversion process of the variance or variance stationarity or stability. Findings also showed statistically significant positive COVID-19 and RUW coefficients at 1% and 10% respectively, implying that both shocks clearly increased the stock market index return volatility during the study time frame. The findings were consistent with those of Baek Et Al. (2020), Erdem (2020), Rashmi Et Al. (2020), Shehzad Et Al. (2020), Nieto and Rubio (2020), Greta and Julius (2021), Ftiti Et Al. (2021), Gherghina Et Al. (2021), Endri Et Al. (2021), Vera-Valdés (2021), Fakhfekh Et Al. (2021), Ganie Et Al. (2022), and Marwan Et Al. (2023) for COVID impact, and similar to Najaf Et Al. 2023, Mahran 2023, and Marwan Et Al. (2023) in regards to the RU effect.

3.2. External Shocks Impact on TUNINDEX Value

Starting with the descriptive statistics in table 4, we notice the high standard deviations of both GPR and NCT.

Table 4. Model 2 Descriptive Statistics

Elements	Ln (TUNDX)	GPR	NCT	GDPg	INFL	IPI	TMM	TB
Mean	8.880	0.895	19117.8	0.007	0.067	90.812	0.068	-1545.4
Median	8.872	0.15	381	0.018	0.067	92.055	0.068	-1524.3
Std. Dev	0.069	1.632	38044.6	0.028	0.011	7.087	0.006	443.021
Kurtosis	0.160	9.536	9.488	1.326	0.623	14.258	-1.117	1.064
Skewness	0.545	2.818	2.89	-1.585	0.594	-3.058	0.107	-0.498
Min	8.734	0.04	0	-0.07	0.048	52.59	0.055	-2924.9
Max	9.038	8.88	189971	0.032	0.101	100.3	0.079	-505.1
Obs.	60	60	60	60	60	60	60	60

Source: Compiled by authors.

GPR, NCT and IPI skewness results are outside [-2,+2] range, and are showing Kurtosis higher than 3 pointing to leptokurtic distributions. This is indicative of a non-normality. The remaining variables can be considered having acceptable normal distributions.

Table 5 displays the pairwise correlations. Results show no apparent sign of multicollinearity problem, as all pairwise correlations between the independent variables are less than 0.7.

Table 5. Independent Variables Correlation Matrix

Variables	LN(TUNDX)	GPR	NCT	GDPg	INFL	IPI	TMM	TB
LN(TUNDX)	1							
GPR	0.285	1						
NCT	0.008	0.345	1					
GDPg	0.550	0.292	0.064	1				
INFL	0.685	0.451	-0.167	0.615	1			
IPI	0.533	0.337	0.111	0.344	0.257	1		
TMM	0.284	-0.103	-0.412	0.134	0.356	-0.027	1	
TB	-0.623	-0.513	0.077	-0.597	-0.711	-0.320	-0.337	1

Source: Compiled by authors.

We notice that INFL and IPI are somewhat highly positively correlated with our dependent variable LN(TUNDX). TB on the other hand is displaying a high negative correlation with the Index value. Correlation results, however, have no predictive power. We shouldn’t draw any conclusion, before running our regression model.

VIF results in table 6 show that our independent variables do not suffer from multicollinearity, since all their VIFs are strictly less than 5.

Table 6. VIF Test Results

Test	GPR	NCT	GDPg	INFL	IPI	INT	TB
VIF	2.0903	1.5362	2.0358	2.7798	1.2297	1.4921	2.7440

Source: Compiled by authors.

Test results in table 7 reveal that Fixed Effect is the appropriate model, that there is absence of both endogeneity and heteroscedasticity. OLS (Ordinary Least Squares) is therefore the appropriate estimation technique for our model.

Table 7. Econometric Tests

Tests	Chi-squared	Prob.	Conclusion
Hausman Test for Model Specification	8.382	0.019	FE model
Hausman Test for Endogeneity	4.346	0.028	No endogeneity
Breusch-Pagan Test for Heteroscedasticity	5.862	0.469	No heteroscedasticity

Source: Compiled by authors.

Table 8 shares the regression model summary and ANOVA test results.

Table 8. Model Summary

Summary		ANOVA	
R ²	Adjusted R ²	F-statistic	Significance F
0.67	0.63	15.547	8.55 E-11

Source: Compiled by authors.

Based on R-squared, our model explains 67% of the TUNINDEX value variations, with an adjusted R-squared of 63%. Moreover, based on the F statistic of 15.547 and its p-value less than 1%, we conclude that our model is a good fit for our data.

Table 9 shares the regression output. Results showed a statistically significant positive impact of COVID-19 confirmed cases (NCT) on the stock market index, at 5% level, though with a very low coefficient (3.73E-07). Therefore, we're rejecting our second hypothesis on the effect of the pandemic on the index performance, as COVID-19 appeared to carry a positive influence on TUNINDEX values across the sample period.

Table 9. Regression Results

Variables	Coefficients	T-stat	P-value
Intercept	8.2115	77.29393	2.39E-55***
GPR	-0.0120	-2.50427	0.015445**
NCT	3.73E-07	2.10511	0.040131**
GDPg	-0.0329	-0.12185	0.903484
INFL	3.1998	4.184806	0.00011***
IPI	0.0037	4.458238	4.43E-05***
INT	0.7398	0.729973	0.468682
TB	-4 E-05	-1.95221	0.056307*

Significant at 0.1 *, Significant at 0.05 **, Significant at 0.01 ***.

Source: Compiled by authors.

The findings are consistent with those of Sansa (2020) and Ramelli and Wagner (2020). Ben Ayed and Lamouchi (2020) found a similar outcome, however with confirmed death cases. These findings could be explained by the efficacy of the efforts of Tunisian authorities in implementing the appropriate preventive measures to contain the spread, and economic incentives and stimulus packages since the early stages of the outbreak. In addition, online business boomed, especially in the consumer goods industry. The banking sector flourished and banks reported abnormal results during and after the pandemic, mostly due to government lending, so did the Pharmaceutical sector. These sectors are heavily weighted in the TUNINDEX due to their large capitalizations.

TUNINDEX return showed lower return short after the first lockdown. However, similar to Khan Et Al (2020) findings, performance went back up gradually in the longer window, following the government drastic measures to contain the virus spread and boost spending and investment confidence. The investors' decisions making were hit in the short term. However, once the confirmed cases started dropping, performance went back up. This may confirm that the pandemic had a diminutive direct impact on stock price overall, as in Jan Et AL (2022).

Results also displayed a statistically negative effect of the RU war (GPR) on the Index values, at 5% as well (-0.0120). We're therefore accepting our second hypothesis on the RU event driving down the index price. Our findings are comparable to those in Boungou and Yatie (2022), Ahmed Et Al. (2022), Boubaker Et Al. (2022), Ahmed and Mariya (2022), in some markets, and Najaf Et Al. (2023). This outcome was expected, as Tunisia, same as Algeria and Egypt, is heavily dependent in the grains imported from Russia and Ukraine. The ongoing war came on top of the COVID pandemic, a political stalemate followed by a coup held in July 2021. It has endangered the country's supply chain, which in turn crippled a fragile, structurally weak economy, already suffering from soaring energy prices, higher inflation, increasing trade balance, worsening fiscal deficits, heavier external debts, and credit rating downgrade. The war impact was felt in the major international stock exchanges. Tunisian stock market was not spared.

Looking at the impacts of our control variables on the index performance, we noticed that inflation (INF) and industrial production index (IPI) had positive effect on the TUNINDEX values during the study period, at 1%. Stock investment is considered an inflation hedge. Higher inflation rates may push investors towards equity markets, pushing prices up. Higher / lower production level would increase / decrease corporate revenues and returns, leading to better / worse stock values and overall index performance. As for the trade balance (TB), it exhibited a negative influence on the index value at 10% however. One possible explanation is that a trade balance deficit can be a sign of a growing economy needing more import for a larger production, ultimately indirectly improving the stock market performance of an economy. GDP growth rate (GDPg) and interest rates (INT) on the other hand, did not seem to have a statistically significant impact on TUNINDEX performance overall.

Finally, the intercept was statistically significant at 1%, indicating a most likely presence of other omitted, unknown variables besides the ones we used for our analysis that can have a significant influence on TUNINDEX prices during our study timeframe.

Table 10 presents the summary of our investigation.

Table 10. Summary Table

Sections	Description
Research Statement	Investigating the impact of the COVID-19 and the Russo-Ukraine (RU) war on TUNINDEX volatility and performance.
Hypothesis Testing	H1: COVID-19 and RU war increase TUNINDEX volatility. H2: COVID-19 and RU war reduce TUNINDEX performance.
Data & Methodology	GARCH (1,1) model to evaluate impact on the index volatility, with daily observations from January 2019 to December 2022. Multiple Linear Regression (OLS) to study impact on the index performance, with monthly observations from January 2018 to December 2022.
Major Findings	GARCH (1,1) results: Higher return volatility from both shocks. OLS findings: Statistically significant but opposite effects by the shocks on the index values: COVID-19 pandemic showed a slight positive impact, whereas RU war had a negative influence.

Source: Compiled by authors.

Conclusion

Our research focused on the impact of COVID-19 pandemic and RU war on Tunisian index (TUNINDEX) return volatility and performance. We applied GARCH (1,1) to investigate the impact on the index return volatility, from January 2019 to December 2022, and a multifactor linear regression (OLS) to study the impact on the index value, from January 2018 to December 2022. We worked with daily index returns, and dummy variables: Russo-Ukraine War (RUW) and COVID-19 pandemic (COVID) for both shocks respectively, under GARCH.

COVID took value of 0 from January 2nd, 2019, till March 1st, 2020, 1 from March 2nd, 2020 to October 22nd, 2021, then back to 0 from October 23rd, 2022 until December 30th, 2022. RUW was assigned 0 from January 2nd, 2019, till February 23rd, 2022, and 1 from February 24th, 2022, to December 30th, 2022. We applied monthly data under the OLS model, with Geopolitical Risk Index (GPR) and Number of COVID-19 cases (NCT) as proxies for the COVID-19 pandemic and RU war respectively. Other control variables were

applied, such as inflation (INFL), industry index production (IPI), trade balance (TB), interest rates (INT) and economic growth rate (GDPg).

GARCH model's findings confirmed that both shocks pushed the index return volatility upward considerably. The regression output revealed that both COVID-19 crisis and the RU dispute had statistically significant yet opposite impacts on the stock market index performance: The pandemic had a positive impact, while the war on Ukraine showed a negative one on TUNINDEX prices, during the sample period. A statistically significant intercept in the regression addresses a possibility for improvement to the model by identifying and adding other relevant explanatory variables for more precision, i.e. mortality rates, unemployment due to the lockdown, travel bans, and trade dependence with Ukraine and Russia. These factors could be considered in further studies, as in Reza and Hassan (2023).

Limitations and Recommendations. We were challenged by the difficult access and scarcity of data on other potentially relevant factors such as those mentioned above, and by a short study period due to the fact that both events are relatively recent, thus we were unable to work with a longer timeframe that could've led to stronger results. We believe that the Time-Varying Vector Auto Regressive model (TVP-VAR) might shed a different light in our context as well, by testing the connectedness and dynamic relationships of either of the shocks among, commodities, industries and markets, similar to the studies of Ben Haddad Et Al. (2021) on the COVID-19 related uncertainty spillover effects, Umar Et Al. (2022), Li Et Al. (2022) and Alam Et Al. (2022) on the connectedness and spillover effects during the RU crisis.

Implications and Originality. Our research contributed to the academic literature on the impact of both exogenous shocks on the Tunisian stock exchange volatility and performance, providing a better understanding of the possible expected effects of unpredicted shocks, and engaging policymakers to identify strategies and procedures to face their potentially sizeable outcomes. There was no previous study investigating the impact of the RU war in Tunisia. In addition, the ones that worked on the COVID-19 pandemic, covered only its impact on the market / industries index (indices) return volatilities, but not on the index (indices) performance.

Author Contributions

Conceptualization: Mohamed Chater, Karim Soussou; **Data curation:** Mohamed Chater; **Formal analysis:** Mohamed Chater, Karim Soussou; **Investigation:** Mohamed Chater, Karim Soussou; **Methodology:** Mohamed Chater, Karim Soussou; **Project administration:** Mohamed Chater, Karim Soussou; **Supervision:** Karim Soussou; **Validation:** Karim Soussou, Mohamed Chater; **Visualization:** Mohamed Chater, Karim Soussou; **Writing – original draft:** Mohamed Chater, Karim Soussou; **Writing – review & editing:** Karim Soussou, Mohamed Chater.

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