International Journal of Economics and Finance; Vol. 15, No. 12; 2023
ISSN 1916-971X E-ISSN 1916-9728
Published by Canadian Center of Science and Education

The VIX Index and the Volatility of the Latin American and G7 Stock Exchanges before and during the COVID-19 Pandemic

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Received: October 11, 2023 Accepted: November 3, 2023 Online Published: November 10, 2023

doi:10.5539/ijef.v15n12p25 URL: https://doi.org/10.5539/ijef.v15n12p25

Abstract

This study analyzes and compares the influence of the VIX index, known as the "fear index," on the volatility of the stock exchanges of the main Latin American countries (Brazil, Chile, and Mexico) and on some of the main international exchanges of the member countries of the G7 (the United States, Germany, France, and the United Kingdom) from January 2017 to December 2021. Through the application of the univariate and multivariate econometric GARCH models of volatility, the research hypothesizes the existence of a negative conditional correlation between the VIX index and the other stock exchange indices, with emphasis on the Brazilian stock exchange. However, except for the pandemic period, it is not possible to identify the presence of a negative conditional correlation between the VIX and the stock exchange indices selected throughout the analyzed period, contrary to expectations, highlighting the need to advance investigations with studies that analyze the VIX index with the respective effects on the stock market as well as investor behavior and the macroeconomic and particular influences of the country of each of the stock exchanges considered.

Keywords: VIX, COVID-19, financial contagion, stock exchange, GARCH model

1. Introduction

The VIX index, known as the "fear index," measures investors' expectations regarding the stocks that make up the S&P 500, which is the index that concentrates the most relevant listed companies in the United States. The higher the VIX index is, the greater the overall uncertainty among investors tends to be, accentuating the fall of assets in general. Conversely, the lower the VIX index, the greater the optimism among investors with a low level of risk perception (Chandra & Thenmozhi, 2015). The COVID-19 pandemic notably affected the VIX index as it increased the volatility of the stock market and made the VIX index more prominent.

In this context, the present study aimed to analyze and compare the effects of the VIX index on the volatility of the stock exchanges of the main Latin American countries (Brazil, Chile, and Mexico) and some of the main international exchanges of the member countries of the G7 (the United States, Germany, France, and the United Kingdom) from January 2017 to December 2021. It intended to answer the following question: How did the VIX index affect, comparatively, the stock exchanges of Latin American countries (Brazil, Chile, and Mexico) and the main international exchanges of some of the G7 countries (the United States, Germany, France, and the United Kingdom), in the period from 2017 to 2021, partially marked by the occurrence of the health crisis caused by COVID-19? Argentina was excluded from the study as it is no longer considered an "emerging market" due to its reclassification as an "autonomous market" in 2021 by the work of Morgan Stanley Capital (MSCI), a supplier of global indices of financial assets. It excluded the country from all MSCI indices as a result of macroeconomic imbalances and distortions in the country's macroeconomic policies, which bring insecurity to investments in the country. Furthermore, in the recent period, Argentina was already being disregarded by studies on emerging countries, such as the analysis by Benachenhou (2011). In addition, Colombia, Venezuela, Peru, and Uruguay were not included in the analysis, which focused on the stock exchanges of Brazil, Mexico, and Chile given the representativeness of these exchanges and countries in Latin America.

The hypothesis of the study is that the Brazilian stock exchange reacted, in the analyzed period, to variations in the VIX index with much more volatility than other stock exchanges in Latin America and the main world stock exchanges. However, it was anticipated that this hypothesis would not be confirmed as the VIX index, especially at the beginning of the COVID-19 pandemic, showed much higher volatility than the other indices analyzed. The

focus of the research was not only on analyzing the VIX index and its influence on stock market volatility comparatively but also on understanding its effects in the midst of an unprecedented health crisis caused by COVID-19. In this context, the relevance of the study is evident in that few studies have established a link between the COVID-19 pandemic and financial market volatility.

Thus, to achieve the objectives of the study, the research is organized as follows. After this brief introduction, the theoretical framework is presented in section 2, followed by the research methodology in section 3, which includes the data used and an approach to the univariate and multivariate GARCH volatility models. Next, section 4 presents the results and discussion, followed, in section 5, by the final considerations.

2. Theoretical Framework

To carry out this study, we considered the fact that the US economy has significant influence and impacts on other international markets, as evidenced during the global financial crisis in 2007-2009, when, according to Karolyi and Stulz (2003), US instability spread to other financial markets, prompting research on contagion and spillovers. According to Giot (2015), studies have already shown that the returns of the VIX and the US stock market were negatively correlated over the period. Sarwar (2012) proved that there was even a negative relationship between the VIX and the Brazilian stock exchange when the Brazilian stock market experienced a high degree of volatility. In fact, the present study proved that, at times, there was a negative correlation between the VIX and the US stock market but not in the same way as when analyzed comparatively with other stock markets. In other markets, including the Brazilian market, such a correlation existed only on a very specific basis, notably at the height of crises, such as the one recently caused by the COVID-19 pandemic. In this context, Table 1 presents a synthesis of several studies on the contagion effect, volatility, the VIX index, and the COVID-19 pandemic. In addition to introducing the authors, the data used, and the methodology, the main objective of each of the studies and the respective results found are provided in the table.

Ceylan (2021), regarding the relationship between the VIX and stock exchanges, showed that a shock to the VIX, as occurred at the height of the crisis caused by the COVID-19 pandemic, actually led to increases in the correlations between the US and each of the European stock markets in the following week, given the fact that investors focused on this global uncertainty, but subsequently a significant part of the shock was absorbed and therefore the correlations decreased in the second week following the shock. This means that the VIX has short-term predictive power for the dynamics of return correlations between countries. This temporal pattern can be explained by the mechanism of reallocation of investors' attention, in which the "emotions" of the international stock market tend to increase until investors resolve this global uncertainty factor and, later, divert their attention to future country-specific information processing. Azevedo and Pereira (2017) reached the same conclusion, stating that the VIX index has some predictive power for short time horizons and during periods of crisis. It was also found, as a result of the studies, that, in many cases in the analyzed period, there was a rise in stock exchange indices at times when the VIX index rose as well as when the stock market fell, even with the fall of the VIX. This phenomenon, according to Agyei et al. (2022), may even have occurred because of heterogeneous investor behavior, which is reflected in market pricing, since the market does not work alone, with different economic actors making investment decisions in different time horizons and in line with their risk appetite.

It cannot be disregarded that, in times of instability, investors and market operators who trade S&P 500 (SPX) options may choose to pay more for put options (puts), which can raise the level of the VIX index at a time when the S&P 500 (SPX) is rising as well, which allows us to conclude that there is an important role of investor behavior in the market decision, which may have caused or contributed to greater volatility of the VIX index when compared with the volatility presented by the other stock market indices analyzed. The possibility that the structural macroeconomic fundamentals of an economy or even the decisions of investors and other financial agents can cause changes in the architecture of the financial market due to the contagion effect has already been analyzed by Dornsbusch et al. (2000). Hernandez and Valdés (2001), in turn, made it clear that countries' macroeconomic fundamentals can be channels for the contamination of crises, being possible mechanisms of transmission to the most diverse connections between countries.

In addition, the contagion effect was mainly observed at the height of the crisis caused by the COVID-19 pandemic, with notable significant changes in connectivity between equity markets and spillovers, resulting in high volatility visible in all markets. The VIX index showed this, serving as a true indicator of fear during the health crisis. Forbes and Rigobon (2002), analyzing the crises in Mexico in 1994 and Asia in 1997 and using data from 29 countries (OECD members and Asian, Latin American, and emerging countries), used a multivariate model of the autoregressive vector (VAR) type and found no evidence of contagion between each of the attacks.

The authors also indicated that an eventual increase in the correlation between countries may have been due to the simple increase in volatility. According to the same authors, there is a contagion effect only when there is an increase in correlations between countries during crises through the return of their stock markets, added to the awareness of the existence of a crisis. Otherwise, it is a mere effect derived from interdependence between markets (shift contagion) and not exactly effective "contagion." Corsetti et al. (2005), when analyzing the contagion effect, concluded that there is no single way to derive a measure of interdependence from an asset model since the noises of each country must be taken into account when carrying out tests of structural breaks in crisis transmissions.

Table 1. Summary of Research on the Contagion/Volatility Effect, VIX Index, and COVID-19

Author/Year	Data Used/Methodology	Purpose of the study	Main results
Agyei et. al. (2022)	Daily stock market indices (Brazil, Russia, India and China) and G7 (Canada, France, Germany, Italy, Japan, UK and US).	Examine the spillover effect between the stock market index of BRIC countries and the stock market index of G7 countries	The spillovers found between BRIC and G7 are significant in the short term, with France, Germany and the United Kingdom transmitting the biggest shocks to the BRIC markets, mainly between 2017 and 2019, and due to the US-China trade tension, with France, United Kingdom (crude term) and Canada and the USA (medium and long term) as sources of contagion between BRIC and G7
Akhtaruzzaman et al. (2020)	Return rates of financial and non-financial sectors in China and the G7 countries. Methodology: VARMA, DCC-GARCH.	To examine how financial contagion occurs through financial and non-financial companies between China and the G7 in the period of Covid-19.	The conditional correlation between stock returns of financial and non-financial companies in all countries has increased during the COVID-19 pandemic period, implying financial contagion.
Amitrano et al. (2020)	Economic measures adopted to reduce the economic effects of the Covid-19 pandemic, by the US, UK and Spain.	Present an international overview of the economic measures adopted in the period between March and the first ten days of April 2020, to reduce the economic effects of the Covid-19 pandemic and analyze the institutional arrangements that organize the process of operationalizing these public policies.	The measures adopted in the three countries have as common characteristics the mobilization of a large volume of fiscal and financial resources, the adoption of a wide range of economic policy instruments and the use of sophisticated institutional arrangements in terms of targeting rules and mechanisms for implementing the measures adopted.
Azevedo e Pereira (2017)	Index VIX. Methodology: GARCH models, multiplicative error model.	Test whether the VIX has greater predictive power of future volatility and contains information not present in time series models for non-negative variables.	The VIX has greater predictive power in periods of economic stability, and in periods of economic crisis it has this power for the short term.
Aziz et al. (2020)	Crude oil, rice and gasoline prices. Methodology: GARCH.	Examine the volatility spillover between the US stock and commodity market.	There is no volatility spillover between gold and the stock market, but oil, rice and gas.
Bekaert, Hoerova e Lo Duca (2013)	Index VIX. Methodology: VAR model.	Analyze the relationship between monetary policy and the VIX and its components.	The VIX index is largely affected even by the US monetary policy stance (pandemic effect with VIX index contagion). The effect of monetary policy on risk aversion is apparent in regressions using high frequency data.
Brenner e Galai (1989)	Instruments for protection against market volatility (options). Methodology: Analysis of variance.	Propose the use of a "Sigma" volatility index as a benchmark for the bond market and foreign exchange market.	Options based on a volatility index cannot be replicated with conventional options other than high-cost dynamic hedging.
Ceylan (2021)	Market and French stock market variance data. Methodology: orthogonal impulse-response analysis	To study the relationship between variance risk premium, market variance and stock correlations in the French stock market from September 2002 to September 2006.	The shock to the VIX index leads to an increase in correlations between international exchanges, but which soon tend to decrease.
Chinaglia (2021)	Bibliographic data on economic crises of the 1990s and early 2000s and on the crisis brought about by Covid-19.	Analyze how the Covid-19 pandemic negatively affected national economies, largely due to the fragility of these economies in the face of the financialization of capital	There is a possibility that the coronavirus outbreak, in addition to the volatility brought to the financial market, will lead to a world-wide economic recession.
Chow, Jiang e Li (2014)	VIX index from January 2005 to May 2014. Methodology: data recalculation according to CBOE procedure.	Demonstrate that the VIX index does not measure the market's expectation of volatility, but a linear combination of moments. Propose the GVIX index.	Vix is a linear combination of ex-ante return moments, not expected volatility, and may underestimate true volatility when the market's return expectation is negatively biased.
Corsetti et al. (2005)	Data on the international effects of the 1997 Hong Kong stock market crash on 17 countries.	Analyze the contagion effect.	Found evidence of contagion effect in 5 countries.
Fassas (2012)	VIX index and S&P500 returns. Empirical analysis.	Analyze the relationship between the VIX index and underlying stock returns.	Found a correlation between the term structure of VIX index futures and subsequent S&P 500 returns.
Fernandes (2020)	China's export, import and GDP data (2005-2020). Tourism data from 24 countries, S&P 500, 2020 multi-country stock exchange performance, world sector returns and the VIX index.	Discuss the economic impact of the Covid-19 crisis across industries and countries.	The economic integration process has led to a larger spillover effect, impacting all supply chains and disrupting demand and supply.
Forbes e Rigobon (2012)	Data from 5 countries (Brazil, Argentina, Mexico, USA, Malaysia, Russia). Bayesian Network Methodology. ARMA-GARCH.	Identify the existence of financial contagion.	The results pointed to a great interconnection between the markets and several evidences of contagion in periods of financial crisis.
Giot (2015)	VIX, VXN, S&P 100 and Nasdaq 100 index data.	Analyze the relationship between volatility indices and stock returns.	He observed that there is a negative correlation between VIX and US stock market returns.
Hernandes e Valdés (2001)	Data from the Thai, Russian and Brazilian crises.	Present evidence on the relative importance of alternative contagion cansis.	When crises are measured by stock market returns, trade linkages and neighborhood effects can be channels of contagion (Thai and Brazilian crisis).
Ibikunle e Rzayev (2020)	London stock index data, Germany. VIX index data. Using calculations of daily estimates of trading activity and volatility.	Exploring the exogenous shock of the Covid-19 pandemic to financial markets.	Volatility has broad implications for trading, asset pricing, investing and risk management.
Mensi et al. (2016)	US, BRICS stock market data (September 1997 to October 2013. Methodology: Bivariate model DCC-FIAPARCH	Evaluate the spillover effect between the US stock market and the BRICS countries.	They found asymmetric volatility spillover effect between developed and emerging markets.
Silvennoinen e Terasvirta (2008)	Data from Multivariate Garch models.	Review multivariate GARCH models.	Multivariate GARCH models (MGARCH) have been most widely used precisely when the objective is to investigate volatility and correlation transmission and spillover effects in contagion studies.
Vartanian (2020)	bovespa, Commodity Price. Methodology: Multivariate Garch	Evaluate relationships between commodity prices and the Ibovespa with the aim of eventual diversification.	There were no signs of correlation between the Ibovespa Return and commodity prices, ensuring the possibility of diversification on the part of investors.

Source: Own elaboration.

3. Methodology

Volatility models have been applied recurrently in the field of finance and other areas. Univariate models, from the ARCH/GARCH family, allow the analysis of volatility over a period of time, while multivariate models permit the analysis of volatility contagion between two or more variables. In this context, multivariate GARCH models (MGARCH) have been widely used when the objective has been to investigate volatility, correlation transmission, and spillover effects in contagion studies (Silvennoinen & Terasvita, 2008). That said, it is noteworthy that the methodology is divided into two subsections: the first subsection will present the data used in the econometric estimate, and the second subsection will describe the models used in this research.Include in these subsections the information essential to comprehend and replicate the study. Insufficient detail leaves the reader with questions; too much detail burdens the reader with irrelevant information. Consider using appendices and/or a supplemental website for more detailed information.

3.1 Data Used

Data from the VIX index and stock market indicators for Latin American countries (Brazil, Chile, and Mexico) and some G7 countries (the United States, Germany, France, and the United Kingdom) were obtained with the help of Bloomberg for the entire period of 2017 to 2021; these are shown in Figure 1. The period studied covers the health crisis caused by the COVID-19 pandemic. The daily closing price of each index was used, represented by points, as disclosed through Bloomberg and quoted in dollars (with the exception of the VIX):

a) Brazilian Stock Exchange: Data from the Ibovespa index, obtained from Bloomberg, represented by IBOV.

b) Chile Stock Exchange: Data from the S&P CLX IPSA index, obtained from Bloomberg, represented by IPSA.

c) Mexican Stock Exchange: S&P/BMV IPC index data obtained from Bloomberg, represented by MEXBOL.

d) United States Stock Exchange: Data from the Dow Jones Industrial Average Index, from the New York Stock Exchange, obtained from Bloomberg, represented by INDU.

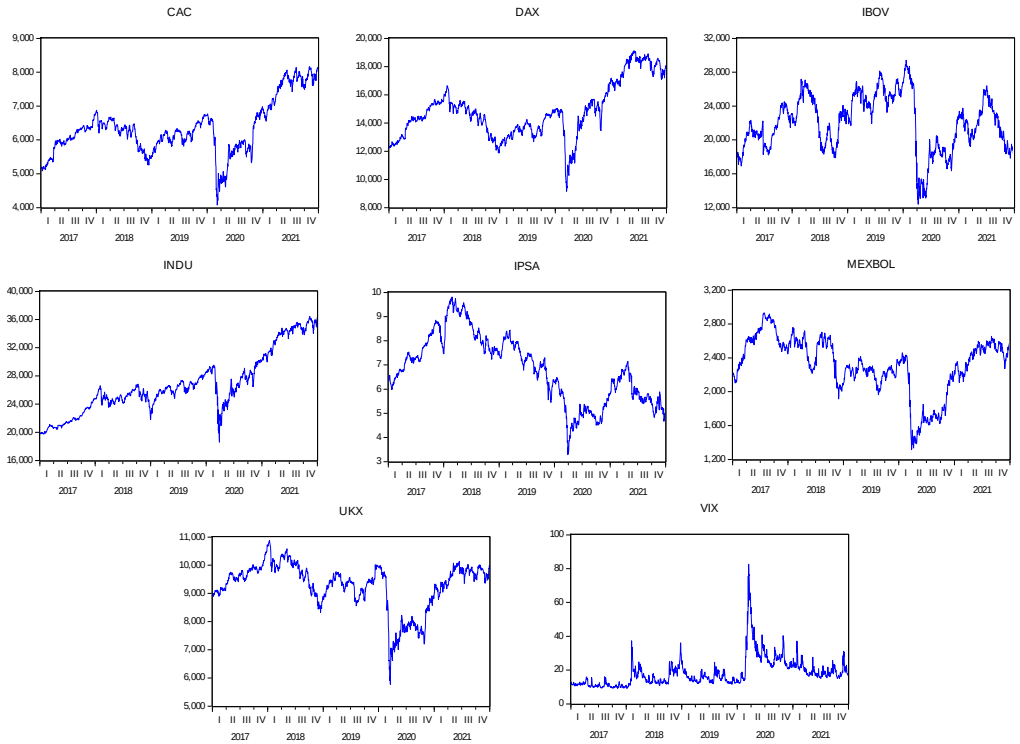
e) German Stock Exchange: Data from the DAX-30 index obtained from Bloomberg, represented by DAX.

f) French Stock Exchange: Data from the CAC-40 index, obtained from Bloomberg, represented by CAC.

g) UK Stock Exchange: Data from the FTSE-100 index, obtained from Bloomberg, represented by UKX.

h) VIX index: Data obtained from Bloomberg, represented by VIX.

Figure 1. Evolution of Variables (Stock Exchanges and VIX Index) from January 2017 to December 2021



Source: Own elaboration based on calculations carried out in the econometric package Eviews 9.

3.2 Econometric Model

Volatility models have gained space in analyses and research since the introduction of the conditional autoregressive heteroscedasticity model (ARCH) by Engle (1982) and later by Bollerslev (1986), who developed a new specification that became known as GARCH (generalized ARCH). To use the GARCH model, the presence of stationarity of the return series for estimation is required. GARCH processes are generalized ARCH processes, which means that the volatilities depend on both the past volatilities and the squared values of the process. Engle (1982) carried out the first studies on univariate volatility by filtering the variance heteroscedasticity, modeling an AR(1) process, and adjusting the series to forecast future periods, naming this process ARCH.

Therefore, being the conditional mean of y_{t+1}:

$$E_t y_{t+1} = \alpha_0 + \alpha_1 y_t \quad (1)$$

The variance of errors with the above conditional mean, according to Belinschi (2015), is given by:

$$E_t[y_{t+1} - \alpha_0 - \alpha_1 y_t]^2 = E_t \varepsilon^2_{t+1} = \sigma^2 \quad (2)$$

If it is considered that $\frac{1}{1-\alpha_1^2} > 1$, the unconditional forecast will have greater variance than the conditional one, with conditional forecasts being preferable to unconditional ones. If the variance of $\{\varepsilon t\}$ is not constant, it is possible to estimate any trend of sustainable movements in variance using ARMA models. Case $\{\varepsilon t\}$ is the estimated residual of the model $y_t = a_0 + a_1 y_t + \varepsilon_t$, the conditional variance y_{t+1} will be:

$$Var(t_{t+1} | y_t) = E_t[(y_{t+1} - \alpha_0 - \alpha_1 y_t)^2] \quad (3)$$
$$E_t[(E_{t+1})^2]$$

Assuming that the conditional variance is not constant, a strategy to predict it would be to use the squares of the estimated errors of an AR(q) process. In addition, V_t being a white noise process, we have:

$$y_t | \psi y_{t-1} \sim N(x_t \beta, h_t) \quad (4)$$
$$h_t = \alpha_0 + \alpha_1 \varepsilon^2_{t-1} + \alpha_1 \varepsilon^2_{t-2} \ \ldots \ + \alpha_q \varepsilon^2_{t-q}$$
$$\varepsilon_t = y_t - x_t \beta$$

If the values $\alpha_1, \alpha_2, \ldots, \alpha_n$ are equal to zero, the estimated variance is the constant itself, α_0. Conversely, if the variance of $\{y_t\}$ evolves through an autoregressive process of the above errors, the following function should be used to predict the conditional variance of $t + 1$:

$$E_t \varepsilon^2_{t+1} = \alpha_0 + \alpha_1 \varepsilon^2_t + \alpha_2 \varepsilon^2_{t-1} \ \ldots \ + \alpha_q \varepsilon^2_{t+1-q} \quad (5)$$

This is the conditional autoregressive heteroscedastic model (ARCH) proposed by Engle. Bollerslev's (1986) adjustment to the GARCH model made it possible to consider structures with a long memory and with more flexible delays, which can be defined as:

$$\varepsilon_t | \psi y_{t-1} \sim (0, h_t) \quad (6)$$
$$h_t = \alpha_0 + A(L)\varepsilon^2_t + B(L) h_t$$

According to Bollerslev (1986), the series will be stationary if $E(\varepsilon_t) = 0$, Var $(\varepsilon_t) = \alpha_0 \ (1 - A(1) - B(1))^{-1}$ e cov $(\varepsilon_t, \varepsilon_s) = 0$ for t≠0 if, $A(1) - B(1)) < 1$, and the identification of a GARCH process can be performed through the functions of autocorrelation and partial autocorrelation.

After a preliminary survey of the literature, it was discovered that not only the investigation of volatility but also the "spillover" effect is relevant. Thus, in many studies, multivariate GARCH models have been widely used precisely when the objective is to investigate the correlation transmission and spillover effects in contagion studies (Silvennoinen & Terasvirta, 2008). In this sense, multivariate GARCH models play an important role in both resource allocation and portfolio selection, according to Lopes (2006).

Thus, in the present study, a multivariate GARCH model with the BEKK specification was applied. The BEKK specification, in the context of multivariate GARCH models, is justified by the small number of estimated parameters and because it is one of the most used in the literature for contagion spillover volatility. Thus, the model was estimated according to the following equation:

$$H_t = C^{*\prime} C^* + \sum_{k=1}^{K} A_K^{*\prime} e_{t-1} e'_{t-1} A_K^* + \sum_{k=1}^{K} G_K^{*\prime} H_{t-1} G_K^* \quad (7)$$

where $C^*, A_K^*,$ and G_K^* are N × N matrices in which C^* is an upper triangular matrix. BEKK model parameters have no relation to past volatilities of values or correlations between sets. Restrictions on identifying a BEKK

model with K = 1 are imposed on the matrices $A_{K,\ 11}^{*}$ and $G_{K,\ 11}^{*}$, which must also be positive, in addition to the diagonal elements, which must also be positive. To reduce the number of parameters in the BEKK model, according to Vartanian (2020), it is possible to apply the BEKK diagonal model, in which the matrices A_K^* and G_K^* are diagonal. The application of the model is carried out in the next section.

4. Results and Discussion

For the estimation of both the univariate GARCH model and the multivariate GARCH model, it is necessary for the series to be stationary. This means that it needs to use the return on assets, such as the return on the Ibovespa, instead of series on a level, such as the score of the stock index. In this sense, the descriptive statistics for each return series are presented in Table 2, in which the mean, median, maximum, minimum, standard deviation, skewness, and kurtosis for each series are presented. The logarithmic difference applied to a series is considered as the return. The returns of the indices of each selected exchange and the VIX were generated, and the results of the descriptive statistics are presented in Table 2. It is also possible to observe the temporal evolution of the returns in Figure 2.

Table 2. Descriptive statistics of returns

	VIX	CAC	DAX	INDU	IBOV	IPSA	UKX	MEXBOL
Average	0.000224	0.000351	0.000300	0.000459	1.88E-05	-0.000181	7.89E-05	0.000118
Median	-0.004655	0.000674	0.000535	0.000491	0.000769	0.000000	0.000192	0.000000
Maximum	0.768245	0.081119	0.104701	0.107643	0.138832	0.112967	0.100929	0.058775
St. Deviation	0.083650	0.012185	0.012481	0.012532	0.022779	0.017405	0.011680	0.015086
Kutosis	12.11014	22.29374	21.87428	29.12604	17.19724	22.52977	24.38800	9.237645
Jarque-Bera	5048.892	20581.25	19563.34	37398.95	11434.86	21044.11	25205.93	2301.571
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Observations	1304	1304	1304	1304	1304	1304	1304	1304

Source: Own elaboration based on calculations carried out in the econometric package Eviews 9.

As shown in Table 2, all the series under analysis have high kurtosis, which is expected for financial time series that normally have a leptokurtic distribution. It can be observed in Table 3 that the VIX index had a positive correlation of returns with the CAC, Ibovespa, INDU, and IPSA indices; that is, such indices do not show the expected correlation with the VIX index in the analyzed period since they show an increase with the rise in the VIX. This phenomenon may have occurred due to the mechanism of reallocation of attention by investors, who change their focus as changes in financial conditions occur.

Table 3. Correlation matrix of stock index and VIX returns

	R_CAC	**R_DAX**	**R_IBOV**	**R_INDU**	**R_IPSA**	**R_MEXBOL**	**R_UKX**	**R_VIX**
R_CAC	1	-0,051089	-0,03307	-0,058706	-0,045853	0,056768	-0,115246	0,000365
R_DAX	-0,051089	1	0,003523	0,143265	-0,005944	-0,126877	0,375192	-0,049151
R_IBOV	-0,03307	0,003523	1	-0,070362	0,063717	-0,019332	0,027783	0,001971
R_INDU	-0,058706	0,143265	-0,070362	1	0,043882	0,038491	0,108577	0,038835
R_IPSA	-0,045853	-0,005944	0,063717	0,043882	1	0,027001	0,015408	0,000826
R_MEX	0,056768	-0,126877	-0,019332	0,038491	0,027001	1	-0,12813	-0,043493
R_UKX	-0,115246	0,375192	0,027783	0,108577	0,015408	-0,12813	1	-0,053617
R_VIX	0,000365	-0,049151	0,001971	0,038835	0,000826	-0,043493	-0,053617	1

Source: Own elaboration based on calculations carried out in the econometric package Eviews 9.

Thus, analyzing the returns of the stock exchange indexes with a normalized axis according to Figure 2, it became clear that the returns of the VIX index presented, throughout the period, greater volatility than those of the stock exchange indexes, followed by those of the Ibovespa index. Even though the Ibovespa index indicates lower volatility than the VIX index itself, its volatility is still higher than that of the other stock exchange indices. In addition, all the stock market indices showed greater volatility, with emphasis only on the beginning of the COVID-19 pandemic, in mid-March 2020, and in other periods they presented specific volatilities when analyzed in a comparative way.

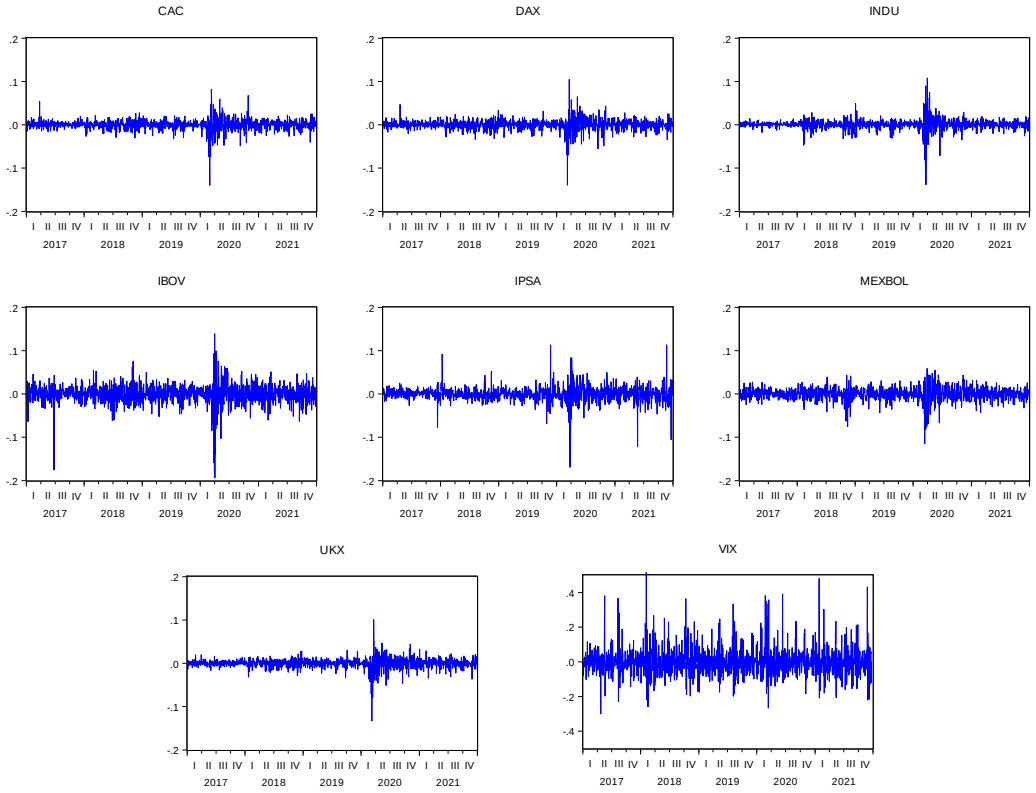


Figure 2. Result of the generation of returns of the stock market indices analyzed

Source: Own elaboration based on calculations carried out in the econometric package Eviews 9.

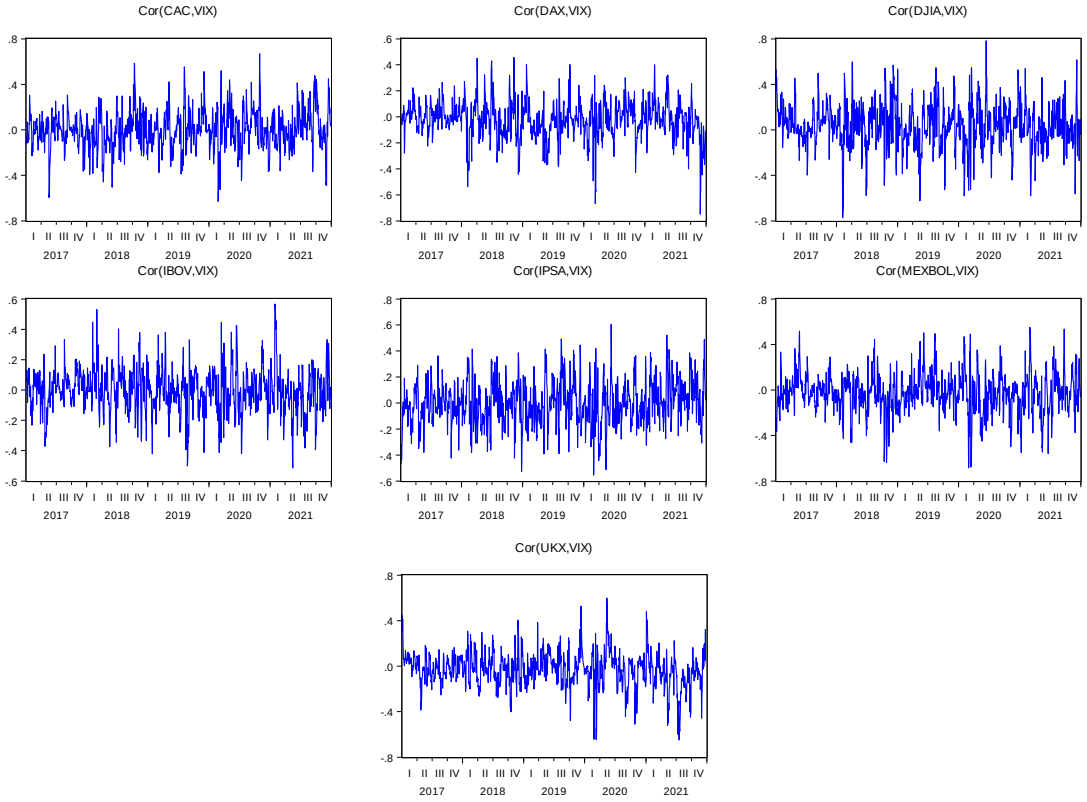


Figure 3. Evolution of the Conditional Correlation of the VIX Index and the Stock Exchange Indices

Source: Own elaboration based on calculations carried out in the econometric package Eviews 9.

A GARCH model with BEKK specification was estimated in accordance with the methodology presented above, which included all the returns of the stock exchange indices and the VIX (CAC, DAX, INDU, IBOV, IPSA, UKX, MEXBOL, and VIX). With the estimation of the multivariate GARCH model and the generation of the conditional correlation between the VIX index and the stock exchange returns, it was expected that the model would find a stronger inverse relationship of the VIX index with the other stock exchange indices over the period analyzed, with a decrease (increase) in the value of the stock index given an increase (decrease) in the expected market volatility (Fleming et al., 1995). In this context, however, in Figure 3, which shows the results of the multivariate GARCH model through the conditional correlation between the variables, it is possible to observe that the conditional correlation between the VIX index and the stock exchange indices of the countries is not as negative as initially imagined, being more notable at the height of the crisis brought about by the COVID-19 pandemic.

The most evident negative correlations of the VIX index in the estimated conditional correlation, shown in Figure 3, can only be seen occasionally in the behavior of the indices. Thus, Table 4 presents some dates and the respective negative conditional correlation of the most pronounced indices, extracted from the estimates presented in Figure 3. In this context, it is possible to highlight the Mexbol, INDU, UKX, and DAX indices with some dates of a strong negative conditional correlation with the VIX index. The Ibovespa, among all the indices, suffered the least negative conditional correlation with the VIX index, on average, the same happening with the IPSA index.

As a complement to the multivariate analysis, univariate GARCH models (GARCH 1.1) were estimated for each of the selected stock exchanges (CAC, DAX, INDU, IBOV, IPSA, UKX, and MEXBOL) to obtain the conditional standard deviation of each of the indices and to look for relationships between the conditional standard deviation peaks and the VIX peaks. Volatility is understood, in this context, as a measure of the dispersion of the prices of the underlying assets in relation to their average, over a certain period of time, generally calculated through the standard deviation of the variation of prices. Based on the estimates shown in Figure 4, the abnormal events of each stock exchange index and of the VIX index were analyzed qualitatively, that is, the events with greater volatility (peaks above 0.02) for each index, as shown in Table 5.

Table 4. Negative correlations between the VIX Index and the Other Stock Indexes

Date	(VIX, INDU)	Date	(VIX, DAX)	Date	(VIX, CAC)	Date	(VIX, MEXBOL)
2018-06-02	-0,67	2018-06-02	-0,43	2017-05-18	-0,32	2018-11-10	-0,33
2018-06-26	-0,42	2018-05-12	-0,31	2020-02-26	-0,38	2018-08-11	-0,28
2018-11-10	-0,42	2020-02-25	-0,3	2021-11-30	-0,29	2020-02-28	-0,38
2019-05-14	-0,53	2020-10-03	-0,59			2020-03-13	-0,63
2019-09-10	-0,34	2020-05-11	-0,26			2021-05-13	-0,29
2020-03-02	-0,44	2021-09-20	-0,2			2021-06-21	-0,23
2020-12-03	-0,31	2021-11-29	-0,5				
2020-03-31	-0,33						
2020-07-14	-0,28						
2020-11-16	-0,24						
2021-08-03	-0,33						
2021-11-29	-0,46						
Date	**(VIX, UKX)**	**Date**	**(VIX, IBOV)**	**Date**	**(VIX, IPSA)**		
2019-07-10	-0,23	2017-04-25	-0,23	2017-10-30	-0,21		
2020-02-25	-0,46	2019-08-15	-0,22	2017-12-13	-0,21		
2020-10-27	-0,24	2019-08-26	-0,31	2018-04-06	-0,22		
2021-11-05	-0,25	2019-03-12	-0,22	2018-12-25	-0,23		
2021-07-20	-0,32	2020-02-28	-0,25	2019-05-29	-0,21		
2021-01-12	-0,38	2021-04-03	-0,22	2020-02-28	-0,31		
		2021-09-29	-0,27	2020-03-31	-0,2		
				2020-08-01	-0,2		

Source: Own elaboration based on calculations carried out in the econometric package Eviews 9.

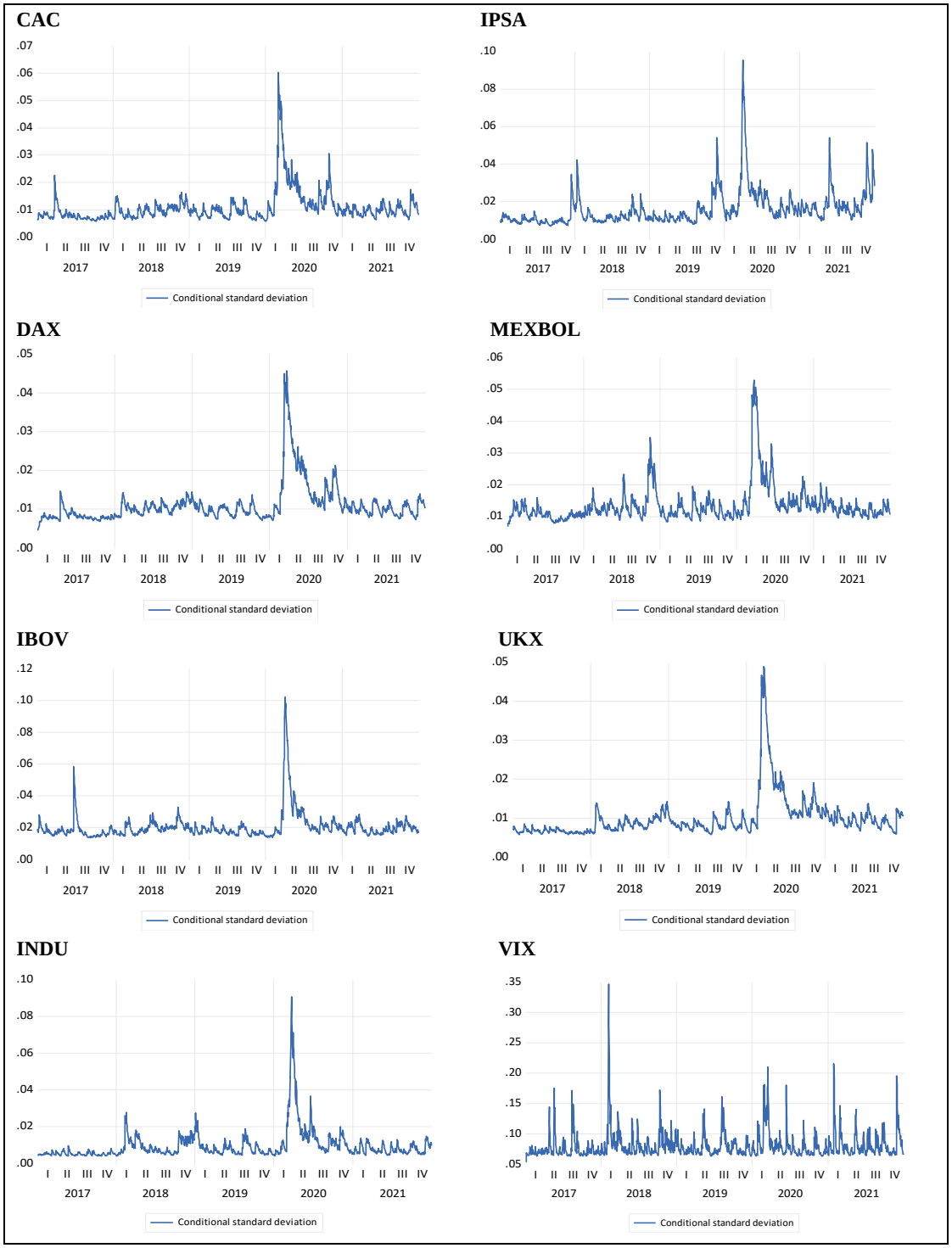


Figure 4. Estimation of Conditional Standard Deviation - Univariate GARCH (1.1) Model

Source: Own elaboration based on calculations carried out in the econometric package Eviews 9.

Table 5. Atypical Events Calculated from Figure 4 in the VIX, CAC, DAX, INDU, IBOVESPA, MEXBOL, IPSA, and UKX Indices

Index	Date	Event	Index	Date	Event
VIX	2017-05-18	US Stock Market Crash - Doubts Over Trump's Policy Implementations	INDU	2018-02-15	Opening in the post-holiday fall. CPI increase with chance to raise interests rates.
	2018-02-07	Fear of global acceleration of inflation		2019-01-03	Fear ś of China ś economic slowdown
	2018-02-08	Fear of tariff war with China		2020-03-16	Covid-19
	2020-02-25	Covid-19		2020-03-23	Covid-19
	2020-03-17	Covid-19		2020-03-31	Covid-19
	2020-06-12	New wave of Covid-19		2020-04-14	Covid-19 and econonomic impacts
	2021-02-28	U.S. stock/bull market crash and interest in GameStop		2020-04-16	Investors seek protection via the US Treasury and the dollar
	2021-11-29	New strain of Covid-19 in South Africa		2020-06-18	Fall in stock markets due to increase in unemployment insurance and increase in Covid-19
CAC	2017-03-27	Stock market drop in Europe following that of the US (abandonment of Trumpcare)	IPSA	2017-12-13	Pension change issues
	2020-02-14	Covid-19		2019-11-25	Popular protests
	2020-03-02	European stock market crash - OECD revises global growth downwards		2020-03-30	Covid-19
	2020-03-06	Covid-19		2021-05-25	Copper gain tax questions
	2020-05-04	Covid-19 and US-China trade tensions		2021-11-24	Local elections
	2020-10-29	Advancement of Covid-19			
DAX	2020-03-06	Covid-19	MEXBOL	2018-07-11	China and US trade war
	2020-03-10	Fall of the Brazilian stock market following the fall of the US stock market		2018-11-14	New president elect
	2020-03-20	Covid-19		2020-03-11	Covid-19
	2020-05-12	New cases of Covid-19 and repercussions of worsening US-CHINA relations		2020-04-01	Covid-19
	2020-05-28	Covid-19 generating need for subsidies		2020-04-06	Tension between energy cartel and G20 - oil price drop
	2020-10-26	Fear of new wave of Covid-19		2020-06-15	Risk of new cases of Covid-19
				2020-11-12	ECB Conference 2020
IBOV	2017-06-26	Instability of Brazilian politics, fears with the Michel Temer government	UKX	2020-02-26	Covid-19
	2018-11-06	Concerns about the ability to implement reforms		2020-03-05	Increase of Covid-19
	2020-03-05	Covid-19		2020-03-20	Measures to combat Covid-19
	2020-03-26	Covid-19 / Six *circuit breaker*		2020-05-13	Stock market crash following the fall of the US stock market after Jerome Powell's speech
	2020-04-02	Increase in cases of Covid-19		2020-06-06	Covid-19 delays planned reopening
	2020-04-04	Global movement of risk aversion, dollar rising and Ibovespa retreating		2020-11-09	President of the Central Bank outlines concern about leaving the European Union
	2020-04-22	Tense atmosphere between the President and Congress driving away investors			
	2020-05-14	Political turmoil with possibility of Moro's resignation by the President, dollar increase			

Source: Own preparation based on results obtained in the Eviews 9 econometric package and research in the electronic newspaper Valor Econ ômico and Bloomberg.

Based on the survey of facts that occurred in each atypical event, it was possible to conclude that there were no coincidences between the atypical events of the indices of the exchanges analyzed and the atypical events of the VIX index. In fact, only a few atypical events with non-coincident dates were identified, despite being close, as

shown in Table 5. Based on the surveys and analysis of atypical events in the VIX index and the INDU and MEXBOL indices, presented in Table 6, it can be observed that they all occurred due to the crisis caused by the COVID-19 pandemic. Thus, it is not possible to point out a direct influence of the VIX index on the stock exchanges analyzed.

Table 6. Atypical Events between the VIX, INDU, and MEXBOL Indices with Non-coinciding Dates but Close to Occurrence Dates

Index	Date	Event
VIX	2020-03-17	Covid-19
INDU	2020-03-16	Covid-19
VIX	2020-06-12	New wave of Covid-19
MEXBOL	2020-06-15	Risks of new cases of Covid-19
INDU	2020-06-18	Stock market operating in fall – increase of Covid-19

Source: Own elaboration based on the results obtained in the econometric package Eviews 9 and research conducted in the electronic newspaper Valor Econômico and Bloomberg.

Thus, due to the analyses carried out using the univariate GARCH and multivariate GARCH models, the result was a negative correlation between the VIX index and the other indices of the stock exchanges analyzed only in a punctual and pronounced way at the height of the pandemic caused by COVID-19. Outside the pandemic period, the VIX index did not maintain the expected negative correlation with the other stock exchange indices in the analyzed period and seems to have served more to facilitate derivative operations than as an instrument effectively predicting future market movements, as already mentioned. This was pondered in the study by Vodenska and Chambers (2013), who, in the period from 1990 to 2009, found that the VIX index overestimated the volatility of the S&P 500 during stable regimes in the financial market and even underestimated its volatility in periods of high volatility. Ceylan (2021), conversely, when analyzing the dynamics of the stock return correlations between the United States, the United Kingdom, Germany, and France, concluded that a shock to the VIX leads to increases in correlations in the following week, which in turn fall in the second week after the shock, and that the revealed temporal pattern of the effect of the VIX index can be explained more by a behavioral structure through mechanisms of reallocation of investors' attention.

Cheng (2020) also noted that, as of March, while cases of COVID-19 were rising rapidly in Europe and there were reports of the spread of the virus and deaths in the United States, the S&P 500 fell slightly at the same time as the VIX index rose from 14 to 33. Peng and Ng (2009) analyzed the behavior of the S&P 100, S&P 500, Nasdaq 100, DJIA and DAX, CAC 40, FTSE, DJ Euro Stoxx 50, and SMI indices between 2001 and 2009 as well as the VIX and VXO, using different methods, and also concluded that there is increased dependency during periods of financial crisis, with a contagion effect but with movements of extreme values and a higher rise of the VIX and VXO volatility indices from 2006 onward. Such behavior, however, did not keep correspondence with the other analyzed indices.

This study certainly did not aim to exhaust the topic. In some recent studies, it is possible to perceive the expansion of analyses involving volatility and the contagion effect due to crises, with the application, for example, of copulas, as in the research by Chollete et al. (2005). The authors, when analyzing the behavior of the G5 (the United States, Germany, the United Kingdom, France, and Japan), as well as Brazil, Argentina, Chile, Mexico, Hong Kong, Singapore, and Taiwan, between 1990 and 2002, obtained results that demonstrate that developed countries have a smaller drop in potential than developing ones, allowing new possibilities for future studies that deal with volatility and the contagion effect mainly in periods of crisis, notably the case of the health crisis caused by the COVID-19 pandemic.

5. Final Considerations

This research aimed to analyze comparatively the influence of the VIX index, known as the "fear index," on the main stock markets of emerging countries in Latin America (Brazil, Chile, and Mexico) and some of the developed countries of the G7 (the United States, Germany, France, and the United Kingdom). The research shows its relevance in that it allows us to understand how, and to what extent, the VIX index, prepared by the Chicago Board Options Exchange (CBOE), really affects the stock market in a unique period, from January 2017 to December 2021. The period in question includes not only the effects of the health crisis caused by COVID-19, analyzed until the end of 2021, but also the pre-pandemic period, allowing a comparative analysis between a period without major shocks (the pre-pandemic period) and a period in which there was an increase in distrust on

the part of investors that was practically unprecedented in history.

In fact, the recent outbreak of COVID-19 generated significant volatility in financial markets, infecting the stock market globally with fears and uncertainty. At the start of the pandemic, the VIX index rose by more than 80 on March 16, 2020, surpassing its 2008 record. The industrial average (DJIA) fell more than 12%, marking the second worst day in its 124 years. However, these occurrences do not fully explain the remarkable volatility, which justifies the need to undertake more studies on the subject.

It was precisely for this reason that the VIX index was chosen to be the object of study in this research. Although the VIX is linked to the financial market in the United States, its variations can affect other economies in the world since it is well known as one of the best existing tools for analyzing investors' risk aversion in the face of existing scenarios. Nevertheless, it has already been found that the VIX index is affected to a large extent even by the conducting of US monetary policy.

To achieve the intended objective, the univariate GARCH and multivariate GARCH econometric models were used, analyzing, in a comparative way, the influence of the VIX on the stock exchanges targeted by the study. The VIX index demonstrated, in the selected period, much more volatility than the other stock exchange indices, followed only by the INDU and Ibovespa indices. Among the results found, it was additionally apparent that there is, as a general rule, no negative correlation as would be expected between the indices of the stock exchanges under analysis in the period between the first day of January 2017 and the last day of December 2021. The negative correlation can only be observed at the height of the crisis caused by the COVID-19 pandemic, which allows us to refute the hypothesis initially formulated in the research. This fact has already been observed in other crises, in which a shock to the VIX index led to a one-off increase in correlations between international exchanges that soon tended to decrease, as already discussed by Ceylan (2021). In fact, far from finding a general rule in which one would observe a downward reaction in the stock markets in response to rises in the VIX, what happened was the opposite, to the extent that, in many cases, there was a rise in the stock markets at moments of a high VIX, as can clearly be seen in the analysis of the conditional correlation estimated by the multivariate GARCH model between the stock exchanges and the VIX.

Complementarily, atypical events obtained through the analysis of the conditional standard deviation of the stock exchanges estimated using a univariate GARCH model showed that there is no clear relationship between the VIX peaks and the volatility peaks of the stock exchanges. The analysis enabled us to verify that relationships between the peaks of the VIX and the volatility of the stock exchanges rarely occurred on close dates. This was observed only in March 2020 (with the INDU index only) and in June 2020 (with the MEXBOL and INDU indices). The influence of the VIX index on the other stock exchange indices that were the subject of the study was therefore felt only in periods of severe crisis, notably in the scenario of the COVID-19 pandemic, as verified by the results of the estimates.

Among the difficulties faced in the research process, one can highlight the scarcity of econometric studies that have considered the effects of the VIX on global stock markets, particularly in the period of the crisis caused by the COVID-19 pandemic. As a suggestion, for future studies, there is a need for research that also addresses other volatility indices offered by the CBOE (the VSTOKK and VXJ, among others), in addition to the effects of macroeconomic, financial, and political variables (for example, the impact of quantitative easing on the VIX and stock market timing) and even the contribution of investor behavior, including market sentiment, to volatility. Other development possibilities include deepening the research by both using the methodologies applied in the present study and adopting other methodologies, such as bivariate copulas and Bayesian networks. Given the relevance of the topic and the existing possibilities, such topics can be considered relevant for the future research agenda.

Acknowledgments

This work has been supported by grants from the Mackenzie Research Fund (MackPesquisa).

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