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Impact of the Global Fear Index (COVID-19 Panic) on the S&P Global Indices Associated with Natural Resources, Agribusiness, Energy, Metals and Mining: Granger Causality and Shannon and Rényi Transfer Entropy

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Abstract: The Global Fear Index (GFI) is a measure of fear/panic based on the number of people infected and deaths due to COVID-19. This paper aims to examine the effects of the GFI on a set of global indexes related to the financial and economic activities associated with natural resources, raw materials, agribusiness, energy, metals and mining, such as: the S&P Global Resource Index, the S&P Global Agribusiness Equity Index, the S&P Global Metals & Mining Index, and the S&P Global 1200 Energy Index. To to this, we first apply several common tests: Wald exponential, Wald mean, Nyblom, and Quandt Likelihood Ratio. Subsequently, we apply Granger causality using a DCC-GARCH model. Data of the global indices are daily from February 3, 2020, to October 29, 2021. The empirical results obtained show that the volatility of the GFI Granger-causes the volatility of the other global indices, except for the Global Resource Index. Moreover, by considering heteroskedasticity and idiosyncratic shocks, we show that the GFI can be used to predict the co-movement of the time series of all the global indices. Additionally, we quantify the causal interdependencies between the GFI and each of the S&P global indices using Shannon and Rényi transfer entropy flow, which is comparable to Granger causality, to confirm directionality more robustly The main conclusion of this research is that financial and economic activity related to natural resources, raw materials, agribusiness, energy, metals and mining were affected by the fear/panic caused by COVID-19 cases and deaths.

JEL Classification: F65, E60.

Keywords: Global indices, Co-movement, Granger causality, DCC-GARCH.

1. Introduction

On March 11 the World Health Organization (WHO) declared Coronavirus or COVID-19 a global pandemic [1]. This fact signified an unusual shock for the world, as it affected most sectors of the economy [2,3]. Shortly after the beginning of the pandemic, stock markets around the world suffered significant declines compared to those that occurred during the 2008 financial crisis, the 1987 market crash, and even the 1929 Great Depression [4]. Similarly, global commodity markets exhibited a significant drop due to supply chain disruption that caused supply and demand mismatch [5]. For example, in March 2020, oil prices recorded their most considerable drop compared to other commodities [6].

In the financial context, the Dows Jones index fell by more than 2,000 points on March 3rd [7], with some sectors of S&P 1500 index (natural gas, health care, software, among others) posting positive returns [8], while others as tourism, entertainment, and hospitality sectors decreased [9,10]. At the same time, the pandemic, and in particular the restrictive measures in place had a negative impact on the management of natural resources [11] and the price of metals [12].

Different studies and investigations analyze causality, impact, co-movement, volatility, and uncertainty among economic/financial sectors, either by country, region, or a specific industry, stock market, currency, or cryptocurrency [13–18]. They have also analyzed the impact that the confirmed number of infected people or deaths had on different financial and economic activities [19–23]. In this regard, it is also worth mentioning that the pioneering work of Baker et al. [4] that developed the Infectious Disease Equity Market Volatility Tracker Index, which includes press news from the United States regarding COVID-19 has been used in various investigations to measure the impact of news on the volatility of different types of financial series [6,24–29].

On the other hand, Salisu and Akanni [30] developed, in 2020, the Global Fear Index (GFI), which is a measure of fear/panic based on the number of people infected and deaths due to COVID-19. Its advantage is that it considers infections and deaths for all countries, regions, and territories. GFI is daily calculated on a scale of 0-100, where zero means no fear/panic, and values closer to 100 when the population feels fear/panic the population feels. GFI has been used in many applications, for instance: 1) to analyze its relationship with market volatility to determine an investment portfolio [31], 2) to measure the efficiency and coverage in the Pakistan stock market [32], and 3) to examine the influence of fear in the bond market for G7 countries [33]. In most cases, GFI has shown an important relationship with many different financial variables.

This paper examines the co-movement of GFI towards the volatility of four global indices the S&P Global Resource Index (GRI), the S&P Global Agribusiness Equity Index (GAEI), the S&P300 Metals & Mining Index (MMI), and, finally, the S&P Global 1200 Energy Index (GEI) through Granger causality time series using a DCC-GARCH. The DCC-GARCH model was proposed by Lu [34] and improved by Caporin and Costola [35] through simulation to obtain better confidence levels needed accept or reject causality. It is worth mentioning that the DCC-GARCH has been widely used to analyze causality over time between pairs of economic and financial time series [29,36–38].

This research differs from others in that; 1) it uses a DCC-GARCH model that has several advantages for determining Granger causality; 2) it allows identifying any immediate impact of news information on the stock market at any time, which occurs asynchronously due to how information flows [38,39]; 3) it uses dynamic cross-correlation to assess causality based on the time window width [34]; 4) it allows to determine the causality in the mean and in a dynamic way, and, finally, 5) it allows to determine the volatility cluster where the causality occurs [40].

This paper also show that GFI can be considered as a variable that could help predict the co-movement of the time series of all the indices considered in this work. The results show that GFI has a unidirectional co-movement through time with the global indices. At the same time, it serves as a variable to forecast the co-movement of the rest of the variables one day ahead.

Additionally, by using information-theoretic concepts, this investigation examines the causal interdependencies between the GFI and each of the S&P global indices using Shannon and Rényi directional transfer entropy flow, which is comparable to Granger causality.

This work is organized as follows: section 2 presents the materials and methods; section 3 gives the results from classical time series analysis; section 4 examines the causal interdependencies between the GFI and each of the S&P global indices using Shannon and Rényi directional transfer entropy flow, which is comparable to Granger causality; and, finally, section 5 provides the conclusions.

2. Materials and Methods

In what follow, four global indices (the S&P Global Resource Index (GRI), the S&P Global Agribusiness Equity Index (GAEI), the S&P300 Metals & Mining Index (MMI), and the S&P Global 1200 Energy Index (GEI)) and the fear/panic index (GFI) are analyzed. The first global index is the GRI, which comprises 90 companies listed in natural resources and raw materials. Investors can diversify their investments in three sectors: agribusiness, energy and metals, and mining. The second is the GAEI, which includes 24 of the largest agribusiness companies listed on the stock exchanges around the world; investment is diversified in production companies, distributors and processors, and suppliers of equipment and materials. The third is the MMI index is made up of companies that are classified in the Global Industry Classification Standard (GICS®). It belongs to the metals and mining sector, which produces aluminum, gold, steel, precious metals, minerals and metals, and diversified minerals. The latest global index is the GEI, which comprises energy sector companies within GICS®. The series were obtained from https://www.refinitiv.com.

GFI is an index that is made up of two other: COVID-19 cases index and the index of reported worldwide COVID-19 deaths, both with equal weights in the GFI. The series of S&P global indices are daily closing prices, and GFI is a daily index on a scale of 0 to 100, from February 3, 2020, to October 29, 2021, with a total of 425 observations. The series are transformed into logarithmic growth rates as $y_t = 100(\ln(p_t) - \ln(p_{t-1}))$. Figure 1 shows the data in nominal form and its logarithmic growth rate. It is observed that at the beginning of studied period the four S&P global indices fall and then they have an upward trend, declining with a valley around March 2020 and others later. GFI index shows several changes over time, highlighting a rise at the beginning of the analyzed period with ups and downs in its trend. Regarding the rest of the variables, they present greater volatility at the beginning of the period, and at the beginning of 2021.

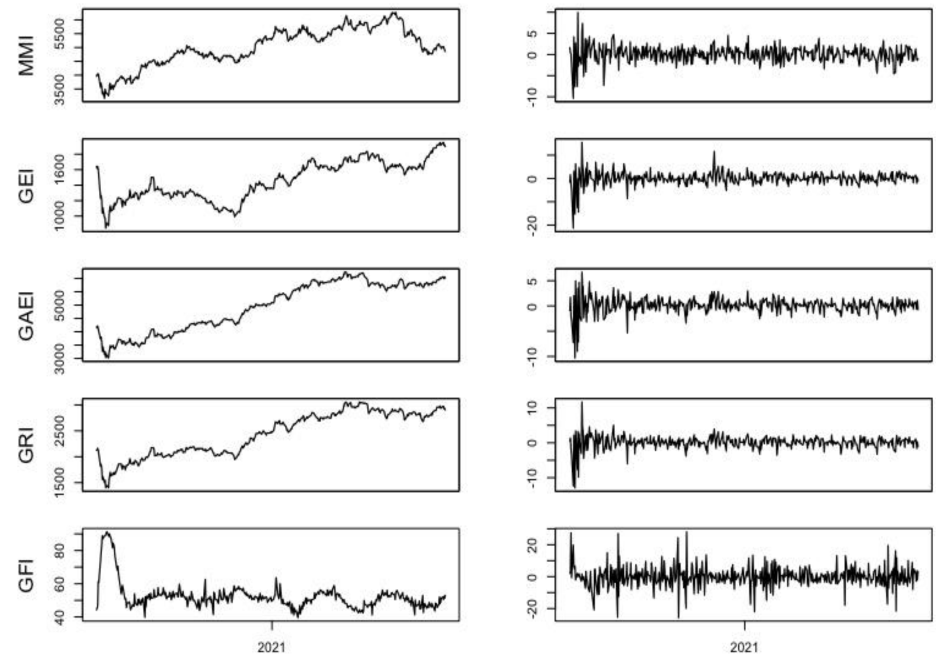

Figure 1. Index and daily logarithmic growth rate

Next, we present in Table 1 the descriptive statistics of the logarithmic growth rates for each time series.

Table 1. Descriptive Statistics

tatistic/y_t	MMI	GEI	GAEI	GRI	GFI
Mean	0.02	0.00	0.06	0.05	0.04
Median	0.07	-0.04	0.10	0.14	-0.35
Min	-10.36	-21.34	-10.31	-12.91	-25.76
Max	9.95	15.52	6.69	11.69	28.06
Variance	3.71	7.69	2.46	3.56	42.9

SD	1.93	2.77	1.57	1.89	6.55
Skewness	-0.31	-1.3	-1.3	-1.41	0.18
Kurtosis	7.51	17.09	12.02	16.6	6.75
JB	369.54***	3681.0***	1683.10***	3667.70***	2018.80***
RALS-LM	-26.06***	-15.13***	-11.07***	-11.11***	-7.00***
	26/08/20	25/01/21	05/08/20	26/10/20	24/07/20
	01/08/21	23/02/21	19/08/20	25/02/21	03/12/21

Note: (**) 5% of significance (***) 1% significance

All four S&P global series are left-skewed, and only GFI is right-skewed. All series are platykurtic. The Jarque-Bera statistic [41] shows that the series have a non-normal distribution. To check whether the series is stationary, the RALS-LM non-parametric unit root test [42] was applied, which allows to determine the periods of change in both the slope and the intercept. The unit root null hypothesis is rejected at 1% significance, with two periods of change. This confirms that the series lacks a unit root (see Table 1).

In order to specify the econometric model and apply the corresponding tests, we first analyzed the standardized residuals for each stationary series $\{y_{i,t}\}, i = 1,2$ and $t = 1, \ldots, T$, defines the sample size from a univariate GARCH(1,1) model in order to remove any autocorrelation effects. To analyze the dynamic correlation, we introduce a DCC-GARCH (1,1) model

$$y_t(j) = \begin{pmatrix} y_{1,t} \\ y_{2,t-j} \end{pmatrix}, \quad (1)$$

where j is the lag order. The Hong test is defined as:

$$H_{1t}(k) = \frac{T\sum_{j=0}^{T-2} k^2\left(\frac{j+1}{M}\right) r_{12,t}^2(j) - C_{1T}(k)}{\sqrt{2D_{1T}(k)}} \quad (2)$$

where M is a positive integer and has a small impact on the size of the DCC-GARCH Hong test (we also use $M = 2$, $M = 5$, and $M = 10$, but results remain relatively constant) and $k(\cdot)$ is the kernel function. The other variables in equation (2) are defined as

$$C_{1T}(k) = \sum_{j=1}^{T-1}\left(1 - \frac{j}{M}\right) k^2\left(\frac{j}{M}\right), \quad (3)$$

and

$$D_{1T}(k) = \sum_{j=1}^{T-1}\left(1-\frac{j}{M}\right)\left(1-\frac{j+1}{T}\right)k^4\left(\frac{j}{M}\right). \quad (4)$$

Notice that

$$H_{1,t}(k) \sim N(0,1) \quad . \quad (5)$$

If $H_{1,t}(k)$ is larger than the critical value of the normal distribution, then the null hypothesis of no causality is rejected. Caporin and Costola [35] mention that the test statistic proposed by Lu [34] must be done through simulations, which allows obtaining better critical values for the null hypothesis and contrast them with the critical values under the assumption of normality, which avoids possible type I errors.

3. Empirical Results from Classical Time Series Analysis

Figure 2 presents the points where the Granger causality occurs, and Table 2 shows the dates where the causality occurs. Observe that GFI Granger-causes MMI until the beginning of May 2021 in a unidirectional way. The same happens for GEI and GAEI, and there is no Granger causality for GRI. Over time the market has suffered periods of abnormal volatility due to the uncertainty generated by financial crises, political risks, or pandemics. Policies are required from governments to react in advance of the markets or to mitigate the impact to a certain extent, although the uncertainty generated by COVID-19 will continue to be present [43]. Figure 2 presents the results of $H_{1,t}(k)$.It can be observed that GFI Granger-causes MMI, GEI, and GAEI in a unidirectional way, except for GRI

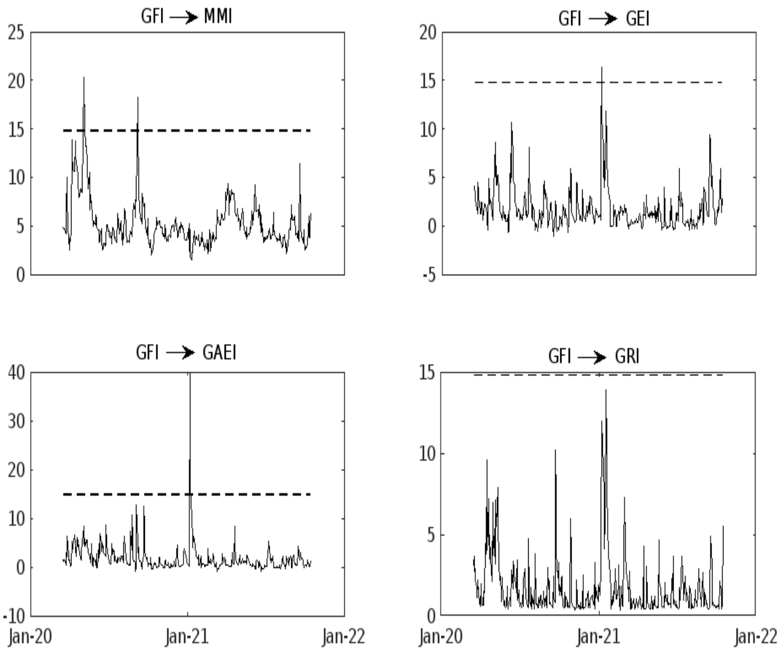

Figure 2. Granger causality of the DCC-GARCH test between the different indices and GFI.

Note: The dotted line indicates the 99% value of the simulated critical values of the normal quantile. → indicate causality from one series to another. Rolling Windows applied considered M=10. The figure is our elaboration with MATLAB.

Table 2. Date of Granger Causality

GFI→MMI	GFI→GEI	GFI→GAEI
05/04/20 05/05/20 05/06/20 05/07/20 09/07/20	01/07/21	01/07/21 01/08/21

The results are in line with Ayyildiz [44] where GFI is related to series of agricultural products to determine their Granger causality. Also, Dogan et al. [45] examine the effects of COVID-19 deaths and cases on natural resources and commodities causing an increase in volatility [3,46–48]. The present research also complements the results of other studies about the relationship of COVID 19 and financial markets, For instance, Sharif et al. [47] measures COVID-19 by the number of infected cases in the US, Zaremba et al. [46] used government interventions, not drugs aimed at curbing the spread of COVID-19, and Zhang et al. [3] are based on global coronavirus infections obtained from the John Hopkins Coronavirus Resource Center.

Therefore, the sentiment generated by GFI due to COVID-19 cases and deaths could affect the psychological behavior of investors. In fact, some studies analyze the impact of sentiment variables on stock market volatility [49,50], and others such as Jawadi et al. [51] have shown that investor sentiment is one of the leading causes of asymmetric returns of the actions. Furthermore, the fear/panic caused by the combined COVID-19 cases and deaths in GFI generates a pessimistic sentiment in the market [52–54]. In this sense, Haroon and Rizvi [55] mention that the coronavirus pandemic resulted in unprecedented information coverage and outpouring of opinion in this era of rapid information, and this has created uncertainty in financial markets that leads to greater price volatility. The pandemic triggered different behaviors in different economic sectors, which with a solid policy on the part of the governments, can reduce the impact on the volatility of these series, originating a renewed economy, which brings with it an optimistic growth forecast for the coming year [43]. Compared to other public health crises that preceded this one, COVID-19 significantly impacted different markets, regardless of developed or non-developed countries [56,57].

We next analyze whether GFI serves as a variable to forecast the co-movement of the series of the S&P global indices studied. One day forecast is considered, applying the Granger causality test with variation in time as in [58]; which can determine local projections assuming heteroscedasticity and idiosyncratic shocks. This test allows a bivariate model not to be constrained like the recursive, or mobile window models of [59], which depend on the chosen window size selection [60].

The tests are based on four statistics: Wald exponential test (ExpW), Wald mean (MeanW), Nyblom (Nyblom), and Quandt Likelihood Ratio (SupLR) test, considering the Schwarz Information Criterion (SIC). An Autoregressive Vector was estimated with a lag, and a cut of 15% for the extremes. The null hypothesis is that the Wald statistics on GFI do not cause the global indices, thus it must be rejected. Table 4 presents the results of the four tests applied to each bivariate series of GFI considered in this study.

Table 3. Univariate Granger causality statistics

Bivariate Series	Statistics			
	ExpW	*MeanW*	*Nyblom*	*SupLR*
GFI→MMI	88.53***	55.34***	2.23*	186.94***
GFI→GEI	20.21***	21.11***	1.76	50.94***
GFI→GAEI	29.94***	25.53***	2.06	71.14***
GFI→GRI	65.23***	40.21***	1.90	139.60***

Note: (*) 10%, (**) 5% and (***) 1% level of significance.

Figure 3 presents the sequential analysis through the time of the Wald statistic where the Granger causality is presented one period ahead as a forecast. We observe that among the four different tests, three were significant (except Nyblom).

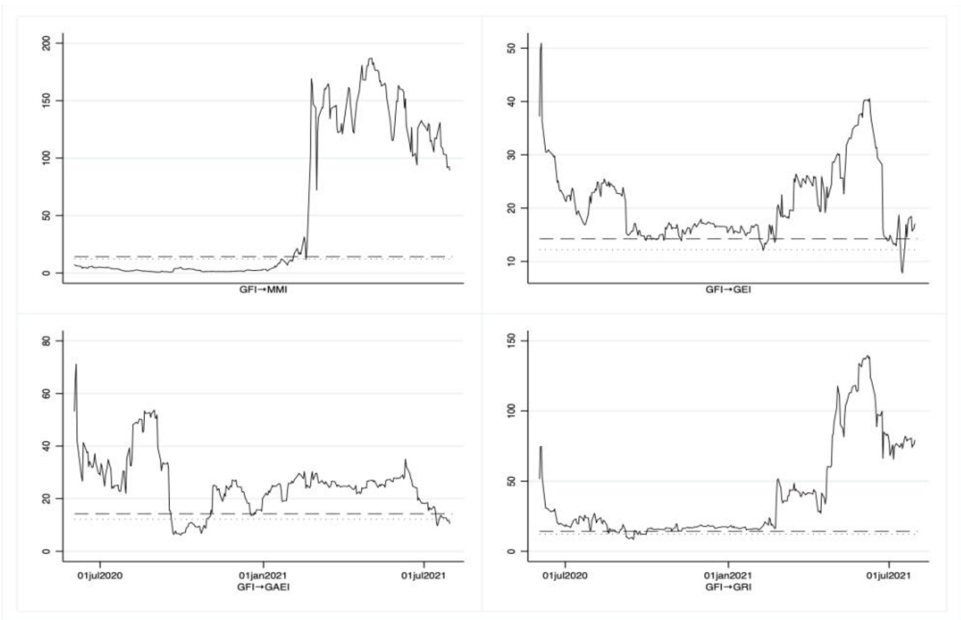

Figure 3. Wald statistic through time for Granger causality.
Note: (---) critical level at 5%, (...) the 10% significance level, and (—) the Wald statistic. Calculations performed in STATA.

The above findings detect that GFI is a variable that can help determine the co-movement of the other indices one day ahead. GFI begins to forecast co-movement toward MMI in March 2021 until the end of the period. Regarding GEI, GAEI, and GRI, the co-movement starts from the beginning of the period to the end, with some points where the Granger causality with heteroscedasticity and idiosyncratic shocks is not found. This shows that GFI is a variable that has co-movement on the volatility of the indices analyzed in this study. This also indicates that the volatility of these series is sensitive to the behavior of GFI, which is based on cases and deaths from COVID-19, so the co-movement in the volatility of these indices may cause investors to react not only because of GFI, but to the economic/financial policies that were applied during the pandemic in order to mitigate market risk. However, false news about cases and deaths from COVID-19 should not be put aside since they could cause an overreaction, which would generate high volatility and uncertainty in these financial markets.

The effect of cases and deaths may present a negative sentiment among economic agents, this would imply greater volatility compared to positive news. However, these agents could overreact due to the pandemic in specific periods. However, as more information arrives, the market corrects itself [61,62]. Finally, one important question is what the side effects will be on these global indices once the pandemic is over, even though different markets can be replenished, most likely it seems that uncertainty will prevail as long as the pandemic continues, and economic policies are not taken to mitigate this uncertainty.

4. Robustness Check with an Information-theoretic Analysis (Shannon and Rényi Entropy)

In this section, to verify Granger causality more robustly, we follow Jizba et al. [63] by using information-theoretic concepts such as Shannon [64] and Rényi [65] information measures. We shall explore the directional information flow between the GFI and each of the S&P Global Indices. That is, we inspect Shannon and Rényi transfer entropy flow between the pairs of series. The transfer entropy flow quantifies causal interdependencies in pairs of time series. This makes the Granger causality and the Shannon and Rényi transfer entropy flow comparable.

Table 4 presents the results of the statistics of the test. Shannon's entropy transfer results are shown in panel A and Renyi's in panel B. Column 1 provides the direction of the information flow (→). Column 2 contains the Shannon and Rényi statistics, respectively, and column 3 is the effective entropy transfer, which was calculated using 300 shuffles. To the right of each panel are the quantiles of entropy transfer, each with its respective direction. This calculation is based on Bootstrap samples for entropy transfer estimates and not effective transfer estimates.

Table 4. Shannon and Rényi transfer entropy flow between the GFI and each of the S&P Global Indices

PANEL A								
Shannon Transfer Entropy			Bootstrapped TE Quantiles					
Direction	TE	Eff. TE	Direction	0%	25%	50%	75%	100%
GFI→MMI	2.5343***	0.06	GFI→MMI	1.88	2.03	2.07	2.11	2.23
GFI→GEI	2.2945***	0.06	GFI→GEI	1.75	1.87	1.91	1.95	2.11
GFI→GAEI	2.4526***	0.07	GFI→GAEI	1.83	1.98	2.01	2.05	2.17

GFI→GRI	2.6126***	0.09	GFI→GRI	1.94	2.14	2.19	2.23	2.38
PANEL B								
Rényi Transfer Entropy			Bootstrapped TE Quantiles					
Direction	TE	Eff. TE	Direction	0%	25%	50%	75%	100%
GFI→MMI	1.8436***	0.05	GFI→MMI	1.36	1.48	1.53	1.57	1.80
GFI→GEI	1.7925***	0.05	GFI→GEI	1.33	1.46	1.50	1.54	1.70
GFI→GAEI	1.921***	0.06	GFI→GAEI	1.43	1.52	1.56	1.61	1.74
GFI→GRI	2.0353***	0.07	GFI→GRI	1.46	1.68	1.74	1.80	1.98

Note: (*) 10%, (**) 5% and (***) 1% level of significance.

Finally, it is worth noting that the empirical results show that the GFI entropy-causes all the other global indices (MMI, GEI, GAEI and GRI) with the direction of the information flow from GFI to all the global indices, while GFI Granger-causes MMI, GEI, and GAEI in a unidirectional way, except for GRI.

4. Conclusions

Our work analyzed the co-movement of GFI, considered as negative news, regarding COVID-19, through Granger causality, using a DCCC-GARCH model with variation in time, during the COVID period towards the volatility of MMI, GEI, GAEI, and GRI.

The empirical results found are a unidirectional causality of GFI towards the global indices, except for GRI. Subsequently, we analyzed Granger causality over time with a model that includes heteroscedasticity and idiosyncratic shocks to forecast a forward period of GFI towards each of the global indices. In this case, we apply four different tests, of which three were significant. Additionally, we obtained that causality was only found from March 2021 from GFI to MMI. The rest of the pairs presented causality from the beginning to the end of the period. This work indicates that GFI has a co-movement with the volatility of the other indices and can serve as a forecast variable within these markets. Additionally, to verify Granger causality more robustly, we show that the GFI entropy-causes all the other global indices (MMI, GEI, GAEI and GRI) with the direction of the information flow from GFI to all the global indices,

Finally, a limitation of this investigation might be that other economic variables should be considered: such as the exchange rate, Gross Domestic Product, among others, and/or other indices that have emerged regarding COVID 19 such as EMV-ID, Vaccination Index, Ciustk.cmp, among others; as well as other financial markets. These might be considered in future works. In this study, we only focused on the co-movement of the volatility of these global indices and GFI.

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