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Modelling economic policy issues

The impact of COVID-19 induced panic on stock market returns: A two-year experience

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ABSTRACT

This paper explores the relationship between the stock markets of emerging and developed economies and the fear triggered by the COVID-19 pandemic crisis in a period that spans from mid-January 2020 to mid-February 2022. The potential relations are analyzed in terms of Granger causality and dynamic correlation, both from the view of raw undecomposed returns and different time–frequency decompositions derived from a previous wavelet transform screening approach. Overall, our Granger and dynamic correlation results suggest that changes in panic indexes resulting from the COVID-19 pandemic do not have a significant relation with the raw stock market returns, but the reverse occurs in terms of time–frequency decompositions. Correlation analysis also indicates that all countries have a quite similar pattern of phase transitions, with certain stages preceded by a hump and others by a valley, i.e., they exhibit both positive and negative correlations. Despite a gradual reduction in media coverage, both causal relationships and correlations between financial markets and panic indexes held in 2021 and early 2022.

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1. Introduction

The COVID-19 pandemic has generated a large amount of literature that analyzes its impact on a wide variety of facets of financial markets and the economy as a whole. Pandemic-related news and government policies, such as social distancing and lockdowns, have a significant impact on investor decisions. The uncertain health and economic conditions during the early stages of the pandemic have caused anxiety, fear, and panic among investors. A number of papers have examined the impact of market sentiment on stock prices. It is important to note that almost all of this literature examines the initial impact of the pandemic, and most have sample periods ending in early 2021. There is, however, a period of particular interest between the mass vaccinations starting in 2021 and the start of the invasion of Ukraine at the end of February 2022, which marked a change in the geopolitical and economic landscape. Confirmed cases and deaths suffered during the first half of 2021 and the early months of 2022 are far higher than those suffered in 2020. Although this is the case, media coverage of COVID-19 has gradually declined in the second year of the pandemic, except for a brief period of more intensive coverage near the end of 2021. These trends may be influenced by several factors, including massive

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vaccine programs, especially in developed countries, increasing relaxation in the rigor of government responses to the pandemic, people’s fatigue and the need to move forward, and the rise of new problems, such as energy price increases and the growing tension in Ukraine. It may be worth considering whether the original effects of the pandemic on a variety of aspects of the financial markets are still relevant when evaluating this two-year period.

This study aims to shed light on the relationship between fear, investor sentiment, and stock market returns during a prolonged COVID-19 pandemic. By examining the first two years of the pandemic, we go beyond analyzing the initial phase of the pandemic. Our sample period extends from mid January 2020, when the World Health Organization (WHO) made public the fact that limited human-to-human transmission of COVID-19 may have occurred, to mid February 2022, when high tensions preceding the invasion of Ukraine plummeted the Russian stock market.

The traditional literature shows that stock prices depend on investor sentiment, distinguishing between internal behavioral biases of investors and exogenous macroeconomic origins of investor sentiment (Baker and Wurgler, 2007). A large number of sentiment proxies have been analyzed, such as surveys, mood proxies, retail investor trades, news media content, advisory services recommendations, textual analysis, etc. (e.g., Lee et al., 2002; Baker and Wurgler, 2007; Tetlock, 2007; Zouaoui et al., 2011; Garcia, 2013; Kearney and Liu, 2014; Renault, 2017). In this context, the information generated around the COVID-19 pandemic provides a new source of investor sentiment metrics, and the WHO’s pandemic declaration serves as a natural experiment to examine the relationship between stock prices and investor sentiment. A growing literature examines various aspects of how COVID-19-related news affects stock markets during the initial phase of the pandemic (e.g., Cepoi, 2020; Haroon and Rizvi, 2020a; Lee, 2020; Baig et al., 2021; Yu et al., 2021). However, there are still some questions that need to be addressed. Does that initial COVID-19 impact persist over time? Are investors still as fearful as they were initially of the pandemic’s then-unknown impact? Have financial markets turned a new leaf on COVID-19? Does the early connection between investor fear of COVID-19 and financial market behavior documented by some papers support extending the sample to a two-year period?

As a proxy for the evolution of the pandemic, prior studies analyzing the impact of the pandemic on financial markets have used the number of confirmed cases and deaths. Most studies have used raw reported numbers (e.g., Albulescu, 2020; Ashraf, 2020; Chowdhury and Abedin, 2020; Just and Echaust, 2020; Onali, 2020; Topcu and Gulal, 2020; Akhtaruzzaman et al., 2021; Ozkan, 2021; Xu, 2021; Yong and Laing, 2021; Yousfi et al., 2021). Other papers directly convert these figures into pandemic anxiety indexes (Salisu and Akanni, 2020; Yu et al., 2021) or combine them with media coverage data (Baig et al., 2021). Google Trends data on coronavirus-related searches is also used as a proxy for panic and fear (Goodell and Huynh, 2020; Lee, 2020; Hevia et al., 2020; Lyócsa et al., 2020; Ramelli and Wagner, 2020). Similarly to other previous studies (e.g., Baig et al., 2021; Cepoi, 2020; Haroon and Rizvi, 2020a; Umar and Gubareva, 2020; Umar et al., 2021; Rakshit and Neog, 2021), our study examines, in contrast, the impact of media coverage on investors, using media coverage indexes provided by RavenPack, a provider of data analytics for financial services, as an indicator of investor fear. In particular, we examine three daily indexes that reflect different aspects of media coverage of COVID-19, namely the percentage of media outlets (Infodemic Index, II), the number of news sources (Media Coverage Index, MCI), and the amount of news (Media Hype Index, MHI) mentioning COVID-19.¹

Most previous work focuses on the USA stock market (e.g. Chowdhury and Abedin, 2020; Haroon and Rizvi, 2020a; Goodell and Huynh, 2020; Just and Echaust, 2020; Onali, 2020; Ramelli and Wagner, 2020; Baig et al., 2021; Yong and Laing, 2021; Yousfi et al., 2021), with some exceptions such as European countries (e.g. Cepoi, 2020; Ozkan, 2021), G7 countries (e.g. Akhtaruzzaman et al., 2021; Yu et al., 2021) and even emerging countries (e.g. Haroon and Rizvi, 2020b; Topcu and Gulal, 2020; Rakshit and Neog, 2021; Yu et al., 2021). In our study, we examine the major developed and emerging economies. Pandemic evolution has been uneven among countries, but the differences between developed and emerging countries are of particular importance. In developed countries, the rates of confirmed cases follow a somewhat similar pattern. A similar “synchrony” does not exist in emerging countries.² The evolution of the number of deaths follows the same pattern as that of the reported cases, except for the initial outbreak of deaths in April 2020 in developed countries. Only Brazil, as of May, and India, as of June, exhibit similar behavior among emerging markets. In addition, there is also a significant difference in the pace of vaccination across countries. In light of this, our study investigates the impact of pandemic fear on investor sentiment and financial market behavior in both developed and emerging countries. Therefore, we examine the stock market returns of the five BRICS countries as emerging economies (Brazil, Russia, India, China, and South Africa) and those of the seven G7 countries as developed economies (the United States, the United Kingdom, Canada, Italy, Germany, France, and Japan). The stock market performance of each country and the world as a whole is evaluated by examining exchange-traded fund (ETF) quotes.

A number of different methodologies have been used in previous studies on the sentiment related to COVID-19 and how it has affected equity markets, such as event studies (e.g., Liu et al., 2020; Yong and Laing, 2021), Vector Autoregression (VAR) models (e.g., Xu, 2021), different regression approaches (e.g., Ashraf, 2020; Cepoi, 2020; Lee,...

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¹ This text refers to RavenPack’s COVID indexes in a variety of ways, including panic indexes, media coverage indexes, pandemic indexes, anxiety indexes, and simply fear indexes. These terms are used interchangeably.

² A significant outbreak of infection occurred in developed countries between November 2020 and January 2021, and particularly between December 2021 and February 2022. Among emerging countries, Brazil is experiencing waves of contagion between June and September 2020, between February and June 2021, and between January and February 2022. There is a slight delay in these waves in India, and there is less severity in South Africa. The main wave of infection in Russia occurs between July and December 2021. Finally, China has a residual amount of confirmed cases until March 2022.
Aside from one ETF for each of the 12 equity markets, we consider the URTH index ETF, which replicates the MSCI World Index, as a benchmark for global markets. The Cboe Volatility Index (VIX), which is a real-time index that reflects market expectations of short-term price changes in the S&P 500 Index (SPX), is also included because it has been considered an indicator of market fear in other studies. Daily data for each benchmark ETF was obtained from the Yahoo Finance API. However, the URTH index ETF was not available for the first few months from the beginning of the pandemic, and therefore, we only consider the first two years of the pandemic for our analysis.

Furthermore, we use exchange-traded fund (ETF) quotes to examine the performance of the equity markets in each country during the pandemic, as well as the world as a whole. ETFs offer several advantages over other financial instruments. First, ETFs allow continuous trading throughout the day at market prices. In contrast to stock indexes, where direct investments are not possible, ETFs allow continuous trading throughout the day at market prices. In addition, Pavlova and de Boyrie (2022) argue that ETFs offer greater transparency and flexibility in daily trading than conventional mutual funds, as well as lower costs and greater tax efficiency.

The choice of the data used in this study was motivated by two distinct interests: (i) quantifying fear in the markets; (ii) assessing the evolution of equity markets in different countries during the crisis triggered by the COVID-19 pandemic. Data were extracted at a daily frequency starting on January 17, 2020, the first date for which pandemic anxiety indexes were available, and ending on February 16, 2022, prior to the collapse of the Russian stock market following the invasion of Ukraine. Regarding the financial market returns, we use exchange-traded fund (ETF) quotes to examine the performance of the equity markets in each country during the pandemic, as well as the world as a whole. ETFs offer several advantages over other financial instruments. In contrast to stock indexes, where direct investments are not possible, ETFs allow continuous trading throughout the day at market prices. In addition, Pavlova and de Boyrie (2022) argue that ETFs offer greater transparency and flexibility in daily trading than conventional mutual funds, as well as lower costs and greater tax efficiency.
Table 1
Description of RavenPack indexes.
Source: RavenPack

| Table of contents                  | Description                                                                 |
|-----------------------------------|-----------------------------------------------------------------------------|
| Infodemic Index (II)              | Calculates the percentage of entities that are reported alongside the coronavirus in the media. The index can take values between 0 and 100, where a value of 50 means that 50 percent of the entities mentioned in the media are being linked to COVID-19. |
| Media Coverage Index (MCI)        | Measures the daily level of all news sources covering the topic of COVID-19. The value of the index can fluctuate from a minimum of 0 and a maximum of 100. The higher the index, the more news sources are talking about the pandemic. |
| Media Hype Index (MHI)            | Quantifies the daily level of news mentioning COVID-19. Index values range from 0 to 100. A value of 100 means that 100 percent of the news mention COVID-19 on that day. |

Table 2
Description of the market data of the ETFs and the indexes they track.
Source: iShares

| Code | ETF                     | Index tracked                | Launch of the Fund | Net assets amount |
|------|-------------------------|------------------------------|--------------------|------------------|
| URTH | iShares MSCI World ETF  | MSCI World Index             | 2012               | 1585             |
| CSUS | iSHARES MSCI USA UCITS ETF | MSCI USA Index             | 2010               | 960              |
| EWC  | iShares MSCI Canada ETF | MSCI Canada Custom Capped Index | 1996           | 3940             |
| EWG  | iShares MSCI Germany ETF| MSCI Germany Index           | 1996               | 2815             |
| EWI  | iShares MSCI Italy ETF  | MSCI Italy 25/50 Index       | 1996               | 572              |
| EWJ  | iShares MSCI Japan ETF  | MSCI Japan Index(SM)         | 1996               | 12,843           |
| EWQ  | iShares MSCI France ETF | MSCI France Index            | 1996               | 698              |
| EWU  | iShares MSCI UK ETF     | MSCI UK Index                | 1996               | 3286             |
| EWZ  | iShares MSCI Brazil ETF | MSCI Brazil 25/50 Index      | 2010               | 4947             |
| ERUS | iShares MSCI Russia ETF | MSCI Russia 25/50 Index      | 2010               | 663              |
| INDA | iShares MSCI India ETF  (INDA) | MSCI India Total Return Index(SM) | 2012 | 6480             |
| MCHI | iShares MSCI China ETF  | MSCI-CHINA                   | 2011               | 6279             |
| EZA  | iShares MSCI South Africa ETF | MSCI South Africa 25/50 Index | 2003         | 273              |

The table details the benchmark indexes for each of the ETFs chosen for each country.

Finance database. Table 2 reports the slate code, fund name, benchmark, inception year, and total net assets. Regarding the choice of the ETFs, they were selected according to their underlying MSCI indexes. Thus, we chose those indexes that measure the performance of the large- and mid-cap segments of the selected equity markets, that is, the indexes that are designed, based on the number of constituents, to cover about 85% of the equity universe in each of the markets included in the study.

Fig. 1 shows the daily quote values of the benchmark ETFs for the G7 and BRICS as well as for the global benchmark ETF and the VIX. During the first quarter of 2020, coinciding with the first wave of the pandemic, all the different countries show a downward shift while the VIX experiences a pronounced increase, which we could attribute to the general uncertainty derived from the health crisis. By the end of March 2020, most ETFs were experiencing moderate upward trends, primarily the USA and the global benchmark. In some countries, the uptrend is corrected in Sept/Oct 2020 and in the second half of 2021, resulting in a stagnant or moderately declining trend. These downward trends has been exacerbated by the entry of 2022 and the ongoing tensions between Russia and Ukraine.

Table 3 presents some descriptive statistics on the ETF return series for the different countries, as well as for the global benchmark and the VIX, separately for two periods: January 17, 2020–January 29, 2021 and February 1, 2021–February 16, 2022. Dividing the sample into two subperiods of approximately equal length allows us to differentiate between the two years of the pandemic. The first subperiod corresponds to the one examined by most previous literature. During the second subperiod, we have the opportunity to extend the analysis and determine whether the conclusions drawn initially are still valid after the second year of the pandemic. Statistics clearly indicate the greatest tension in equity markets during the first stage of the sample and the greatest calm and a gradual growth during the second stage. Overall, daily average returns remain moderately positive during the entire sample period, with some countries experiencing negative values mainly during the first subperiod. The median returns are always above the mean values, and they are significantly higher in the second subperiod, with the exception of Brazil and China. The dispersion, attending at the standard deviation, is ostensibly higher during the first subperiod. A particular point to be noted is the high volatility of the ETFs representing Brazil, Russia, and South Africa. Almost all ETF show negative skewness during the entire sample, which indicates an asymmetric tail skewed towards negative returns distribution. Interestingly, the returns present a very high kurtosis during the first subperiod, implying a leptokurtic distribution, while during the second subperiod a negative excess kurtosis is observed in most cases, denoting a platikurtic distribution. This change in the sample kurtosis from one year to the next may reflect the normalization of the pandemic context in terms of financial shocks. All augmented Dickey–Fuller (ADF) test results for the returns are significant at the 1% level, so that the series are stationary, and almost all are significant at 1% level for Ljung–Box and Lagrange Multiplier tests for autocorrelation, which denotes the need of fitting an autoregressive model to the data.
Fig. 1. National MSCI ETFs price series. The price series of the ETFs corresponding to all BRICS and G7 countries, as well as the world’s MCHI ETF and the VIX, are presented for the entire sample considered (January 17, 2020–February 16, 2022).

The indexes reflecting the COVID-19 panic are depicted in Fig. 2. Having initially risen in mid-January, panic indexes hatch during the last week of February 2020. The peak value of the MCI and MHI is reached at the end of March, while the peak value of the II is reached in the first week of May. The lockdowns begin in all countries considered in the second half of March, except in some areas of China at the end of January and in Italy on March 9. The three indexes moderated their downward trend in June 2020, with some small upturns at the end of 2020, July/August 2021, and the end of 2021. The latter upturn coincides with the outbreak of the Omicron variant. It is worth noting that the MHI index was the one that underwent the greatest variation throughout the sample period and reacted most sharply to the successive waves of the pandemic. Divergent trends are observed not only among the three indexes, but also in the evolution of each index for each country. While the Russian and Brazilian values were lowest at the beginning of the pandemic, they have been significantly higher at the beginning and end of 2021 when compared to the other countries. Among the G7 countries, Japan has maintained the highest and most stable values.

The panic index series are also transformed into log-differences in order to induce stationarity (ADF tests show 1% significant for all of them). The basics descriptive statistics of the transformed series are also presented in Tables 4 and 5 for the two subperiods. These series reveal an even more pronounced regime shift than ETF returns. In the first subperiod, all three indexes presented a positive log-difference average, while in the second subperiod, this average was clearly lower or negative. The dispersion of the observations is much higher during the first half of the sample, as would be expected given the pandemic context, and there is a markedly positive skewness and excess kurtosis. In the second subperiod, the values for both statistics are greatly reduced, and even become kurtosis-defective. Almost all the series present autocorrelation in mean and variance, as reflect the results of the Ljung–Box and Lagrange-Multiplier tests on standardized residuals and squared standardized residuals, respectively.

3. Methodology

This study analyzes the relationship between investor sentiment related to COVID-19 fear and stock market returns on major developed and emerging countries over the course of the two-year pandemic in three steps. Firstly, to examine fluctuations for different time horizons, a wavelet method decomposes the time series in the time–frequency domain.

For simplicity, only the panic indexes for the global benchmark have been included in Fig. 2, and the indices for each country have been omitted.
Table 3
Summary statistics of the daily returns of the ETFs and the VIX.

|                | Minimum | Mean | Median | Maximum | Std. | Skewness | Kurtosis | ADF   | Q (1) | LM (7) |
|----------------|---------|------|--------|---------|------|----------|----------|-------|-------|--------|
| **Jan20-Jan21** |         |      |        |         |      |          |          |       |       |        |
| World          | −0.1208 | 0.0004 | 0.0020 | 0.0871 | 0.0204 | −1.2480 | 10.4291  | −6.69*** | 36.91*** | 235.98*** |
| Brazil         | −0.2026 | −0.0010 | −0.0003 | 0.1623 | 0.0400 | −1.4901 | 10.5515  | −7.83*** | 50.78*** | 258.07*** |
| Russia         | −0.2353 | −0.0006 | 0.0000 | 0.1624 | 0.0334 | −1.4959 | 16.1286  | −7.23*** | 52.84*** | 184.98*** |
| India          | −0.1677 | 0.0003 | 0.0020 | 0.1199 | 0.0274 | −1.4027 | 10.9270  | −3.57*** | 61.67*** | 260.77*** |
| China          | −0.1028 | 0.0010 | 0.0016 | 0.0576 | 0.0192 | −0.8073 | 4.1892   | −16.03*** | 12.36*** | 129.6*** |
| South Africa   | −0.1604 | −0.0001 | 0.0017 | 0.0961 | 0.0302 | −1.3391 | 7.0569   | −5.94*** | 12.4***  | 210.93*** |
| Germany        | −0.1357 | 0.0003 | 0.0017 | 0.1022 | 0.0229 | −1.4546 | 9.7239   | −7.61*** | 6.9***   | 180.46*** |
| Canada         | −0.1430 | 0.0001 | 0.0024 | 0.1210 | 0.0232 | −1.4240 | 15.0550  | −6.58*** | 8.96***  | 132.94*** |
| US             | −0.0772 | 0.0003 | 0.0005 | 0.0814 | 0.0167 | −0.7559 | 5.7639   | −6.07*** | 1.9***   | 113.67*** |
| France         | −0.1356 | 0.0000 | 0.0017 | 0.0871 | 0.0235 | −1.5171 | 9.6066   | −5.83*** | 8.68***  | 208.88*** |
| Italy          | −0.1701 | −0.0001 | 0.0010 | 0.1064 | 0.0250 | −2.1151 | 14.4994  | −7.49*** | 17.83*** | 136.92*** |
| Japan          | −0.1032 | 0.0005 | 0.0007 | 0.0671 | 0.0158 | −1.1824 | 9.5485   | −5.11*** | 10.84*** | 115.03*** |
| UK             | −0.1277 | −0.0005 | 0.0015 | 0.1093 | 0.0228 | −1.1291 | 8.2484   | −8.28*** | 13.83*** | 208.08*** |
| VIX            | −0.2662 | 0.0037 | −0.0095 | 0.4802 | 0.0927 | 1.6980  | 5.9133   | −12.78*** | 6.11***  | 33.82***  |
| **Feb21-Feb22** |         |      |        |         |      |          |          |       |       |        |
| World          | −0.0218 | 0.0006 | 0.0008 | 0.0226 | 0.0080 | −0.2069 | 0.2838   | −6.69*** | 36.91*** | 235.98*** |
| Brazil         | −0.0639 | 0.0003 | 0.0014 | 0.0425 | 0.0187 | −0.5660 | 0.8573   | −7.83*** | 50.78*** | 258.07*** |
| Russia         | −0.0823 | 0.0007 | 0.0018 | 0.0667 | 0.0173 | −0.7789 | 4.5278   | −7.72*** | 52.84*** | 184.98*** |
| India          | −0.0374 | 0.0007 | 0.0007 | 0.0396 | 0.0106 | −0.0900 | 1.2331   | −5.37*** | 61.67*** | 260.77*** |
| China          | −0.0579 | −0.0012 | −0.0013 | 0.0600 | 0.0167 | 0.0946 | 1.1194   | −16.03*** | 12.36*** | 129.6*** |
| South Africa   | −0.0525 | 0.0008 | 0.0011 | 0.0499 | 0.0163 | −0.0745 | 0.1051   | −5.94*** | 12.4***  | 210.93*** |
| Germany        | −0.0275 | 0.0002 | 0.0006 | 0.0297 | 0.0090 | −0.0767 | 0.3589   | −7.61*** | 6.9***   | 180.46*** |
| Canada         | −0.0265 | 0.0009 | 0.0011 | 0.0232 | 0.0093 | −0.1563 | −0.0119  | −6.58*** | 8.96***  | 132.94*** |
| US             | −0.0437 | 0.0009 | 0.0021 | 0.0395 | 0.0094 | −0.3632 | 3.0438   | −6.07*** | 1.9***   | 113.67*** |
| France         | −0.0308 | 0.0007 | 0.0013 | 0.0272 | 0.0093 | −0.1982 | 0.1455   | −5.83*** | 8.68***  | 208.88*** |
| Italy          | −0.0277 | 0.0006 | 0.0006 | 0.0282 | 0.0101 | −0.1216 | 0.0216   | −7.49*** | 17.83*** | 136.92*** |
| Japan          | −0.0348 | −0.0001 | 0.0003 | 0.0280 | 0.0092 | −0.2123 | 0.6829   | −5.11*** | 10.84*** | 115.03*** |
| UK             | −0.0283 | 0.0008 | 0.0012 | 0.0208 | 0.0083 | −0.4019 | 0.4690   | −8.28*** | 13.83*** | 208.08*** |
| VIX            | −0.2204 | −0.0011 | −0.0080 | 0.3029 | 0.0818 | 0.3714 | 0.9923   | −12.78*** | 6.11***  | 33.82***  |

Basic statistics of the returns of the ETFs considered are presented for two differentiated periods: January 17, 2020 to January 29, 2021 and February 1, 2020 to February 16, 2022. ADF indicates the statistic of the augmented Dickey–Fuller test for stationarity, while Q(1) denotes the statistic of the Ljung-Box autocorrelation test for one lag, and LM(7) the Lagrange-Multiplier test on squared residuals on lag 7. ADF, Ljung–Box, and LM tests are applied to the entire sample, ranging from January 17, 2020 to February 16, 2022. *, ** and *** representing statistical significance at 10%, 5% and 1% levels, respectively.

Fig. 2. Panic indexes for the global benchmark. Infodemic, Media Coverage and Media Hype indexes at worldwide level are shown for the sample period (January 17, 2020–February 16, 2022).
decomposed in its low-frequency components, which can be interpreted as trend components, and its high-frequency components of the G7 and BRICS countries.

Lastly, we also examine the conditional comovements between stock markets and panic indexes in terms of returns and frequency decompositions.

3.1. Wavelet methods

The wavelet methodology allows to decompose time series in the time–frequency domain without wasting valuable information, and has become widely used to assess dynamic interactions between financial series in the frequency domain (Jammazi et al., 2017). There already exist some papers in the literature that use wavelet methodology to investigate the impact of the pandemic on the stock market, such as Karamti and Belhassine (2022), which studies the connection between COVID-19 fear and the international financial markets using the wavelet coherence analysis, finding contagion effects. Our paper goes more in line with Umar et al. (2021), which uses wavelet analysis to investigate the leakage between pandemic anxiety (measured through an index reflecting the presence of pandemic-related themes on the overall media) and several commodities, and study the dependencies between other similar indices and the stock markets of the G7 and BRICS countries.

We use wavelet methods to decomposed the series in the time–frequency domain. A signal or time series can be decomposed in its low frequencies components, which can be interpreted as trend components, and its high frequency components.
components or fluctuation components. The first is captured by the so-called father wavelet (Φ), while the second is captured by the mother wavelet (ψ). These are wavelet functions that can be generally expressed as follows:

\[
\Phi_{j, k, t} = 2^{-j/2} \Phi \left( \frac{t - 2^j k}{2^j} \right); \quad \psi_{j, k, t} = 2^{-j/2} \Psi \left( \frac{t - 2^j k}{2^j} \right)
\]

(1)

For our study, we follow Lim (2020) by choosing the Maximum Overlap Discrete Wavelet Transform (MODWT), which has the advantage of data length flexibility, which means not requiring the integral power of 2 (Maghyereh et al., 2019; Risse, 2019; Jiang and Yoon, 2020; Kumah and Mensah, 2020; Karim et al., 2022). Furthermore, according to Shafaa and Masih (2013), the MODWT variance is asymptotically more efficient than that of the DWT; no shifts are introduced in the wavelet coefficient under the MODWT (Gencay et al., 2001), which implies that any peaks in the original series will be correctly aligned with similar events in the multiresolution analysis (Masset, 2008; Mensi et al., 2018).

Using MODWT, a signal or time series can be expressed in terms of fluctuation and scaling coefficients:

\[
r_t = S_{j, t} + D_{j, t} + D_{j-1, t} + \cdots + D_{1, t}
\]

(2)

where

\[
S_{j, t} = \sum_k S_{j, k} \Phi_{i, k, t}; \quad D_{j, t} = \sum_k D_{j, k} \psi_{j, k, t} \quad j = 1, 2, \ldots, J
\]

(3)
where $S_j,t$ and $D_j,t$ represent the fluctuation and scaling coefficients, respectively, at the $j$th level wavelet that reconstructs the time series in terms of a specific frequency. The wavelet-transformed series can be thus represented as a linear combination of wavelet functions:

$$x_t = \sum_j S_{j,k} \Phi_{j,k,t} + \sum_j D_{j,k} \Psi_{j,k,t} + \sum_k D_{j-1,k} \Phi_{j-1,k,t} + \cdots + \sum_k D_{1,k} \Phi_{1,k,t}$$

(4)

### 3.2. Granger causality test

We carry on a study on linear causality by means of the Granger test (Granger, 1969). The aim is to enable the determination of whether an explanatory variable, the log-difference of one of the considered pandemic indexes from RavenPack corresponding to country $i$, $r_{i,\text{ETF}}$, provide statistically significant information on the values of the future returns of the ETF of country $i$, $r_{i,\text{ETF}}$. There are two models of causality test: (i) the restricted model, in which $r_{i,\text{ETF}}$ is explained only by its own past; and (ii) an unrestricted model, in which $r_{i,\text{ETF}}$ is explained by the past of $r_{i,\text{ETF}}$ and $r_{i,\text{RP}}$. It is assumed that $r_{i,\text{RP}}$ causes $r_{i,\text{ETF}}$ in the Granger sense when predictions of $r_{i,\text{ETF}}$ based on past observations of $r_{i,\text{ETF}}$ and $r_{i,\text{RP}}$ have better predictive effectiveness than those based on past values of $r_{i,\text{ETF}}$ alone. Thus, the Granger equation would be expressed as follows:

$$r_{i,\text{ETF},t} = \sum_{j=1}^{p} \alpha_{i,\text{ETF},t-j} r_{i,\text{ETF},t-j} + \sum_{j=1}^{p} \beta_{i,\text{ETF},t-j} r_{i,\text{RP},t-j} + \epsilon_{i,\text{ETF},t}$$

(5)

where $r_{i,\text{ETF},t}$ would be the daily return of the ETF of country $i$ at time $t$, $\alpha_{i,\text{ETF},t}$ and $\beta_{i,\text{ETF},t}$ are the estimated coefficients that capture the contribution of each lagged observation of $r_{i,\text{RP}}$ and $r_{i,\text{ETF}}$ in predicting the future value of $r_{i,\text{ETF}}$. $r_{i,\text{RP},t}$ represents the log-differences of one of the three RavenPack indexes considered at time $t$ and corresponding to country $i$, and $\epsilon_{i,\text{ETF},t}$ is the error term or random disturbance. Also, $i = \text{Global, Brazil, Russia, India, China, South Africa, USA, UK, Canada, Italy, Germany, France, and Japan}$, when used in those respective contexts, and $\text{RP} = \text{MCI, MHII}$, in their respective contexts. The null hypothesis of the Granger test is that $\sum_{j=1}^{p} \beta_{i,\text{ETF},t} = 0$. Rejection of the null hypothesis implies that the COVID-19 pandemic panic indexes cause changes in returns on funds.

Causality is assessed only in one direction, i.e., we do not study the existence of causal effects of financial markets on media coverage of the coronavirus.

### 3.3. Conditional correlation modeling

The returns of the ETF from country $i$ at a particular moment $t$ are modeled as follows:

$$r_{i,\text{ETF},t} = \phi_0 + \phi_i r_{i,\text{ETF},t-1} + \epsilon_{i,\text{ETF},t}$$

(6)

where $\phi_0$ and $\phi_i$ are the AR(1) parameters used to fit the conditional mean, $\epsilon_{i,\text{ETF},t} = \sigma_{i,\text{ETF},t} \eta_{i,\text{ETF},t}$ represents the non-standardized residual, where $\eta \sim N(0, 1)$. The univariate conditional variance $\sigma_{i,\text{ETF},t}^2$ is fitted by means of a one of the GARCH-type models described in Appendix. The choice of the proper GARCH model is explained in further detail in Section 4.3. The model described in (6) is also used to fit the pandemic indexes series in log-differences, $r_{i,\text{RP},t}$.

Then, an ADCC model (Cappiello et al., 2006) is used to estimate the conditional correlation between the series. This model uses instrumental variables, $q_{i,\text{ETF},t}$, for the estimation process of each asset pair:

$$q_{i,\text{ETF},t} = (\tilde{q}_{i,\text{ETF},t} - \alpha_{\text{ADCC}} q_{i,\text{ETF},t} - \beta_{\text{ADCC}} q_{i,\text{RP},t} - \tilde{\epsilon}_{i,\text{ETF},t} + \tilde{q}_{i,\text{RP},t})$$

$$+ \alpha_{\text{ADCC}} (\tilde{\eta}_{i,\text{ETF},t-1} - \tilde{\eta}_{i,\text{RP},t-1}) + \beta_{\text{ADCC}} q_{i,\text{ETF},t-1} + \tilde{\sigma}_{\text{ADCC}} (\tilde{\eta}_{i,\text{ETF},t} \tilde{\eta}_{i,\text{RP},t})$$

(7)

where $\tilde{q}_{i,\text{ETF},t}$ is an instrumental variable playing the role of unconditional covariance between the ETF and the pandemic index $\text{RP}$ of country $i$. The parameters $\alpha_{\text{ADCC}}$ and $\beta_{\text{ADCC}}$ quantify both the effect of new market information shocks and the time it takes for them to disappear in the multivariate process, i.e., how long they persist. Besides, $\tilde{\sigma}_{\text{ADCC}}$ is the parameter that allows to fit the skewed dependence behavior, whereas $\tilde{\eta}_{i,\text{ETF},t}$ represents the standardized innovation of the ETF of country $i$ at time $t$ and $\tilde{\eta}_{i,\text{RP},t}$ that of country $i$ pandemic index $\text{RP}$, both estimated from (6) by means of the AR(1) and univariate GARCH models. Lastly, $\tilde{\eta}_{i,\text{ETF,RP},t} = \min(\tilde{\eta}_{i,\text{ETF},t}, 0)$ and equivalently for $\tilde{\eta}_{i,\text{RP},t}$.

Conditional correlations $\rho_{i,\text{ETF,RP},t}$ among each asset pair can then be deduced as:

$$\rho_{i,\text{ETF,RP},t} = \frac{q_{i,\text{ETF,RP},t}}{\sqrt{q_{i,\text{ETF},t} \sqrt{q_{i,\text{RP},t}}}}$$

(8)

5 Media Hype Index (MHI), Infodemic Index (II) and Media Coverage Index (MCI) denote the different indexes or metrics of COVID-19 induced panic. These indexes and their specificities are discussed in more detail in Section 2.

6 The estimates between each pair of assets are estimated jointly for the global series that make up the multivariate analysis by the quasi-maximum likelihood method. Therefore, Eq. (6) is the one used for pairs combining the ETF and a RavenPack index of the same country, which are the ones we ultimately want to evaluate. Note, however, that the model estimates correlation for all possible pairwise combinations between all series in the system, including correlations between ETFs of different countries, between different RavenPack indexes for the same country, or between the same RavenPack index for different countries.
4. Empirical evidence

This section is understood in terms of two implemented methodologies, Granger causality and ADCC-GARCH. Series expressed as log-returns and wavelet decompositions are used in both approaches. Our return series are decomposed into a number of scales by using the MODWT wavelet technique (see Eqs. (2) and (3)), similar to Maghyereh et al. (2019). This study considers wavelet scales of 2–4 days, 4–8 days, 8–16 days, 16–32 days, 32–64 days, and 64–128 days. The short-term horizon is defined as \( D_1 = (d_1 + d_2) \) and it represents the pandemic indexes log-differences and international stock market returns due to shocks happening from 2 to 8 days. The medium-term horizon is defined as \( D_2 = (d_3 + d_4) \) which shows variations due to shocks occurring from 8 to 32 days. Finally, the long-term horizon is defined as \( D_3 = (d_5 + d_6) \) which represents fluctuations occurring from 32 to 128 days. Although the estimates have been done considering all frequencies, to save space we only display the results regarding \( d_1, d_3 \) and \( d_6 \). We consider \( d_1 \) as a proxy of the short-run (i.e., high frequencies/timescales), \( d_3 \) for the mid-run and \( d_6 \) for the long-run (i.e., low frequencies/timescales) along this empirical section.

4.1. Causal analysis

To explore the causality between the effects generated by COVID-19 and international stock market returns, the Granger linear causality test was employed. This causality is estimated separately for two distinct subperiods, one related to the early pandemic turmoil and the first vaccines (from January 17, 2020 to January 29, 2021) and another more centered on the transition to normality but with the avoidance of the Ukraine invasion (from February 1, 2021 to February 16, 2022). It should be noted that both, ETF returns and all panic indexes met the stationarity requirements for causal analysis.\(^7\) Tables 8 and 9 in Appendix B show the results of the Granger test on causality effects from pandemic anxiety indexes to stock markets in each subperiod. Raw stock market returns are examined in conjunction with their wavelet decomposition at different frequencies.

According to the Granger causality test, there are few significant relationships. Overall, changes in panic indexes resulting from the COVID-19 pandemic do not appear to have a significant impact on the raw stock market returns. It is noteworthy that the number of statistically significant Granger-causal relationships is higher during the second subperiod. Concretely, it is found that there is a significant Granger-causal relationship between II and the Canada stock market, MCI and the World stock market and VIX, and no Granger-causal relationship exists between MHI and any of the markets during the first subperiod. However, there are a number of stock markets and VIX returns that are significantly caused in Granger sense by II, MCI, and MHI in the second subperiod.

Granger causality analysis of panic indexes towards the different time–frequencies resulting from wavelet decomposition of raw returns is an important source of valuable information. For high time–frequency, \( d_1 \), and medium time–frequency, \( d_3 \), the results indicate that fluctuations on most stock markets are caused by these three panic indexes in the Granger sense. But the most striking finding is that the fluctuations in long-term horizons, i.e. low time–frequency (\( d_6 \)), in all the countries evaluated are significantly Granger-caused by the panic indexes in the first year of COVID-19. Most cases in the second subperiod show statistically significant relationships. Accordingly, this result suggests that despite the gradual reduction in media coverage of the pandemic beginning in mid-2020, and especially during the second year of the pandemic, this media coverage has continued to impact investor sentiment and stock market behavior.

4.2. Conditional connectedness analysis

To analyze the co-movements among various COVID-19 induced panic indexes and the equity market returns in each country and at different time–frequencies, the ADCC-GARCH model is implemented.\(^8\) In this Subsection the ADCC structure is estimated for the total sample (from January 17, 2020 to February 16, 2022), but then the resulting correlation summary statistics are split into two subperiods, one related to the early pandemic turmoil and the availability of the first vaccines (from January 17, 2020 to January 29, 2021) and another more focused on the transition to normality but with the avoidance of the Ukrainians–Russian conflict effects (from February 1, 2021 to February 16, 2022).

First, the ADCC structure is implemented to properly fit the dependence in the tails of the distribution from the \( \xi \) and \( \nu \) parameters, as we consider that the connectedness among the extreme impacts of the pandemic in the different time series could be of great relevance. Regarding the correlation estimation process, it is conducted in two stages. In the first step, the conditional volatilities are obtained by estimating different univariate GARCH specifications. In the second step, time-varying correlations are estimated based on the resulting standardized innovations from the previous step (residuals divided by conditional volatilities). The potential GARCH-type specifications to model the variance are the GARCH (1,1), the E-GARCH (1,1), the GJR-GARCH (1,1), the CS-GARCH (1,1) or the l-GARCH (1,1). We select the multivariate ADCC-AR(1)-GARCH-type (1,1) structure from among the aforementioned univariate specifications based on the minimization of the

\(^7\) The augmented Dickey–Fuller unit root test was conducted and the null hypothesis was rejected in all cases. The test results for the different ETF returns are presented in Table 3.

\(^8\) The parameters \( \alpha, \beta, \xi \) and \( \nu \) of the correlation model equation are estimated by maximizing the logarithm of the Skewed t-Student quasi-likelihood.
Akaike Information Criterion (AIC). From Table 10 (Appendix B) the specification that minimizes the AIC for the study of emerging and developed stock markets can be assessed. The ADCC-AR(1)-GARCH(1,1) model shows the best fit for the study of the correlations between the II and the stock market for the series in log-returns, whereas the ADCC-AR(1)-CS-GARCH(1,1) is the pertinent choice when dealing with the correlations among II and stock market in terms of frequency decompositions. When measuring correlations between the MCI and the stock markets, the model selected on the basis of AIC is the ADCC-AR(1)-CS-GARCH(1,1), except for series at frequency d6, where the ADCC-AR(1)-I-GARCH(1,1) is chosen. Lastly, for the case of correlations among the MHI and stock markets, the choice is the ADCC-AR(1)-CS-GARCH(1,1) model.

Table 11 in Appendix B provides the estimation parameters that fit the correlation process among the stock market and the II in terms of log-returns. Overall, we find that the univariate $\alpha$ and $\beta$ parameters are statistically significant. We find slightly higher $\alpha$ and $\beta$ parameters on average for panic indexes than for ETFs, which seems to indicate that new information shocks are more influential and persistent in equity markets than in pandemic news-related series. Furthermore, the Q and LM tests validate our analysis, as in most cases (especially for ETFs) they report time independence for both residuals and squared residuals. Thus, we are ensuring well-filtered innovation series as an input for the subsequent multivariate estimation. At the multivariate level, we find that both the parameters related to persistence ($\alpha_{ADCC}$ and $\beta_{ADCC}$) and those of skewness ($\xi_{ADCC}$) and shape ($\nu_{ADCC}$) are highly significant, indicating that the process properly captures both the connectedness in the mid-range of the dependence distribution and in the tails of the multivariate distribution, also considering the existing jumps. Specifically, the low value of the $\alpha_{ADCC}$ parameter and the high value of the $\beta_{ADCC}$ indicate that the new information shocks affect the dependence process weakly, but take a long time to disappear, i.e., they persist.

Second, once the parameters have been calibrated and the models have been properly estimated, Figs. 3–5 depict the dynamics of the conditional correlations between the panic indexes (MCI, MHI and II) and the stock markets (MSCI ETFs) for each model calibrated. Each figure includes an upper subplot depicting the time evolution of the correlations for the BRICS countries, and a lower subplot displaying the dependencies related to the G7 countries. As a benchmark, both subplots present the correlations between the global world pandemic anxiety index and the global world ETF. The oscillating nature of these correlations in terms of original returns limits the extent to which the aforementioned Figures can be interpreted. The wavelet decomposition of the original return series into different time–frequencies now provides a more detailed understanding of the connection between panic indexes and stock market movements. Figs. 6–8 present the correlations between the low frequency components (d6) of the original series which capture the long-term investment horizons.

In Tables 6 and 7, the mean correlations between the three panic indexes and the returns and time–frequency components are shown for each country and for both subperiods. An overlapping of lines is observed between the groups of developed and emerging countries with the correlations for stock market returns and panic indexes (Figs. 3–5). It is noteworthy that the correlations oscillate around low values in absolute terms. Higher correlations have been observed with the outbreak of the pandemic and at specific times depending on the country. COVID–19 cases and deaths have evolved differently in different countries, which might explain the observed asynchrony in the jumps. Tables 6 and 7 illustrate that, overall, all the countries present a negative correlation, but close to zero for the three panic indexes, which is slightly lower in the second subperiod. Nevertheless, there are only minor differences between the two subperiods. Also, it is noteworthy that developing countries exhibit higher correlations in absolute terms than emerging markets, except for the MCI index, which appears to be more influential in emerging markets.

Correlations usually fluctuate between $-0.20$ and $+0.20$, with peaks of $-0.40$ and $+0.33$. The correlation between MCI (number of news sources) and II (percentage of media outlets) with stock market returns is quite similar. In both cases, the most negative correlations are found in Italy, the UK, and France, while the correlations closest to zero are found in Canada, India, and the USA. It is slightly different in the case of the MHI (the amount of news). MHI has the lowest average negative correlation with stock market returns in all developed countries, while it has almost no correlation with stock market returns in emerging economies.

Tables 6 and 7 also show the mean and standard deviation of the correlation between our panic indexes and VIX, which has been referred to as a panic index in many previous studies. The absolute value of these figures is too low to represent the same reality. The conditional correlation average values range from $-0.03$ for II in the second subperiod to $0.06$ for the MHI in the first subperiod. In spite of the fact that all of these are considered panic indexes, they are actually measuring different aspects of panic. Our panic indexes are based on COVID–19 media coverage indicators for each country, and VIX measures the expectation of “implied” stock-market volatility in the prices of options on the S&P 500 index.

Figs. 6–8 show the time evolution of the dynamic correlation between the low frequency components (d6) of the stock market returns and the RavenPack indexes. Most countries show a fairly consistent pattern across all three Figures, with some differences in levels and some lags and leads. The largest discrepancies are observed in South Africa and Russia. During the sample period, there is an initial hump with mostly positive correlations, followed by a valley or U-shape with

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9 For the sake of brevity, the remaining estimations regarding the different frequencies and considered indexes will be provided upon author request.

10 There is a much greater variability in the correlation processes for frequencies d1 and d3 than for frequencies d6. For the sake of brevity, the Figures corresponding to high (d1) and medium (d3) frequency components are not included, but are all available upon author request.
Fig. 3. Correlations between stock market returns and MCI in log-differences. Pairwise correlations between each country's ETF returns and its MCI in log-differences. BRICS are shown above and G7 below. The correlation between the world's MSCI ETF and the MCI at worldwide level is shown in both plots as a benchmark.

a minimum around April 2020. A clear and long hump lies behind this valley, spanning half a year for many countries, providing the highest positive correlations. This period begins with the end of the lockdowns and the lifting of other anti-COVID measures and ends with the rebound in new cases of COVID-19. The stock market has continued to recover in this period. As of the last few months of 2020, correlations have stabilized around −0.20 and +0.20, although in several cases, a new valley with more negative relations is observed towards the middle of 2021, which coincides with the rebound in the number of COVID-19 deaths.

There is a moderate correlation between low time–frequency fluctuations in returns (d6) and panic indexes (Tables 6 and 7). These average values of correlation illustrate how high positive correlations in certain periods tend to be compensated for by high negative correlations in other periods, as shown in the Figures. Even though the Figures showed differences between developed and emerging countries, these differences are not evidenced in the average daily correlation values, which are fairly similar. The mean correlation ranges from +0.08 for the three panic indexes in the developed countries (also the MHI in emerging countries) to +0.02 for the MCI in emerging countries during the first year of the pandemic. The correlations are slightly reduced in the second subperiod, ranging between −0.07 with the MHI and −0.01 with the MCI for the developed countries.

Across each group of countries, the mean values of the correlation between panic indexes and low time–frequencies (d6) exhibit greater divergences. The highest correlations in the case of II index are observed in the first subperiod with the USA, Canada, and Germany (0.21, 0.17, and 0.15 respectively), while the lowest average correlations are observed with the UK in the first subperiod (−0.09), and with Russia and France in both subperiods (−0.09 and −0.08). Similarly, the average correlations for the two other indexes are also noteworthy. The values for MCI range between 0.15, 0.14, and 0.12 for Italy, Brazil, and Canada in the first subperiod, and −0.14 and −0.11 for India and the UK in the second subperiod. Lastly, the mean correlations of the MHI reach their maximum values for the USA and South Africa in the first subperiod (0.14 and 0.13, respectively) and their minimum values for France, the UK and Germany in the second subperiod (−0.18, −0.12 and −0.11).

In light of all the above, we may conclude that panic indexes have played an important role in explaining movements in stock market returns on developed and emerging economies. In spite of the similarities in behavior patterns, the impact varies over time and is affected by the economic and health situation in each country. Phase patterns in all countries are very similar, with certain leads and lags and periods of greater positive correlations and greater negative correlations, characterized by hump-shaped and valley-shaped stages. The results of this study are consistent with those of previous

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Fig. 4. Correlations between stock market returns and MHI in log-differences. Pair-wise correlations between each country's ETF and its MHI in log-differences. BRICS are shown above and G7 below. The correlation between the world's MSCI ETF and the MHI at worldwide level is shown in both plots as a benchmark.

We have obtained consistent and conclusive findings in previous sections, supporting the existence of a relationship between what we called panic indexes and the evolution of stock markets in developed as well as emerging economies over a two-year period. The three panic indexes considered in this study, i.e. II, MCI and MHI, are COVID-19 indexes reported by RavenPack. There are several papers that use at least one of the seven RavenPack COVID-19 indexes as a proxy for market sentiment (Baig et al., 2021; Haroon and Rizvi, 2020a), the COVID-19 related news (Cepoi, 2020; Haroon and Rizvi, 2020a; Rakshit and Neog, 2021), and the investor panic (Haroon and Rizvi, 2020a; Umar and Gubareva, 2020; Umar et al., 2021). Even with these different denominations, these indexes are in fact media coverage indexes of the COVID-19 pandemic. As such, these indexes have faced several challenges.

Firstly, literature on media hypes documents that these are relatively brief periods of intensive media coverage that are eventually followed by a progressive disinterest on the part of both audiences and media.\footnote{\textsuperscript{11} It is well documented that media coverage of diseases, famines, wars, and deaths can be characterized by several week-long hypes. The stage of alarmed discovery is followed by some sort of fatigue in the media, with the audience, and/or with the players (Moeller, 2002). Downs (1972) suggests that declining public interest can be attributed to discouragement, repression of feelings by people who are threatened by the issue, and} We observe this typical hump
with the peak in media coverage occurring in mid-March 2020 and the rapid decline through May 2020. Considering two years of media coverage of COVID-19 does not conform to these studies. After the media hump ended in June 2020, the analysis should have been particularly challenging. Despite all this, our results indicate that the correlation between these indexes and stock market returns held over the full two-year sampling period.

Secondly, a large media coverage of a pandemic does not necessarily lead to a greater sense of panic, except in the early stages of the outbreak or when new variants are emerging. COVID-19 news were sometimes positive, sometimes negative. The media coverage associated with the start of testing the first vaccines and the start of the mass vaccination, for example, caused the population to become more hopeful rather than panicked. In the same way, COVID-19 media coverage also captures the information related to measures taken by central banks to provide further monetary policy accommodation in order to ensure well-functioning financial markets, as well as measures taken by governments to support workers and businesses and contribute to the real economic recovery. Consequently, there can be a variable relationship between media coverage, panic, and investor sentiment over time. In addition, to measure panic generated by bad news regarding COVID-19, these indexes also capture good news that could lead to an increase in the investor optimism. The results should be interpreted more appropriately as a result of media coverage of COVID-19 on stock market returns rather than as a result of investor panic.

5. Conclusions

The COVID-19 outbreak in early 2020 was completely unexpected for international financial markets, giving rise to a scenario of great uncertainty that influenced investor decisions. The outbreak started in China, but the gradual spread of the disease worldwide resulted in an unprecedented deterioration of international trade relationships. As a result, financial markets panicked, and governments and central banks had to implement extraordinary stimulus measures to prevent the economy from collapsing. This paper aims to provide further insights on the relations between the panic caused by the successive waves of the COVID-19 pandemic, measured through pandemic media coverage indexes, and the international boredom. Due to market mechanisms the media are forced to move on to covering new issues as soon as their audience’s interest declines. Based on the experience of previous pandemics, Huremović (2019) states that societies usually respond to infectious diseases that spread rapidly by first observing the outbreak with great interest, horror, and panic, and then dispassionately ignoring it as soon as it subsides.
revealed for the two subperiods under analysis. On the other hand, similarly to the Granger study, conditional correlations are in the lowest frequencies or long-term horizons where the largest number of statistically significant evidences are impact on the raw stock market returns, but the reverse occurs in terms of time–frequency decompositions. Indeed, it Granger test results suggest that changes in panic indexes resulting from the COVID-19 pandemic do not cause a significant effect on the analysis of the underlying connections between stock markets and pandemic fear.

Our study reveals several appealing findings for academics, policy makers and practitioners. On the one hand, our Granger test results suggest that changes in panic indexes resulting from the COVID-19 pandemic do not cause a significant impact on the raw stock market returns, but the reverse occurs in terms of time–frequency decompositions. Indeed, it is in the lowest frequencies or long-term horizons where the largest number of statistically significant evidences are revealed for the two subperiods under analysis. On the other hand, similarly to the Granger study, conditional correlations offer much more information when conducted on wavelet decompositions than in terms of raw returns, confirming the relevance of our research technique. Based on our connectedness findings, panic indexes have played an important role in the economic analysis and policy-making process.
in explaining stock market movements in both developed and emerging economies. Though the behavior patterns are similar, their impact varies over time depending on the country’s economic and health conditions. Each country has a similar pattern of phase transitions in which certain stages are preceded by a hump and others by a valley, i.e., undergoing both positive and negative correlations.

Regarding the first year of the pandemic, our study confirms the findings of previous literature and concludes that the COVID-19 disease is related to a volatility spike in the stock market and a number of subsequent declines over the first quarter of 2020. Our study goes beyond the scope of previous literature by extending the analysis up to the early 2022, covering several waves of contagions observed during the second year of the pandemic as well as the impact of monetary stimulus policies and vaccination programs. The results show that both causal relationships and correlations between financial markets and panic indexes held during 2021 and early 2022 despite the gradual reduction in media coverage. Investors and policy makers should be aware that COVID-19-related news affects financial markets not only during the initial months of the pandemic but also continues over time. An interesting extension for this study would be to consider indicators of the evolution of the real economy, such as unemployment rates, industrial production or retail trade.
Fig. 6. d6 correlations between national ETF returns and MCI in log-differences. Pairwise correlations between each country’s ETF returns and its MCI in log-differences at the d6 component. BRICS are shown above and G7 below. The correlation between the world’s MSCI ETF and the MCI at worldwide level is shown in both plots as a benchmark.

sales as a variable to be explained by or connected to COVID-19 fear, and to test whether economic stimulus policies in the face of the pandemic would have been successful in this area as well.

CRediT authorship contribution statement

Paula Cervantes: Data curation, Formal analysis, Investigation, Methodology, Software, Writing – original draft. Antonio Díaz: Formal analysis, Investigation, Methodology, Project administration, Supervision, Validation, Writing – review & editing. Carlos Esparcia: Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Software, Supervision, Validation, Writing – review & editing. Diego Huélamo: Data curation, Formal analysis, Investigation, Methodology, Software, Writing – original draft.

Appendix A. Univariate GARCH models

A.1. Standard GARCH model

Originally proposed in Bollerslev (1986), the Generalized Autoregressive Conditional Heteroscedasticity model (GARCH) specified with one lag for both the innovation term and the variance, can be expressed as follows:

$$\sigma_t^2 = \omega + \alpha \eta_{t-1}^2 + \beta \sigma_{t-1}^2$$

where $\omega$ is the model intercept, $\alpha$ captures the influence of past innovations $\eta_{t-1}$ on the conditional variance $\sigma_t^2$ and $\beta$ is the autoregressive parameter.

A.2. iGARCH model

The integrated GARCH model iGARCH developed by Engle and Bollerslev (1986) is a further variant of the GARCH model. It assumes that the persistence of the variance $\alpha + \beta = 1$. In other words, the effect of innovations on the conditional variance does not disappear because the model considers that past information remains important for all periods $t$. In
addition, the variance does not show mean reversion. Therefore, a long time must elapse before the variance returns to its mean value. This being the case, the conditional variance equation for the model can be written as follows:

$$\sigma^2_t = \omega + \sigma^2_t - 1 + \alpha(\eta^2_{t-1} - \sigma^2_t)$$ (10)

where, under conditional normality, $\eta^2_t$ is strictly stationary and ergodic if $\omega > 0$.

A.3. E-GARCH model

The virtue of the exponential GARCH model (E-GARCH) developed by Nelson (1991) is its ability to capture the asymmetric effect that positive and negative shocks have on volatility. The model is useful in capturing the leverage effect, that is, when positive and negative shocks have effects of different magnitude on volatility. In the financial series, it can be seen that volatility is higher when prices fall and tends to be lower when prices rise. The E-GARCH model attempts to model this asymmetry in volatility.

The equation defining the logarithm of the conditional variance is presented below: it depends on both the magnitude and sign of the lagged residuals

$$\ln(\sigma^2_t) = \omega + \alpha \eta_{t-1} + \beta \ln(\sigma^2_{t-1}) + \gamma \left( |\eta_{t-1}| - \sqrt{2/\pi} \right) \Theta g(\eta_t - j)$$

where $\omega$ is the model intercept, $\alpha$ captures the influence of past innovations $\eta_{t-1}$ on the conditional variance $\sigma^2_t$, $\beta$ is the autoregressive parameter and $\gamma$ captures the leverage effect, with $\sqrt{2/\pi}$ representing the expected absolute value of residuals.

A.4. GJR-GARCH model

The model proposed by Glosten et al. (1993) can capture clustering of the volatility in the series, heavy tails, skewness, and leverage effects. The indicator function distinguishes between positive and negative shocks. Therefore, the conditional variance specification of a GJR-GARCH(1,1) model, is expressed as follows:

$$\sigma^2_t = \omega + (\alpha + \gamma \mathbb{1}_{t-1}) \eta^2_{t-1} + \beta \sigma^2_{t-1}$$ (11)
Fig. 8. d6 correlations between national ETF returns and II in log-differences. Pairwise correlations between each country’s ETF returns and its II in log-differences at the d6 component. BRICS are shown above and G7 below. The correlation between the world’s MSCI ETF and the II at worldwide level is shown in both plots as a benchmark.

where:

\[ I_{t-1} = \begin{cases} 
1 & \text{if } \eta_{t-1} < 0 \\
0 & \text{if } \eta_{t-1} \geq 0 
\end{cases} \]

This model usually provides a good fit to financial series because, as it allows to capture leverage effects (Tavares et al., 2008).

A.5. C-GARCH model

The component GARCH model (C-GARCH), proposed by Lee and Engle (1993), is characterized by the intercept parameter, which consists of a time-varying first-order autoregressive process. This allows us to study in greater depth the short- and long-term volatility movements. The C-GARCH(1,1) specification is presented below:

\[ \sigma_t^2 = q_t + \alpha(\eta_{t-1}^2 - q_{t-1}) + \beta(\sigma_{t-1}^2 - q_{t-1}) \]  \hspace{1cm} (12)

where \( q_t \) is the permanent component of the conditional variance:

\[ q_t = \omega + \rho q_{t-1} + \eta(\nu_{t-1}^2 - \sigma_{t-1}^2) \]  \hspace{1cm} (13)

The stationarity of the process holds if \( \omega + \beta < 1 \) and \( \rho < 1 \). The conditions of non-negativity of the conditional variance can be seen in Lee and Engle (1993).

Regarding the properties of the model, it is observed that the conditional variance is composed of two factors: first, a permanent component that defines the trend of the process, and second, a transitory component, which is nothing more than the difference between the conditional variance and its trend, \( \sigma_t^2 - q_t \).

Appendix B. Tables

See Tables 8–11.
Table 8
Granger test on linear causality from pandemic indexes log-differences towards ETF returns from January 17, 2020 to January 29, 2021.

| Infodemic Index | World | VIX | Brazil | Russia | India | China | South Africa | Canada | USA | France | Italy | Japan | UK |
|-----------------|-------|-----|--------|--------|-------|-------|-------------|--------|-----|--------|-------|-------|----|
| Returns         | 0.22  | 0.26 | 0.502  | 0.657  | 0.139 | 0.363 | 0.99        | 0.179  | 0.070 | 0.178  | 0.922 | 0.719 | 0.59 | 0.519 |
| d1              | 6     | 6    | 2      | 2      | 6     | 4     | 2           | 5      | 0.023 | 0.028  | 0.072 | 0.785 | 0.152 | 0.858 |
| d3              | 0.666 | 0.044 | 0.012 | 0.413 | 0.84  | 0.229 | 0*          | 0**    | 0.005 | 0.011  | 0.206 | 0**   | 0.657 | 0.911 |
| dis             | 18    | 18   | 18     | 18     | 18    | 18    | 18          | 18     | 18   | 18     | 18    | 18    | 18   | 18    |
| For each country, the p-value of the test is presented, where *, **, *** indicate significance at the 10%, 5% and 1%, respectively. Below each p-value, the lag for which the test is applied is shown.

Table 9
Granger test on linear causality from pandemic indexes log-differences towards ETF returns from February 1, 2021 to February 16, 2022.

| Infodemic Index | World | VIX | Brazil | Russia | India | China | South Africa | Canada | USA | France | Italy | Japan | UK |
|-----------------|-------|-----|--------|--------|-------|-------|-------------|--------|-----|--------|-------|-------|----|
| Returns         | 0.352 | 0.036 | 0.042 | 0.575  | 0.312 | 0.187 | 0.926       | 0.911  | 0.317 | 0.67   | 0.048  | 0.933  | 0.295 | 0.956 |
| d1              | 4     | 4    | 4      | 2      | 4     | 2     | 4           | 4      | 4    | 4      | 4     | 4     | 4   |
| d3              | 0.287 | 0.032 | 0.308 | 0.758  | 0.816 | 0.373 | 0.072*      | 0.595  | 0.024 | 0.27   | 0.052  | 0.448  | 0.336 | 0.773 |
| dis             | 18    | 18   | 18     | 18     | 18    | 18    | 18          | 18     | 18   | 18     | 18    | 18    | 18   |
| For each country, the p-value of the test is presented, where *, **, *** indicate significance at the 10%, 5% and 1%, respectively. Below each p-value, the lag for which the test is applied is shown.
Table 10

Information criteria.

| Infodemic Index | GARCH | E-GARCH | QR-GARCH | C-GARCH | iGARCH |
|-----------------|-------|---------|----------|---------|--------|
| Returns         | −116.18 | −115.49 | −115.85  | −116.11 | −115.62 |
| d1              | −145.16 | −144.05 | −144.96  | −145.90 | −144.75 |
| d3              | −208.31 | −207.36 | −208.07  | −208.32 | −208.21 |
| d6              | −346.78 | −346.03 | −346.72  | −347.24 | −346.96 |

| Media Coverage Index | Returns | d1 | d3 | d6 |
|----------------------|---------|----|----|----|
| Returns              | −121.74 | −121.71 | −121.65 | −121.88 |
| d1                   | −151.26 | −150.93 | −151.17 | −152.24 |
| d3                   | −214.29 | −213.60 | −214.08 | −214.42 |
| d6                   | −340.54 | −348.95 | −340.73 | −349.98 |

| Media Type Index | Returns | d1 | d3 | d6 |
|-----------------|---------|----|----|----|
| Returns         | −109.78 | −109.73 | −109.67 | −109.94 |
| d1              | −139.84 | −139.27 | −139.58 | −140.55 |
| d3              | −202.45 | −201.44 | −202.24 | −202.68 |
| d6              | −339.27 | −338.76 | −339.33 | −339.88 |

Akaike Information Criteria (AIC) of the different GARCH-type models used to fit the univariate conditional variances. The model that minimize the AIC, indicated in bold, is the one chosen.

Table 11

II. ADCC-AR(1)-GARCH(1,1) model.

- Panel A: ETF returns
- Panel B: parameters of the variance equation
- Panel C: Infodemic Index log-differences
- Panel D: parameters of the variance equation
- Panel E: ADCC parameters

Sections A and B show the parameter estimates and, in parenthesis, the t-statistics of the AR(1) and GARCH(1,1) used to fit the conditional mean and variance of the ETF returns and pandemic indexes log-differences, respectively. Ljung-Box (Q) and Lagrange-Multiplier (LM) statistics calculated with one and seven lags, respectively, are reported to evaluate first order autocorrelation. The p-value of these tests is reported in parenthesis below the statistic. Section C contains the estimation and t-statistic of the joint distribution parameters and the different information criteria: Akaike Information Criteria (AIC), Bayes Information Criteria, Shibata Information Criteria and Hannan-Quinn Criteria. *, ** and *** indicate significance at 10%, 5% and 1% confidence levels, respectively.

References

Akhtaruzzaman, M., Boubaker, S., Sensoy, A., 2021. Financial contagion during COVID–19 crisis. Finance Res. Lett. 38, 101604.
Albuslecu, C., 2020. Coronavirus and financial volatility: 40 days of fasting and fear. arXiv preprint arXiv:2003.04005.
Ashraf, B.N., 2020. Stock markets’ reaction to COVID-19: Cases or fatalities? Res. Int. Bus. Finance 54, 101249.
Xu, L., 2021. Stock return and the COVID-19 pandemic: Evidence from Canada and the US. Finance Res. Lett. 38, 101872.
Yong, H.H.A., Laing, E., 2021. Stock market reaction to COVID-19: Evidence from US firms’ international exposure. Int. Rev. Financ. Anal. 76, 101656.
Yousfi, M., Zaied, Y.B., Cheikh, N.B., Lahouel, B.B., Bouzgarrou, H., 2021. Effects of the COVID-19 pandemic on the US stock market and uncertainty: A comparative assessment between the first and second waves. Technol. Forecast. Soc. Change 167, 120710.
Yu, X., Xiao, K., Liu, J., 2021. Dynamic co-movements of COVID-19 pandemic anxieties and stock market returns. Finance Res. Lett. 102219.
Zouaoui, M., Nouyrigat, G., Beer, F., 2011. How does investor sentiment affect stock market crises? Evidence from panel data. Financial Rev. 46 (4), 723–747.