Emerging and advanced economies markets behaviour during the COVID-19 crisis era

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Abstract
This article examines the consequences of the COVID-19 crisis on the interdependencies between emerging and advanced economies. Using daily market index data from 22 developed and emerging markets, we develop a combination of statistical methods based on Diebold and Yilmaz spillover index and Toda–Yamamoto and Dolado and Lütkepohl causality approach. The results substantiate an increase in the interdependence between emerging and advanced economies, which suggests an increase in the transmission of the stress and uncertainty between financial markets during the pandemic period. Our findings show that the emerging countries are affected by the financial markets of advanced economies during the COVID-19 crisis and, in particular, by European markets, which appear to be the primary driver of contagion and transmission of stress and uncertainty to all other regional markets.

KEYWORDS
contagion effect, COVID-19, developed economies, emerging economies, equity markets

1 | INTRODUCTION

After being first identified in Wuhan City in 2019,1 the COVID-19 – a new strain of coronavirus from the SARS species – was declared a global pandemic by the World Health Organization on 11 March 2020. Two months before that date, on 15 January, to be precise, the risk of ‘infectious diseases’ was considered unlikely by the World Economic Forum’s Global Risks Report 2020. The pandemic is now present in almost all countries, changing the outlook unexpectedly and foreshadowing severe human, economic, and financial consequences (Ozili and Arun, 2020; Belaid, Youssef, Chiao, & Guesmi, 2020).2 Indeed, following the transition of the recent COVID-19 from a regional crisis in China’s Hubei Province to a global pandemic, stocks have fallen, and market volatility has risen sharply around the world. Including the Spanish flu, no previous pandemic has had such a damaging impact on the global economy and stock market as COVID-19.

However, even before the appearance of the COVID-19, there was some research in the literature that had already explored the economic and financial risks of pandemics and infectious diseases (Barro, Ursua, & Weng, 2020; Fan, Jamison, & Summers, 2018; Saker, Lee, Cannito, & Gilmore, 2004). For instance, Saker et al. (2004) explored the potential economic, environmental, demographic and technological consequences of infectious diseases in a highly integrated world. Their results suggest that there are potentially positive and negative impacts of globalization on the burden of infectious diseases. In 2018, a Bulletin of the World Health Organization had already estimated the losses (in terms of national incomes) that might occur as the result of a major epidemic or pandemic to be around 500 billion U.S. dollars per year, that is, 0.6% of global income (Fan et al., 2018). According to Barro et al. (2020), the three waves of the Spanish Flu pandemic (1918–1920) reduced the real per capita GDP by 6% on average in the 43 countries for which detailed data are available and killed about 2% of humans at the time. About a century after the Spanish flu,
the COVID-19 outbreak hits almost all the world countries in a concise period. Given its very high human, economic and financial costs, this pandemic is currently receiving increasing attention among researchers and policymakers.3

Over the past two decades, the overlap of several factors has led to greater international financial markets integration (Gamba-Santamaria et al., 2019). Greater financial integration implies more significant interaction between markets, which is likely to exacerbate the cross-border effects of the COVID-19 pandemic. Indeed, the financial deregulation that has taken place since the 1980s and the financial innovation movement that has accompanied it has not only intensified the speed at which crises spread through markets and economies but have also contributed to the amplification of their effects and the lengthening of their duration (Ait-Sahalia, Cacho-Diaz, & Laeven, 2015; Forbes & Rigobon, 2002).

The study of the interdependency between financial markets has recently received particular attention in the literature (see among others: Diebold & Yilmaz, 2009, 2012; Antonakakis & Badinger, 2016; Belke & Dubova, 2018; Bouri, Cepni, Gabauer, & Gupta, 2020; Bouri, Demirer, Gupta, & Pierdzioch, 2020; Ben Amar, Bélaïd, Ben Youssef, & Guesmi, 2020; Ben Amar, Bélaïd, Ben Youssef, Chiao, & Guesmi, 2020; Gupta, Subramaniam, Bouri, & Ji, 2021). Indeed, understanding the interdependence between different financial markets would allow investors and regulators to understand better why and to what extent markets vary together and to make decisions accordingly (Kang, McIver, & Yoon, 2017; King & Wadhwani, 1990; Liu, Gao, Hou, & Tan, 2019; Mensi, Beljïd, Boubaker, & Managi, 2013; Silvennoinen & Thorp, 2013). Several econometric methodologies can be used to investigate the spread of financial disturbances among different markets. For instance, Kenourgios, Samitas, and Paltalidis (2011) report alternative tests of contagion under the frameworks of dynamic conditional correlation models, regime-switching models (see Baele and Inghelbrecht, 2010), and copulas (see Rodríguez, 2007). For instance, Diebold and Yilmaz (2012) used a generalized vector autoregressive framework to measure total, directional and net volatility spillovers among U.S. stock, bond, foreign exchange and commodities markets from January 1999 to January 2010. Their results show that Lehman Brothers' bankruptcy on 15 September 2008 has intensified the cross-market volatility spillovers. Antonakakis and Badinger (2016) used the Diebold and Yilmaz's (2012) measure of spillover to explore the relationship between economic growth and output volatility in the G7 countries over the period February 1958 to August 2013 and find that spillovers have jumped to unprecedented levels during the 2008 financial crisis, with the United States being the largest transmitter of growth and volatility shocks. In the same vein, Belke and Dubova (2018) focus on the volatility spillovers within and across bond and stock markets in four systemic markets (U.S. Euro area, Japan and UK) on daily data spanning from 3 January 1995 to 31 October 2016. Using the Diebold and Yilmaz’s (2012) framework, they show that across classes, spillovers in almost all markets have increased after the global financial crisis. Using a TVP-VAR connectedness approach, Bouri, Cepni, et al. (2020) investigate connectedness among five types of assets (gold, oil, equities, currencies and bonds) before and during the COVID-19 outbreak. Their results reveal that the intensity of interdependence across the five assets was moderate and broadly stable before the COVID-19 outbreak but became much more pronounced during the COVID-19 crisis, reflecting the speedy disruptive effects of the COVID-19 outbreak, which matters for investors and regulators when dealing with financial risks. Al-Awadhi, Al-Saifi, Al-Awadhi, and Alhamadi (2020), Ben Amar, Hachicha, and Halouani (2020), and Bouri, Demirer, et al. (2020) confirm these disruptive effects of the COVID-19 outbreak. These findings are consistent with earlier studies that have examined how financial markets responded to previous epidemic diseases as the SARS outbreak (Chen, Chen, Tang, & Huang, 2009; Chen, Jang, & Kim, 2007) and the EVD outbreak (Ichev & Marić, 2018). More recently, Gupta et al. (2021) focus on the impact of infectious diseases-related uncertainty (EMVID) on the safe-haven characteristic of U.S. treasury securities using a DCC-MGARCH framework. The authors find evidence supporting that the U.S. treasury securities can be used as a safe-haven during the COVID-19 outbreak.

While there is considerable literature examining financial contagion and volatility transmission between financial markets, a lot of the issues are still outstanding regarding, (a) volatility spillovers as well as (b) shift contagion among country and regional stock markets around the COVID-19 outbreak. This article attempts to enrich the existing literature by examining the extent to which the magnitude of the interdependence and causal links among stock markets has evolved before and during the COVID-19 crisis. Accordingly, we develop a combination of statistical methods to investigate the COVID-19 impact on selected countries, including both developed and emerging countries. First, we use the Diebold and Yilmaz’s (2012) spillover measure to examine the independence level among stock markets in developed and emerging countries. Then we employ Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996) causality approach (TYDL) to explore the existence of shift contagion phenomenon between the two aforementioned markets. Thus, the goal of this article is threefold. First, using
the Diebold and Yilmaz’s (2012) spillover measure index investigates the evolution over time of the interdependence between developed and emerging stock markets indices, at the country and regional level, before and during the COVID-19 outbreak. Second, it uses the TYDL causality test procedure to investigate the evolution of the structure of causal links between a set of regional stock markets before and during the COVID-19 crisis. Third, and in line with Marais and Bates (2006), it uses a measure of causal intensity to highlight differences in links between the considered stock markets indices before and during the COVID-19 outbreak. Studying volatility spillovers among different markets would help understand the extent to which markets are segmented or interconnected, thus enabling investors to diversify their portfolios better and manage risk.

To the best of our knowledge, ours is the first study to address volatility spillovers as well as shift contagion among a broad spectrum of different developed and emerging markets, at both country and regional levels, around the COVID-19 outbreak.

Our empirical results are essential for both investors and policymakers. So far, it is uncertain how long and how deep the crisis will last, what form the recovery will take, and, consequently, how markets in different regions will be affected. Therefore, monitoring market developments and examining the impact of COVID-19, both in developed and emerging markets can help investors and regulators to deal effectively and adequately with financial risks related to the COVID-19 pandemic.

The remainder of this article is as follows: Section 2 presents the empirical strategy and the data. Section 3 documents and discuss the results. Section 4 concludes and offers policy implications based on the empirical results of the model.

## 2 | EMPIRICAL STRATEGY AND DATA

### 2.1 | Empirical strategy

Our empirical strategy consists of two steps. First, we use the generalized spillover index of Diebold and Yilmaz (2012), as it enables us to compute the connectedness level between stock markets while overcoming the inadequacies of potentially order-dependent outcomes due to the Cholesky factorization in the original work by Diebold and Yilmaz (2009). Diebold and Yilmaz (2012) consider a reduced N-variable VAR(p), $x_t = \sum_{i=1}^{p} \phi_i x_{t-i} + \epsilon_t$, where $x_t = (x_{1t}, x_{2t}, ..., x_{nt})$ is a vector of endogenous variables; $\phi_i$, $i = 1, ..., p$, are $N \times N$ parameter matrices and $\epsilon - (0, \Sigma)$ is a $N \times 1$ vector of iid disturbances. The moving average representation of this process is $x_t = \sum_{i=0}^{\infty} A_i \epsilon_{t-i}$, where the $N \times N$ coefficient matrices $A_i$ are recursively defined as $A_i = \phi_1 A_{i-1} + \phi_2 A_{i-2} + ... + \phi_p A_{i-p}$ with $A_0$ the $N \times N$ identity matrix and $A_i = 0$ for $i < 0$. Using the Pesaran and Shin (1998) forecast error variance decompositions, Diebold and Yilmaz (2012) define a spillover index ($S^g(H)$) as follows:

$$S^g(H) = \frac{\sum_{i=1}^{N} \tilde{\theta}^g_{ij}(H)}{n} \cdot 100, \text{with} \tilde{\theta}^g_{ij}(H) = \frac{\theta^g_{ij}(H)}{\sum_{j=1}^{N} \theta^g_{ij}(H)}.$$  

where $\theta^g_{ij}(H)$ is the H-step-ahead forecast error variance decomposition. The $S^g(H)$ spillover index measures, on average over all variables, the contribution of volatility spillovers from shocks to all variables $j = 1, ..., N$ to the $H$-step-ahead of the total generalized forecast error variance of variables $i = 1, ..., N$, with $i \neq j$.

By using the normalized elements of the generalized variance decomposition matrix, this approach enables us to calculate the directional volatility spillovers received by variable $i$ from all other variables $j$, $S^g_{i-j}(H)$, which is given by

$$S^g_{i-j}(H) = \frac{\sum_{j=1}^{N} \tilde{\theta}^g_{ij}(H)}{N} \cdot 100,$$  

and, similarly, the directional volatility spillovers transmitted by variable $i$ to all other variables $j$ is given by

$$S^g_{i-j}(H) = \frac{\sum_{j=1}^{N} \tilde{\theta}^g_{ij}(H)}{N} \cdot 100.$$  

The net volatility spillovers from variable $i$ to all other variables $j$, $S^g_i(N)$, can be obtained from Equations (2) and (3) as follows:

$$S^g_i(N) = S^g_{i-j}(H) - S^g_{i-j}(H),$$  

which indicates whether a variable $i$ is a net receiver or a net transmitter of volatility shocks.

We use, in a second step, the TYDL test, based on the works of Toda and Yamamoto (1995) and Dolado and...
Lütkepohl (1996), to examine the existence of shift contagion phenomenon between a set of regional stock markets. This approach has no restrictions on the integration order of the variables, which is consistent with financial data whose maximal integration order is usually 1 or 2.

The TYDL procedure consists of two main steps. The first step identifies the lag length \((p)\) of the VAR that will be used for the causal analysis. \((p)\) is the sum of the optimal order \((k)\) of the VAR and the maximum order of integration \((I_{\text{max}})\) of the endogenous variables in the VAR. The Schwarz (1978) Information Criterion is used to identify \(k\), and the Phillips and Perron (1988) and the KPSS (Kwiatkowski, Phillips, Schmidt, & Shin, 1992) tests are used to determine \(I_{\text{max}}\). Consequently, the VAR\((p)\), estimated in level by OLS, accurately captures the joint dynamics of the endogenous variables, whatever their integration order. The second step is to test the null hypothesis \((H_0)\) of Granger non-causality against the alternative hypothesis \((H_1)\) of Granger causality from standard Wald statistics \((WS)\) that only considers the first \(k\) matrices of coefficients. The alternative hypothesis \((H_1)\) of causality is accepted when the \(p\)-value of the WS is lower than the significance level \(\alpha\). As in Marais and Bates (2006), once \(H_0\) is rejected, we derive the elasticity of the caused variable with respect to the causal one from the estimated parameters of the VAR\((p)\) and use it as an indicator of the causal intensity.

### 2.2 Data

To test our assumptions, we use daily market index data from 22 developed and emerging markets (cf. Table 1), as well as six regional stock indices (cf. Table 2). To choose the financial markets to be examined, we first chose as a starting-point the 51 markets making up the MSCI ACWI Index (cf. MSCI ranking), which are grouped into developed markets (24 markets) and emerging markets (27 markets). We then classified their local-currency denominated stock market indices according to their respective market capitalizations (as of 12 May 2020). Finally, for each of the two categories of markets, developed and emerging markets, we selected the 11 stock indices with the largest market capitalizations. The data were collected from Bloomberg and cover the period running from 1 February 2019 to 12 May 2020 (a total of 333 observations).

To examine the return spillovers (first step), all the stock market indices are expressed in the first differences of their natural logarithm, as in Diebold and Yilmaz (2009, 2012). To investigate the existence of shift contagion (second step), and to be able to interpret the relations between variables in terms of elasticity, a log-transformation of the data is chosen, as in Marais and Bates (2006). Tables A1 and A2 in the appendix provide descriptive statistics.

### 3 Empirical Results

#### 3.1 Spillover analysis

Table 2 reports the total spillover index as well as its ‘input–output’ decomposition for both categories of countries, developed and emerging, over the full sample

| Countries       | Indices | Mnemonics | Countries       | Indices | Mnemonics |
|-----------------|---------|-----------|-----------------|---------|-----------|
| Developed       | United  | S&P 500   | US              | Emerging| KOSPI     |
| markets         | States  |           |                 | markets |           |
|                 | Canada  | S&P/TSX   | CN              | South   | CN        |
|                 | Composite|          |                 | Korea   | Korea     |
|                 | United  | FTSE 100  | UK              | China   | CSI 300   |
| Kingdom         | Germany | DAX       | GE              | Taiwan  | TCWS      |
|                 | France  | CAC 40    | FR              | Malaysia| FBM KLCI  |
|                 | Italy   | FTSE MIB  | IT              | Indonesia| JCI      |
|                 | Japan   | NIKKEI 225| JP              | Poland  | WIG 20    |
|                 | Hong    | HANG SENG | HK              | Russia  | MOEX      |
| Kong            | Singapore| FTSE Straits| Times      | Turkey  | BIST 100  |
|                 | Australia| S&P/ASX 200| AU            | India   | NIFTY     |
|                 | New Zealand| S&P/NZX 50| NZ            | Dubai   | DFM       |
|                 |          |           |                 | Saudi Arabia | TADAWUL  |
|                 |          |           |                 |         | SA        |
period. Its \((i,j)\)-th elements are the estimated contributions to the forecast error variance components of stock market return \(i\) coming from shocks to stock market return \(j\). The total spillover index for returns, reported in the south-east corner of Table 3, is the off-diagonal column (or row) sum relative to the column (or row) sum, including diagonals, expressed as a percentage. In other words, while the off-diagonal row sums (labelled from others) or column sums (labelled contr. to others), when totalled across markets, give the numerator of the spillover index, the column sums including diagonals (labelled contr. incl. own), when totalled, give the denominator of the index.

Table 3a,b presents the total, as well as the directional and net return spillovers results for developed and emerging markets. While the total spillover among the developed markets is relatively high (62.2%), indicating a high interdependence among them on average and across the entire sample, only one-third of the return forecast error variance among emerging markets results from spillovers, reflecting a weak connectedness among them. Moreover, a diagonal comparison between Table 2a and b reveals that, with contributions to own return forecast error variance ranging between 30 and 50% only, developed markets are, on average, much more open than emerging markets, which contribution to own could be

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**Table 2** Components of the MSCI regional indices

| Index | Description and included countries |
|-------|-----------------------------------|
| Developed markets | **MSCI Europe Index [EUR]**  
Captures large and mid-cap representation across 15 developed markets countries in Europe.  
Countries in MSCI Europe Index include: Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the UK. |  
**MSCI North America Index [NAM]**  
Designed to measure the performance of the large and mid-cap segments of the U.S. and Canada markets. |  
**MSCI Pacific Index [PAS]**  
Captures large and mid-cap representation across five developed markets countries in the Pacific region. Countries in the MSCI Pacific Index include: Australia, Hong Kong, Japan, New Zealand and Singapore. |
| Emerging and frontier markets | **MSCI Emerging Markets Asia Index [EMS]**  
Captures large and mid-cap representation across nine emerging markets countries. Emerging markets Asia countries include: China, India, Indonesia, Korea, Malaysia, Pakistan, the Philippines, Taiwan and Thailand. |  
**MSCI Emerging Markets Latin America Index [LAM]**  
Captures large and mid-cap representation across six emerging markets countries in Latin America. EM Latin America countries include: Argentina, Brazil, Chile, Colombia, Mexico and Peru. |  
**MSCI GCC Countries Index [GCC]**  
Captures large and mid-cap representation across GCC countries. GCC Countries include: Bahrain, Kuwait, Oman, Qatar, Saudi Arabia and United Arab Emirates. |

*Source: www.msci.com*
As high as 80%. From the directional spillovers—that is, the return spillovers to others (i) from each of the considered economies (j), we also record different intensities between the developed and emerging markets, reflecting that return spillovers differ significantly according to the level of market development, and within each market, with significant differences depending on the geographical location of the market. Indeed, not only do developed markets tend to be more integrated than emerging markets over the entire sample period but also markets tend to be geographically clustered.

| TABLE 3 Spillovers from stock market return \((j)\) to stock market return \((i)\) – full sample period |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **To \((i)\)** | **US** | **CN** | **UK** | **GE** | **FR** | **IT** | **JP** | **HK** | **SG** | **AU** | **NZ** | From others |
| US | **31.3** | 22.6 | 5.1 | 4.7 | 5.5 | 5.5 | 1.1 | 0.3 | 9.5 | 10.6 | 3.9 | 68.7 |
| CN | 20.6 | **31.9** | 3 | 4.2 | 4.2 | 4.2 | 0.9 | 0.4 | 13.8 | 12.5 | 4.1 | 68.1 |
| UK | 5.7 | 3.4 | **29.4** | 16.9 | 19.2 | 16.1 | 2.4 | 0.4 | 3 | 1.6 | 2 | 70.6 |
| GE | 4.8 | 4.1 | 16 | **27.9** | 17.5 | 18.8 | 2.5 | 0.1 | 3.6 | 2 | 2.9 | 72.1 |
| FR | 5.7 | 3.9 | 18.2 | 17.6 | **28** | 15.9 | 2.2 | 0.1 | 3.7 | 2.5 | 2.3 | 72 |
| IT | 6.7 | 4.8 | 15.3 | 18.6 | 15.9 | **27.8** | 1.4 | 0.3 | 3.4 | 3.5 | 2.3 | 72.2 |
| JP | 3.5 | 3.1 | 6.3 | 9.2 | 6.1 | 5.6 | **55** | 0.5 | 6.2 | 1.9 | 2.6 | 45 |
| HK | 3.1 | 2 | 10.5 | 13.1 | 11.4 | 8.6 | 2.6 | **42.7** | 3 | 0.8 | 2.1 | 57.3 |
| SG | 7.9 | 6.5 | 5.7 | 6.5 | 6.9 | 4.7 | 0 | 2 | **54.9** | 1.7 | 3.2 | 45.1 |
| AU | 14 | 15.2 | 2.2 | 2.9 | 4.5 | 4.2 | 1.3 | 1 | 11.6 | **39.4** | 3.5 | 60.6 |
| NZ | 9.4 | 9.1 | 2.8 | 3.8 | 4.1 | 3.6 | 0.5 | 0.5 | 14.4 | 4.5 | **47.3** | 52.7 |
| Contr. to others | 81.5 | 74.6 | 85.2 | 97.4 | 95.2 | 87.1 | 15 | 5.7 | 72.4 | 41.6 | 28.9 | **Spillover index** |
| Contr. incl. own | 112.8 | 106.6 | 114.5 | 125.2 | 123.2 | 114.9 | 70 | 48.4 | 127.3 | 81.1 | 76.2 | (684.5/1100.2) |
| Net spillovers | 12.8 | 6.5 | 14.6 | 25.3 | 23.2 | 14.9 | −30 | −51.6 | 27.3 | −19 | −23.8 | **62.2%** |

| TABLE 3 Spillovers from stock market return \((j)\) to stock market return \((i)\) – full sample period (b. Emerging markets) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **To \((i)\)** | **KR** | **CH** | **TW** | **MY** | **ID** | **PN** | **RU** | **TR** | **IN** | **DU** | **SA** | From others |
| KR | **50.2** | 0 | 13 | 12.7 | 7.5 | 4.1 | 2.4 | 6.3 | 0.8 | 1.1 | 1.7 | 49.8 |
| CH | 2.7 | **80** | 5.3 | 3.2 | 1.5 | 2 | 1.1 | 2.2 | 0.3 | 1 | 0.6 | 20 |
| TW | 13.9 | 0.3 | **51.4** | 8.7 | 12.2 | 3.2 | 2.1 | 4.7 | 0.7 | 0.3 | 2.4 | 48.6 |
| MY | 14.1 | 0.3 | 9.6 | **57.4** | 5.6 | 4 | 4.4 | 3.9 | 0.2 | 0.1 | 0.3 | 42.6 |
| ID | 12.3 | 0.1 | 13 | 6.9 | **52.9** | 4.2 | 1.7 | 6.4 | 0.3 | 0.2 | 1.9 | 47.1 |
| PN | 2.6 | 1.1 | 3.7 | 3.6 | 3.7 | **52.2** | 12.5 | 11.4 | 2.4 | 1 | 5.7 | 47.8 |
| RU | 2.4 | 0.3 | 2.2 | 3.4 | 0.4 | 6.5 | **71.3** | 9.9 | 0.8 | 0.3 | 2.6 | 28.7 |
| TR | 2.1 | 0.9 | 1.4 | 1.6 | 0.2 | 2.8 | 10 | **77.4** | 1 | 0.9 | 1.7 | 22.6 |
| IN | 7.4 | 0.5 | 8.9 | 6.6 | 8.3 | 1.6 | 4.9 | 4.3 | **50.2** | 2.8 | 4.5 | 49.8 |
| DU | 1.6 | 0.7 | 1.3 | 1.1 | 0.1 | 0.6 | 5.3 | 1.9 | 3.6 | **68.6** | 15.2 | 31.4 |
| SA | 0.1 | 0.4 | 0.3 | 1.8 | 0.5 | 1.2 | 2.4 | 1.4 | 4.5 | 13.5 | **74** | 26 |
| Contr. to others | 59.2 | 4.5 | 58.7 | 49.7 | 40 | 30.4 | 46.6 | 52.5 | 14.6 | 21.3 | 36.8 | **Spillover index** |
| Contr.incl. Own | 109.5 | 84.5 | 110.1 | 107.2 | 92.8 | 82.7 | 117.9 | 129.9 | 64.8 | 89.9 | 110.8 | (414.4/1100.1) |
| Net spillovers | 9.4 | −15.5 | 10.1 | 7.1 | −7.1 | −17.4 | 17.9 | 29.9 | −35.2 | −10.1 | 10.8 | **37.7%** |

Notes: The bold values in the diagonal represent the market’s own connectedness. A VAR of order 1 was selected: the Bayesian Information Criterion was used to choose the lag order. Values reported are variance decompositions of the estimated VAR model for the returns of the series. Variance decompositions are based on 10-days-ahead forecasts. The \((i,j)\)-th value is the estimated contribution to the variance of the 10-days-ahead stock return forecast error of country \((i)\) coming from innovations to stock returns of country \((j)\). The mnemonics are in Table 1.
In parallel with the movement towards the globalization of national markets, some economic areas have continued to improve their institutional properties, as shown by the rising number of regional economic agreements (EU, MERCOSUR, NAFTA, ASEAN etc.). These regional trade agreements result in part from a better openness of the member countries, and a desire to become more competitive in world economies. Numerous emerging regions such as the European Union and ASEAN are also keeping with these dynamics, both on the regional and global levels. However, the associations between global and regional integration are not the same in a different field.

In the table below, we present the spillovers from stock market return (j) to stock market return (i) – pre-COVID-19 period for both developed and emerging markets.

| To (i) | From (j) | US | CN | UK | GE | FR | IT | JP | HK | SG | AU | NZ | From others |
|-------|----------|----|----|----|----|----|----|----|----|----|----|----|-------------|
| US    | 61.8     | 9.2 | 4.3 | 1.9 | 8.9 | 0.3 | 0.5 | 1.3 | 0.3 | 11 | 0.4 | 38.2        |
| CN    | 16.5     | 62.7 | 3.2 | 0.6 | 3.9 | 1.3 | 0.3 | 1.1 | 0.3 | 9.8 | 0.2 | 37.3        |
| UK    | 8.7      | 3.9 | 54.5 | 0.4 | 12.3 | 0.3 | 0.6 | 0.1 | 0.1 | 19 | 0.1 | 45.5        |
| GE    | 3.1      | 1.5 | 3.2 | 63.4 | 1.9 | 23.1 | 0.1 | 0.9 | 0.8 | 1.8 | 0.1 | 36.6        |
| FR    | 4.7      | 1.8 | 2.6 | 0.8 | 71.6 | 0.8 | 0.1 | 0.8 | 0.4 | 16 | 0.4 | 28.4        |
| IT    | 1.9      | 2.6 | 6.1 | 10.7 | 3.2 | 69   | 0.2 | 1.6 | 1.2 | 3.3 | 0.3 | 31          |
| JP    | 0.5      | 0.8 | 0.1 | 0.4 | 0.4 | 95.5 | 0.2 | 0.3 | 1.3 | 0.5 | 4.5 | 4.6         |
| HK    | 1.6      | 0.3 | 0.5 | 1.7 | 0.8 | 1.7 | 0 | 92.4 | 0.2 | 0.4 | 0.3 | 7.6         |
| SG    | 0.9      | 1   | 0.5 | 0.9 | 0.6 | 1   | 0.8 | 0.2 | 93.1 | 0.3 | 0.7 | 6.9         |
| AU    | 3.3      | 1.6 | 5   | 0.7 | 17.8 | 1.1 | 0.4 | 0.4 | 0.1 | 69.5 | 0.2 | 30.5        |
| NZ    | 0.3      | 0.7 | 2   | 1.8 | 1.3 | 1   | 0.3 | 0.1 | 2.1 | 2.4 | 88.1 | 11.9        |
| Contr. to others | 41 | 23.2 | 28.1 | 19.6 | 51.1 | 31.1 | 3.3 | 6.5 | 5.7 | 65.4 | 3.3 | Spillover index |
| Contr. incl. own  | 102.8 | 85.9 | 82.7 | 83 | 122.7 | 100.1 | 98.8 | 99 | 98.8 | 134.9 | 91.3 | (278.3/1100) |
| Net spillovers  | 2.8 | −14.1 | −17.4 | −17 | 22.7 | 0.1 | −1.2 | −1.1 | −1.2 | 34.9 | −8.6 | 25.3% |

| To (i) | From (j) | KR | CH | TW | MY | ID | PN | RU | TR | IN | DU | SA | From others |
|-------|----------|----|----|----|----|----|----|----|----|----|----|----|-------------|
| KR    | 80.5     | 0.3 | 0.5 | 0.9 | 0.7 | 6.5 | 0.9 | 5.8 | 1.6 | 0.2 | 2 | 19.5 |
| CH    | 0.4      | 91.1 | 2.5 | 0.5 | 0.6 | 1   | 0.7 | 0.2 | 0.7 | 2   | 0.4 | 8.9 |
| TW    | 0.8      | 1.1 | 90.7 | 0.3 | 1.3 | 0.3 | 0.7 | 0.6 | 2   | 1.5 | 0.8 | 9.3 |
| MY    | 1.6      | 0.6 | 0.1 | 87.9 | 3.2 | 2.2 | 0.8 | 0.4 | 0   | 2.3 | 1 | 12.1 |
| ID    | 2.2      | 2.5 | 0.1 | 2.9 | 83.6 | 0.7 | 1.2 | 3.2 | 0.7 | 0.9 | 2.2 | 16.4 |
| PN    | 4.5      | 0.2 | 0   | 2.1 | 0.7 | 82.4 | 4.8 | 1.3 | 0.8 | 0   | 3.2 | 17.6 |
| RU    | 0.8      | 0.5 | 0.8 | 1.1 | 2.6 | 0.9 | 91.1 | 1.8 | 0.2 | 0   | 0.2 | 8.9 |
| TR    | 6.2      | 0.1 | 0.3 | 1.5 | 0.4 | 1.6 | 2.2 | 85.8 | 0   | 1.4 | 0.4 | 14.2 |
| IN    | 2.3      | 0.2 | 1.5 | 0.2 | 0.3 | 1.1 | 1.1 | 0.3 | 91.5 | 1.4 | 0.3 | 8.5 |
| DU    | 0.2      | 2.4 | 0.8 | 1.8 | 0   | 0   | 0.2 | 1   | 0   | 88.2 | 5.3 | 11.8 |
| SA    | 0.3      | 1   | 0.1 | 0.8 | 1   | 0.1 | 0.2 | 0.2 | 0   | 0.2 | 96.1 | 3.9 |
| Contr. to others | 19.1 | 8.9 | 6.6 | 11.9 | 10.8 | 14.4 | 12.9 | 14.7 | 6.2 | 10 | 15.7 |
| Contr. incl. own  | 99.6 | 100 | 97.3 | 99.8 | 94.4 | 96.8 | 104 | 100.5 | 97.6 | 98.2 | 111.8 | (131.2/1100) |
| Net spillovers  | −0.4 | 0   | −2.7 | −0.2 | −5.6 | −3.2 | 4   | 0.5 | −2.3 | −1.8 | 11.8 | 11.90% |

Notes: The bold values in the diagonal represent the market’s own connectedness. A VAR of order 1 was selected: the Bayesian Information Criterion was used to choose the lag order. Values reported are variance decompositions of the estimated VAR model for the returns of the series. Variance decompositions are based on 10-days-ahead forecasts. The (i,j)-th value is the estimated contribution to the variance of the 10-days-ahead stock return forecast error of country i coming from innovations to stock returns of country j. The mnemonics are in Table 1.
For example, in Asia, international integration is headed the regional one. In Europe, the dynamic of integration is different; the regional integration preceded international integration. In the context of the COVID-19 pandemic, the process of economic integration has become faster and uncontrollable. In Table 2, we observe that both the evolution and the level of shocks are different across regions. Specifically, the degree of market integration in Europe during COVID-19 pandemic crisis times, for example, shocks to the French stock market returns are responsible for only 19.2% of the error variance in forecasting the 10-days-ahead UK returns.

### Table 5: Spillovers from stock market return (j) to stock market return (i) – COVID-19 period

| To (i) | US | CN | UK | GE | FR | IT | JP | HK | SG | AU | NZ | From others |
|-------|----|----|----|----|----|----|----|----|----|----|----|-------------|
| US    | 25.4 | 20.7 | 5.3 | 6.7 | 6.5 | 6.5 | 1.3 | 0.9 | 11.2 | 10.5 | 5 | 74.6 |
| CN    | 19.4 | 26.2 | 3.5 | 5.5 | 5.8 | 4.9 | 1.2 | 0.6 | 16.1 | 11.9 | 4.8 | 73.8 |
| UK    | 6.4 | 4.7 | 21.5 | 18.5 | 19.1 | 16.9 | 2.5 | 0.9 | 4.2 | 1.5 | 3.7 | 78.5 |
| GE    | 6.6 | 5.2 | 16.9 | 20.2 | 19.2 | 16.5 | 2.8 | 0.7 | 5.5 | 2.1 | 4.2 | 79.8 |
| FR    | 6.5 | 5.3 | 17.4 | 19 | 19.9 | 16.2 | 2.8 | 1 | 5.8 | 2.1 | 4 | 80.1 |
| IT    | 8 | 6 | 16.3 | 17.1 | 17.1 | 20.6 | 2 | 0.7 | 4.5 | 3.8 | 3.9 | 79.4 |
| JP    | 5.6 | 4.3 | 8 | 12.6 | 10.5 | 8.5 | 34.8 | 0.9 | 8.3 | 3.1 | 3.4 | 65.2 |
| HK    | 4.9 | 3.9 | 14.6 | 15.5 | 16.4 | 9.6 | 4.3 | 20.6 | 4.9 | 2.2 | 3.3 | 79.4 |
| SG    | 8.3 | 7.3 | 7.7 | 10.3 | 11.5 | 6.5 | 0.1 | 2.9 | 40.1 | 1.3 | 4 | 59.9 |
| AU    | 13.3 | 13 | 2.5 | 4 | 4.4 | 4.8 | 1.9 | 3.7 | 17.2 | 30.1 | 5 | 69.9 |
| NZ    | 10.7 | 8.8 | 4.9 | 7.2 | 7.5 | 6.2 | 0.9 | 1 | 15.5 | 5.8 | 31.4 | 68.6 |
| Contr. to others | 89.7 | 79.3 | 97.1 | 116.5 | 118.1 | 96.5 | 19.9 | 13.2 | 93.3 | 44.2 | 41.2 | Spillover index |
| Contr.incl. Own | 115.1 | 105.5 | 118.6 | 136.7 | 138 | 117.1 | 54.8 | 33.9 | 133.3 | 74.4 | 72.7 | (809/1100.1) |
| Net spillovers | 15.1 | 5.5 | 18.6 | 36.7 | 38 | 17.1 | -45.3 | -66.2 | 33.4 | -25.7 | -27.4 | 73.5% |

| To (i) | KR | CH | TW | MY | ID | PN | RU | TR | IN | DU | SA | From others |
|-------|----|----|----|----|----|----|----|----|----|----|----|-------------|
| KR    | 36.7 | 0.1 | 15.6 | 14.7 | 8.5 | 2.4 | 3.6 | 11.9 | 1.5 | 2 | 3 | 63.3 |
| CH    | 10.3 | 44.2 | 9.2 | 10.1 | 6.7 | 2.9 | 2.8 | 8 | 1 | 0.9 | 3.9 | 55.8 |
| TW    | 15.4 | 0.6 | 36.3 | 10 | 14.4 | 3.2 | 3.4 | 9.7 | 1.9 | 1.4 | 3.7 | 63.7 |
| MY    | 16.6 | 1.1 | 12.4 | 43.4 | 5.9 | 4.4 | 5.9 | 7.1 | 1.3 | 0.6 | 1.1 | 56.6 |
| ID    | 14.3 | 1.2 | 16.9 | 7.1 | 40.5 | 4.3 | 2.3 | 9.3 | 0.8 | 0.6 | 2.6 | 59.5 |
| PN    | 1.1 | 4 | 4.9 | 5.3 | 3.3 | 33 | 13.3 | 20.4 | 4.1 | 2.5 | 8.2 | 67 |
| RU    | 2.3 | 0.8 | 2.9 | 5.4 | 0.4 | 6.8 | 54.1 | 16.3 | 2.9 | 1.9 | 6.2 | 45.9 |
| TR    | 1.1 | 3.2 | 2.3 | 1.8 | 0.3 | 2.6 | 16.6 | 62.4 | 3 | 1.5 | 5.1 | 37.6 |
| IN    | 7.4 | 3.2 | 10.9 | 7.8 | 8.1 | 1 | 8.3 | 7.7 | 32 | 6.9 | 6.7 | 68 |
| DU    | 1.9 | 0.9 | 2.3 | 1.8 | 0.2 | 1.2 | 8.3 | 4.4 | 9.2 | 44.3 | 25.3 | 55.7 |
| SA    | 0.7 | 2.3 | 0.4 | 2.3 | 0.8 | 2.7 | 4.7 | 3.9 | 7.5 | 26 | 48.7 | 51.3 |
| Contr. to others | 71.2 | 17.4 | 77.8 | 66.5 | 48.6 | 31.5 | 69.2 | 98.8 | 33.1 | 44.4 | 65.90 | Spillover index |
| Contr. incl. Own | 107.9 | 61.7 | 114.1 | 110 | 89.1 | 64.5 | 123.3 | 161.2 | 65.1 | 88.7 | 114.6 | (624.3/1100.2) |
| Net spillovers | 7.9 | -38.4 | 14.1 | 9.9 | -10.9 | -35.5 | 23.3 | 61.2 | -34.9 | -11.3 | 14.6 | 56.8% |

Notes: The bold values in the diagonal represent the market’s own connectedness. A VAR of order 1 was selected: the Bayesian Information Criterion was used to choose the lag order. Values reported are variance decompositions of the estimated VAR model for the returns of the series. Variance decompositions are based on 10-days-ahead forecasts. The (i,j)-th value is the estimated contribution to the variance of the 10-days-ahead stock return forecast error of country i coming from innovations to stock returns of country j. The mnemonics are in Table 1.
More interestingly, results also suggest that return spillovers to others (i) from all others are different between groups – that is, that they tend to be grouped according to ‘markets’ level of development – and within each group. Indeed, for the developed markets, 50 [JP] to 75% [GE, IT and the UK] of the error variance in forecasting the stock market return (i) come from others, but only 20 [CH] to 50% [KR, IN and TW] for the emerging markets. Similarly, from the directional spillover ‘contribution to others’ row, we can see that the directional return spillovers to others from each of the considered markets tend to be homogeneous within each group of markets. As for the net spillover, which is the difference between the ‘to’ and the ‘from’ directional spillovers, we notice that SG, GE, FR and IT are the main net volatility transmitters (27.3, 25.3, 23.2 and 14.9%, respectively) to all other developed markets, and TR, RU, SA and TW are the main net volatility transmitters (29.9, 17.9, 10.8, and 10.1%, respectively) to all other emerging markets. At the opposite side, HK, JP, NZ and AU are the main developed markets volatility receivers (−51.6, −30, −23.8 and −19%, respectively), and IN, PN, CH and DU are the main emerging markets volatility receivers (−35.2, −17.4, −15.5 and −10.1%, respectively). We can also see that the Chinese market is hardly influenced by the other emerging stock markets and that spillovers to others from innovations to the returns of the Chinese stock market are relatively low and not very different. This result may imply that the Chinese stock market is weakly integrated into the world market.

To examine the incidence of the COVID-19 medical shock, we decompose the period into two sub-periods: the pre-COVID-19 period (1 February 2019 to 30 December 2019) and the COVID-19 crisis period (30 December 2019 to 12 May 2020). Tables 4 and 5 present return spillovers based on the pre-COVID-19 and the COVID-19 sample estimation, respectively. Connectedness clustering is evident as, during the COVID-19 crisis, the total return spillover index increased dramatically to 73.5 and 56.8% for developed and emerging markets, respectively, whereas low interdependences are recorded during the pre-COVID-19 crisis. Furthermore, it is interesting to note that spillovers seem to be time-varying. More specifically, directional spillovers among developed markets (respectively emerging markets) fluctuate as low as 0.1% to as high as 20.7% (respectively as low as 0.1% to as high as 26%) during the COVID-19 medical shock. However, we do not observe any directional return spillover exceeding 19% (respectively 6.5%). Moreover, net spillover indices increased dramatically, in absolute values, between the two sub-periods, with a clear dominance for European markets during the medical shock. This result is suggestive of the fact that, during the COVID-19 crisis, a non-negligible part of the return volatilities in the world's major financial centres is driven from the European stock markets.

To sum up, the results obtained show that the interdependence structure between the two groups of markets and within each one of them has profoundly changed between the two sub-periods, suggesting that the differences observed over the whole sample period between the two blocks of markets are due, at least in part, to the COVID-19 medical shock.

Despite the interesting findings presented in Tables 2–4, the static spillover index may not capture how the interdependence between markets evolves over time. As we have shown, through the results of Tables 3 and 4, that the total return spillover index is likely to be
time-varying, it is important to estimate drifting spillovers, as in Diebold and Yilmaz (2009, 2012), to better understand how it evolved over time. Figure 1 presents the time-varying spillovers using 30, 60 and 100-day rolling windows and 10-day-ahead forecast horizon.

From the spillover plot, we notice that the spillover index fluctuates from about 40% to almost 85% in developed markets, and from about 25% to almost 70% in emerging markets. More specifically, it started to show an increasing pattern since 2020, before reaching its peak around March 2020 in both markets, the developed as well as the emerging one. This indicates that the developed and emerging financial markets reacted most similarly to the significant economic uncertainty brought by the COVID-19 medical shock.

To complete our investigation and better understand how the dependence between stock market returns has shifted before and during the COVID-19 crisis, we extend the spillover analysis to more aggregated markets. Figures 2 and 3 report directional spillovers among...
developed and emerging market aggregate indices before and during the COVID-19 crisis, respectively. Interdependency clustering is evident. Indeed, results show that, compared to the tranquil period, the COVID-19 crisis period is characterized by a higher total spillover index among regional stock markets (70.4% during the COVID-19 crisis period versus 49% before the crisis period). The results reveal not only an increase in the total spillover among regional stock markets during the COVID-19, but also a change in the magnitude of directional spillovers between the two periods, reflecting shift contagion during the COVID-19 crisis period, which is consistent with the results of Ben Amar, Belaïd, Ben Youssef, and Guesmi (2020), Ben Amar, Belaïd, Ben

**FIGURE 4** Causal links – pre-COVID-19 crisis period

[Colour figure can be viewed at wileyonlinelibrary.com]

**FIGURE 5** Causal links – COVID-19 crisis period

[Colour figure can be viewed at wileyonlinelibrary.com]
Youssef, Chiao, and Guesmi (2020) and Ben Amar, Hachicha, and Halouani (2020). Before the COVID-19 crisis period, the North American stock market [NAM] seems to have a significant influence on the rest of the regional stock market indices. Indeed, with the U.S. stock market’s dominance, the directional spillover structure during the tranquil period is largely expected. However, during the COVID-19 crisis period, the European [EUR] and, to a lesser extent, North American [NAM] stock markets seem to become the node that influences all the other regional markets. Indeed, attention paid by market participants to the COVID-19 increased considerably when the World Health Organization warned that the virus is highly infectious and when European countries became widely infected (Ramelli & Wagner, 2020). Furthermore, except for NAM, the intensity of transmission from all regional stock markets increased during the COVID-19 period, but with a clear dominance for European and North American markets.

Interestingly, during the COVID-19 crisis period, the European [EUR] and North American [NAM] markets are the primary recipient and transmitter of spillovers. These findings suggest that, during the COVID-19 crisis period, a significant part of the return volatilities in the world’s leading regional stock markets are driven by the European and North American stock markets. To sum up, the results point out that the structure, as well as the magnitude of interactions between regional stock markets, has changed significantly between the two sub-periods, with much more intense interdependencies during the crisis period, which suggests that the shifts observed are due, at least in part, to the COVID-19 outbreak.

3.2 TYDL causality

The results of the TYDL causality test and the measure of causal intensities are detailed in Table A3 in the appendix and summed up by Figures 4 and 5. They show that all elasticities are positive. During the pre-COVID-19 period, the North American market [NAM] seems to have the strongest influence on the rest of the regional stock markets. Indeed, with the dominance of the U.S. and Canadian stock markets, this finding is largely expected during calm periods. However, the results reveal a change in the causal structure between the two periods, reflecting a shift contagion phenomenon during the COVID-19 crisis period. Indeed, we count 11 causal relations during the COVID-19 crisis period, and about 46% of them arise from the European market [EUR], against 22% during the tranquil period.

Initially, it was perceived that the COVID-19 outbreak would be contained in China (Ozili and Arun, 2020), which is why markets did not attach importance to this medical shock. Yet China is the origin of the COVID-19 pandemic shock; no causal relations stemming from the Emerging Asia [EMS] market are found. Indeed, the drop in the Chinese market during the COVID-19 period has curiously not led to the fall of the other regional indices. However, after January 20, when Chinese health authorities alerted that the virus could be transmitted person-to-person, with each patient infecting an average of two or three others, attention to the new disease increased dramatically, and the European market [EUR] seems to become the main driver of all other regional markets during the COVID-19 crisis period. It highly causes (a) NAM, which in turn influences PAS, EMS, and GCC; (b) PAS, which in turn influences EMS and GCC; (c) LAM, which in turn influences EMS; (d) EMS. This result suggests that the drop in the European stock market had a major effect on market sentiment. This result suggests that the speed and extent to which the COVID-19 has spread across Europe appears to have damaged the market sentiment about the resilience of the global economy, exacerbating the spread of the ‘bad news’ to all stock markets around the world by a domino effect. This explains why EUR and to a lower extent NAM and PAS were the most affected by the COVID-19 crisis.

4 CONCLUSIONS AND POLICY IMPLICATIONS

In this article, we investigate the interdependency and the magnitude of the relationship between emerging and advanced economies’ stock markets, at the country and regional level, in the wake of the ongoing COVID-19 pandemic. Accordingly, we use the Diebold and Yilmaz’s (2012) measure of spillover to analyse the impact of the COVID-19 pandemic on the intensity of interdependency and transmission of shocks among these markets. This methodology enables us to examine the evolution over time of the interdependence between developed and emerging stock markets before and during the COVID-19 outbreak. We also use the TYDL causality test provided by Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996) to explore the evolution of the structure of causal links between the aforementioned stock markets before and during the COVID-19 crisis. The methodology of this test enables us (a) to examine the existence of the shift contagion phenomenon and (b) to measure the causal intensity between the
considered markets before and during the COVID-19 outbreak.

Regarding results, we provide a set of stylized facts on the heterogeneity of the impact of COVID-19. The results from the spillover measure on average over the full sample period suggest a high interdependence among developed markets but a weak connectedness among emerging markets, reflecting that return spillovers differ significantly according to the level of market development. Moreover, the decomposition of the entire period into two sub-periods not only reveals that spillovers appear to be time-varying but also highlights a greater interdependence within emerging and advance economies during the COVID-19 pandemic, which suggests an increase in the transmission of the stress and uncertainty between financial markets during the pandemic. The time-varying spillover index confirms these results, as it indicates that the developed and emerging financial markets reacted most similarly to the economic uncertainty that resulted from the COVID-19 outbreak. The results from TYDL causality test reveal a structural change in the links, which signals the existence of shift contagion among regional stock markets, with a clear dominance for the European market during the COVID-19 outbreak.

Our findings provide investors and regulators with a better understanding of the intensity and synchronization of the co-movement between stock markets during the tranquil and crisis period. While, from an investor perspective, it is essential to understand the extent to which markets are segmented or interconnected for better portfolio diversification and more efficient hedging strategies, from the regulator's point of view, a better understanding of the interdependence between markets would enable to fine-tune macroprudential policies and thereby prevents volatility spillover from international markets to the national market, strengthens financial stability and promotes economic growth.

Although to the best of our knowledge, ours is among the first studies that attempt to assess volatility spillovers as well as shift contagion among a broad spectrum of different developed and emerging markets, at both country and regional levels, over the COVID-19 crisis, there are, nevertheless, some limitations to the analysis: as only one vector of transmission (stock markets) has been studied, spillovers, as well as the causal structure, are only partially identified. It would therefore be interesting for future studies to (a) broaden this analysis by including more financial and economic indicators in order to obtain a complete picture of how the COVID-19 crisis has spread through financial markets and economies and (b) explore the channels through which the main measures taken to limit the human and economic consequences of the COVID-19 outbreak were transmitted to the financial markets.

DATA AVAILABILITY STATEMENT
The data that support the findings of this study are available from the corresponding author upon reasonable request.

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ENDNOTES
1 The first case of pneumonia detected in Wuhan was reported to the World Health Organization Country Office in China on 31 December 2019.
2 According to Ozili and Arun (2020), global stock markets have lost about 6 trillion U.S. dollars in terms of capitalization in 5 days only, from 24 to 28 February.
3 According to the IMF’s World Economic Outlook (June 2020), the global GDP will experience in 2020 a recession at least as severe as the financial crisis of 2007–2008, followed by a recovery in 2021.
4 While the Cholesky factorization of the covariance matrix allows to achieve orthogonality, this identification scheme makes the variance decompositions sensitive to the ordering of the variables in the vector of endogenous variables.
5 As the calculation of variance decompositions necessitates orthogonal innovations, Diebold and Yilmaz (2012) used the generalized restriction method developed by Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1998), which generates generalized impulse responses invariant to the variable ordering. The H-step-ahead forecast error variance decompositions, \( \theta_H(H) \), is given by \( \theta_H(H) = \frac{1}{\Sigma} \sum \sigma_{ij}^2 \sigma_{i0} \sigma_{j0} \) where \( \Sigma \) is the variance matrix of \( e \), \( \sigma_{ij}^2 \) is the standard deviation of the error term for the \( j \)th equation volatility’s and \( e_j \) is a \( N \times 1 \) vector containing one as the \( j \)th element and zeros otherwise. See Pesaran and Shin (1998) for further details.
6 See Dolado and Lütkepohl (1996) for more details about the Wald test.
7 Shift contagion, which was first indicated by Forbes and Rigobon (2001) to describe the increase in co-movements among markets after a shock, is defined by Marais and Bates (2006) as ‘significant differences in cross-market links between tranquil and crisis periods’.
8 It should be noted that the coronavirus search intensity in Google increased significantly after 20 January 2020 when the Chinese health authorities announced that the SARS-CoV-2 can be transmitted human-to-human.
9 It should be noted that the GCC Market neither influences nor is influenced by the other regional stock markets, which suggest that the GCC market is weakly connected to the world financial market.

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APPENDIX A.

**TABLE A1** Descriptive statistics for returns | $Y_t = \log(X_t) - \log(X_{t-1})$

|        | US     | CN     | UK     | GE     | FR     | IT     | JP     | HK     | SG     | AU     | NZ     |
|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| Mean   | 0.000177 | −0.000123 | −0.000476 | −0.0001 | −0.000386 | 1.53E−05 | −0.000516 | −0.000691 | 0      | 0.000038 | 0.00055 |
| Median | 0.000689 | 0.000604 | 0.000642 | 0.0001078 | 0.000397 | 0.000428 | 3.47E−05 | 0      | 0.000748 | 0.000419 |
| Maximum| 0.089683 | 0.112945 | 0.086668 | 0.104143 | 0.080561 | 0.085495 | 0.077314 | 0.04925 | 0.038946 | 0.06765 | 0.08369 |
| Minimum| −0.127652 | −0.131761 | −0.115124 | −0.130549 | −0.130983 | −0.138411 | −0.062736 | −0.049849 | −0.076573 | −0.10203 | −0.068045 |
| SD     | 0.018177 | 0.01761 | 0.014634 | 0.010403 | 0.016281 | 0.01851 | 0.013641 | 0.012617 | 0.011454 | 0.011115 |
| Skewness| −0.971602 | −1.704358 | −1.730239 | −1.505284 | −2.125221 | −3.694093 | 0.213771 | −0.34136 | −0.9374 | −1.574848 | −0.496668 |
| Kurtosis| 17.64785 | 27.53372 | 20.53005 | 21.62559 | 20.13755 | 38.71666 | 10.09997 | 5.63073 | 14.98642 | 15.14971 | 13.52299 |
| Jarque-Bera| 3,020.307 | 8,487.062 | 4,416.674 | 4,924.338 | 4,312.705 | 18,402 | 699.8605 | 102.1951 | 2036.116 | 2,179.185 | 1,545.343 |

|        | KR     | CH     | TW     | MY     | ID     | PN     | RU     | TR     | IN     | DU     | SA     |
|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| Mean   | −0.00029 | 0.000598 | 0.000253 | −0.000599 | −0.00168 | −0.00187 | 0.000152 | −0.00033 | −0.000444 | −0.00516 | −0.000733 |
| Median | 0.000354 | 0.00035 | 0.000362 | −0.000138 | 0      | −0.00022 | 0.000055 | 0      | 0      | 0      | 0.00613 |
| Maximum| 0.082513 | 0.069331 | 0.061726 | 0.066263 | 0.097042 | 0.06353 | 0.074394 | 0.058104 | 0.084003 | 0.078821 | 0.068315 |
| Minimum| −0.08676 | −0.145327 | −0.060055 | −0.054047 | −0.06805 | −0.142456 | −0.08646 | −0.08416 | −0.189038 | −0.092837 | −0.098646 |
| SD     | 0.04295 | 0.016576 | 0.011171 | 0.009101 | 0.013566 | 0.016741 | 0.013592 | 0.015488 | 0.017185 | 0.019909 | 0.013924 |
| Skewness| −0.180473 | −2.283245 | −0.82467 | −0.341403 | 0.292307 | −2.052716 | −1.61865 | −0.970308 | −1.769807 | −0.571218 | −1.593448 |
| Kurtosis| 13.38785 | 23.33916 | 12.05482 | 18.27014 | 20.6061 | 15.4833 | 20.7941 | 8.465042 | 21.06317 | 7.184806 | 14.37931 |
| Jarque-Bera| 1,494.522 | 6,011.055 | 1,171.824 | 3,232.069 | 2,161.116 | 4,521.39 | 2,902.844 | 465.2539 | 4,686.83 | 260.3124 | 193.759 |

|        | D(NAM)  | D(EUR)  | D(PAS)  | D(MEMS) | D(GCC)  | D(LAM)  |
|--------|---------|---------|---------|---------|---------|---------|
| Mean   | 0.000239 | −0.000222 | −0.000199 | −5.38E−05 | −0.00804 | −0.00746 |
| Median | 0.000739 | 0.000936 | 0.000438 | 0.00075 | 0 | −6.58E−05 |
| Maximum| 0.091082 | 0.076437 | 0.065273 | 0.050849 | 0.05904 | 0.095413 |
| Minimum| −0.128153 | −0.119952 | −0.059287 | −0.056814 | −0.169811 | −0.123782 |
| SD     | 0.018002 | 0.013941 | 0.010499 | 0.011113 | 0.014269 | 0.018967 |
| Skewness| −1.111954 | −2.322958 | −0.19343 | −0.818787 | −5.421075 | −1.748748 |
| Kurtosis| 18.67314 | 24.25661 | 12.24663 | 10.2049 | 63.3243 | 17.96488 |
| Jarque–Bera| 3.466.539 | 6.549.087 | 1.184.822 | 755.1934 | 51.9659 | 3.267.16 |
| IO     | 0       | 0       | 0       | 0       | 0       | 0       |

Note: The table reports descriptive statistics of log first difference data (i.e., returns). First row displays mean. The second row displays standard errors. Third and fourth rows show the smallest and largest observations, respectively. Fifth and sixth rows display raw skewness and kurtosis coefficients, respectively. Seventh and eighth rows display the Jarque–Bera test and the order of integration, respectively. We use Phillips-Perron and KPSS tests to determine the integration order (available upon request). The mnemonics are in Table 2.
**Table A2** Descriptive statistics | $Y_t = \log(X_t)$

|          | NAM   | EUR   | PAS   | EMS   | GCC   | LAM   |
|----------|-------|-------|-------|-------|-------|-------|
| Mean     | 8.017738 | 7.347516 | 6.84331 | 6.741904 | 6.30275 | 16.02176 |
| Median   | 8.018678 | 7.366609 | 6.855978 | 6.742916 | 6.332622 | 16.04765 |
| Maximum  | 8.165466 | 7.461566 | 6.941084 | 6.850497 | 6.424529 | 16.14892 |
| Minimum  | 7.744102 | 7.05131 | 6.610104 | 6.534632 | 5.999879 | 15.60993 |
| SD       | 0.073508 | 0.080064 | 0.065676 | 0.05381 | 0.094491 | 0.105577 |
| Skewness | −0.426617 | −1.390013 | −1.180277 | −0.562581 | −1.531608 | −1.882919 |
| Kurtosis | 3.703292 | 4.892171 | 4.489611 | 3.952678 | 4.586285 | 5.859875 |
| IO $[I_{max}]$ | 1 | 1 | 1 | 1 | 1 | 1 |

Note: The table reports descriptive statistics of daily log-data. First row displays mean. The second row displays standard errors. Third and fourth rows show the smallest and largest observations, respectively. Fifth and sixth rows display raw skewness and kurtosis coefficients, respectively. The seventh row displays the order of integration. As in Marais and Bates (2006), we use Phillips-Perron and KPSS tests to determine the integration order (available upon request). The mnemonics are in Table 2.
### TABLE A3  TYDL causality test results and causal intensities

#### Pre-COVID-10

| H1 hypothesis [X → Z] | $I_{\text{max}}$ | k | $p = k + I_{\text{max}}$ | Marginal significance levels of the TYDL | Decision | Causal intensities $\epsilon_{ZX}$ |
|-----------------------|------------------|----|------------------------|----------------------------------------|----------|----------------------------------|
| NAM → EUR             | 1                | 1  | 2                      | 0.2540                                  | Accept H0 | NAM ↛ EUR                         |
| NAM → PAS             | 1                | 2  | 3                      | 0.0000                                  | Accept H1 | 0.8559                           |
| NAM → EMS             | 1                | 2  | 3                      | 0.0000                                  | Accept H1 | 0.8533                           |
| NAM → GCC             | 1                | 1  | 2                      | 0.0002                                  | Accept H1 | 0.7914                           |
| NAM → LAM             | 1                | 1  | 2                      | 0.1289                                  | Accept H0 | NAM ↛ LAM                         |
| EUR → NAM             | 1                | 1  | 2                      | 0.0882                                  | Accept H1 | 1.0914                           |
| EUR → PAS             | 1                | 2  | 3                      | 0.0000                                  | Accept H1 | 0.9324                           |
| EUR → EMS             | 1                | 2  | 3                      | 0.0002                                  | Accept H1 | 0.9260                           |
| EUR → GCC             | 1                | 1  | 2                      | 0.0003                                  | Accept H1 | 0.8621                           |
| EUR → LAM             | 1                | 1  | 2                      | 0.3742                                  | Accept H0 | EUR ↛ LAM                         |
| PAS → NAM             | 1                | 2  | 3                      | 0.0395                                  | Accept H1 | 1.1736                           |
| PAS → EUR             | 1                | 2  | 3                      | 0.0198                                  | Accept H1 | 1.0763                           |
| PAS → EMS             | 1                | 1  | 2                      | 0.6057                                  | Accept H0 | PAS ↛ EMS                         |
| PAS → GCC             | 1                | 1  | 2                      | 0.0414                                  | Accept H1 | 0.9269                           |
| PAS → LAM             | 1                | 2  | 3                      | 0.1718                                  | Accept H0 | PAS ↛ LAM                         |
| EMS → NAM             | 1                | 2  | 3                      | 0.0399                                  | Accept H1 | 1.1993                           |
| EMS → EUR             | 1                | 2  | 3                      | 0.0433                                  | Accept H1 | 1.0980                           |
| EMS → PAS             | 1                | 1  | 2                      | 0.0010                                  | Accept H1 | 1.0252                           |
| EMS → GCC             | 1                | 1  | 2                      | 0.0109                                  | Accept H1 | 0.9418                           |
| GCC → LAM             | 1                | 1  | 2                      | 0.8497                                  | Accept H0 | GCC ↛ LAM                         |
| GCC → EUR             | 1                | 1  | 2                      | 0.7747                                  | Accept H0 | GCC ↛ EUR                         |
| GCC → PAS             | 1                | 1  | 2                      | 0.7675                                  | Accept H0 | GCC ↛ PAS                         |
| GCC → EMS             | 1                | 1  | 2                      | 0.9926                                  | Accept H0 | GCC ↛ EMS                         |
| GCC → LAM             | 1                | 1  | 2                      | 0.3231                                  | Accept H0 | GCC ↛ LAM                         |
| LAM → NAM             | 1                | 1  | 2                      | 0.3040                                  | Accept H0 | LAM ↛ NAM                         |
| LAM → EUR             | 1                | 1  | 2                      | 0.0466                                  | Accept H1 | 0.4598                           |
| LAM → PAS             | 1                | 2  | 3                      | 0.0000                                  | Accept H1 | 0.4278                           |
| LAM → EMS             | 1                | 2  | 3                      | 0.0000                                  | Accept H1 | 0.4210                           |
| LAM → GCC             | 1                | 1  | 2                      | 0.0482                                  | Accept H1 | 0.3956                           |

#### During COVID-19

| H1 hypothesis [X → Z] | $I_{\text{max}}$ | k | $p = k + I_{\text{max}}$ | Marginal significance levels of the TYDL | Decision | Causal intensities $\epsilon_{ZX}$ |
|-----------------------|------------------|----|------------------------|----------------------------------------|----------|----------------------------------|
| NAM → EUR             | 1                | 2  | 3                      | 0.6590                                  | Accept H0 | NAM ↛ EUR                         |
| NAM → PAS             | 1                | 2  | 3                      | 0.0626                                  | Accept H1 | 0.8610                           |
| NAM → EMS             | 1                | 2  | 3                      | 0.0216                                  | Accept H1 | 0.8383                           |
| NAM → GCC             | 1                | 2  | 3                      | 0.0309                                  | Accept H1 | 0.6694                           |
| NAM → LAM             | 1                | 3  | 4                      | 0.1168                                  | Accept H0 | NAM ↛ LAM                         |
| EUR → NAM             | 1                | 2  | 3                      | 0.0134                                  | Accept H1 | 1.0944                           |
| EUR → PAS             | 1                | 2  | 3                      | 0.0109                                  | Accept H1 | 1.1279                           |
| EUR → EMS             | 1                | 1  | 2                      | 0.0110                                  | Accept H1 | 0.9206                           |
| H1 hypothesis \([X \rightarrow Z]\) | \(I_{\text{max}}\) | \(k\) | \(p = k + I_{\text{max}}\) | Marginal significance levels of the TYDL | Decision | Causal intensities \(\varepsilon_{XZ}\) |
|---|---|---|---|---|---|---|
| EUR → GCC | 1 | 1 | 2 | 0.0268 | Accept H1 | 0.8434 |
| EUR → LAM | 1 | 2 | 3 | 0.0080 | Accept H1 | 2.1492 |
| PAS → NAM | 1 | 2 | 3 | 0.1093 | Accept H0 | PAS ↛ NAM |
| PAS → EUR | 1 | 2 | 3 | 0.2256 | Accept H0 | PAS ↛ EUR |
| PAS → EMS | 1 | 1 | 2 | 0.0032 | Accept H1 | 0.9885 |
| PAS → GCC | 1 | 1 | 2 | 0.0004 | Accept H1 | 0.9057 |
| EMS → NAM | 1 | 2 | 3 | 0.1193 | Accept H0 | EMS ↛ PAS |
| EMS → EUR | 1 | 1 | 2 | 0.2232 | Accept H0 | EMS ↛ EUR |
| EMS → PAS | 1 | 1 | 2 | 0.6516 | Accept H0 | EMS ↛ PAS |
| EMS → GCC | 1 | 1 | 2 | 0.3479 | Accept H0 | EMS ↛ GCC |
| EMS → LAM | 1 | 2 | 3 | 0.5378 | Accept H0 | EMS ↛ LAM |
| GCC → NAM | 1 | 2 | 3 | 0.4574 | Accept H0 | GCC ↛ NAM |
| GCC → EUR | 1 | 1 | 2 | 0.9158 | Accept H0 | GCC ↛ EUR |
| GCC → PAS | 1 | 1 | 2 | 0.1124 | Accept H0 | GCC ↛ PAS |
| GCC → EMS | 1 | 1 | 2 | 0.7114 | Accept H0 | GCC ↛ EMS |
| GCC → LAM | 1 | 1 | 2 | 0.3645 | Accept H0 | GCC ↛ LAM |
| LAM → NAM | 1 | 3 | 4 | 0.5376 | Accept H0 | LAM ↛ NAM |
| LAM → EUR | 1 | 2 | 3 | 0.3133 | Accept H0 | LAM ↛ EUR |
| LAM → PAS | 1 | 2 | 3 | 0.1275 | Accept H0 | LAM ↛ PAS |
| LAM → EMS | 1 | 2 | 3 | 0.0727 | Accept H1 | 0.4223 |
| LAM → GCC | 1 | 1 | 2 | 0.4012 | Accept H0 | LAM ↛ GCC |

Note: To take into account the highest number of potential causal links while minimizing the risk of imprecision, a 10% significance level was used for all causality tests.