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Connectedness between the COVID-19 related media coverage and Islamic equities: The role of economic policy uncertainty

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ABSTRACT

This paper examines the static and dynamic return and volatility connectedness among Islamic equity indices and a Coronavirus coverage index over the ongoing COVID-19 pandemic crisis. We employ ten major sectoral equity indices covering main economic sectors and the Coronavirus media coverage index (MCI) and apply the time-varying parameter vector autoregressive methodology (TVP-VAR). The results show a high degree of connectedness between the return and volatility series of the different sectoral indices. Moreover, the information transmission between these indices and the media coverage index shows that Islamic equities are net receivers of shocks from the coronavirus MCI. Additionally, we investigate the causality between the different connectedness measures and the Economic Policy Uncertainty (EPU). Our results indicate that EPU has predictive power on the net connectedness between the Islamic sectoral equities and the Coronavirus MCI.

1. Introduction

Islamic Finance and Sharia-compliant investments have experienced an exponential growth in the aftermath of the global financial crisis of 2008 due to its postulated decoupling from the conventional financial assets (Shamsuddin, 2014; Umar, 2017). Due to its unique features, Sharia-compliant assets are argued to have diversification and safe-haven attributes compared to conventional assets (Masih et al., 2018; Al-Yahyaee et al., 2020; Umar et al., 2020). The recent systemic crisis induced by the COVID-19 pandemic has once again enhanced the desirability of diversification and safe-haven attributes of different asset classes, including Shariah-compliant investments. The existing literature on the effect of the pandemic on Islamic assets has mixed results. Ashraf et al., 2020 document desirable attributes of Sharia-compliant investments during the pandemic. On the contrary, Erdogan et al. (2020) and Yarovaya et al. (2021) document fewer desirable results. This paper extends the literature on the behavior of Sharia-compliant investments during the COVID-19 crisis by accounting for the media coverage and the role of policy uncertainty.

A large volume of existing literature on Sharia-complaint investments focuses on the relationships among markets or countries in...
terms of directionality and degree of connectedness. However, the role of policy uncertainty stemming from turmoil periods is largely underexplored (Albulescu et al., 2019; Umar et al., 2022a, 2022b). Some studies argue that policy uncertainty is an important factor affecting the relationship of financial markets as it affects investors’ and consumers’ decisions (Pásstor and Veronesi, 2012; Gomes et al., 2012). However, limited evidence on the linkages of policy uncertainty and the co-movements of the markets is documented see, (e.g., Fang et al., 2018; Badshah et al., 2019). The findings of Albulescu et al. (2019) confirm this theory since they reported that policy uncertainty is one of the main factors in the connectedness between crude oil and currency markets. The COVID-19 pandemic crisis is prompting governments to adopt numerous policy measures that affect investors and consumers, thus adding to the policy uncertainty.

Hence, the ongoing COVID-19 crisis is a propitious environment for the development of this research work since this crisis affects not only the real economy at all levels but also a wide range of financial and commodity markets. The aim of this research is twofold: i) to examine the relationship between the COVID-19 crisis and the Islamic stocks at a sectoral level, and ii) to investigate whether Economic Policy Uncertainty (EPU) drives the connectedness between the Dow Jones sectoral equities and the Coronavirus media coverage index (MCI). To that purpose, first, we study the static and dynamic return and volatility connectedness between ten sub-indexes of the Islamic Dow Jones equity index (Basic Materials, Consumer Goods, Consumer Services, Financials, Health Care, Industrial, Oil-Gas, Technology, Telecom, and Utilities), and the Coronavirus MCI, by applying the connectedness approach of the time-varying parameter vector autoregression (TVP-VAR) of Antonakakis and Gabauer (2017). This procedure presents some advantages over other methodologies and improves connectedness modeling in some ways. On the one hand, this framework allows capturing possible changes in the underlying structure of the data in a more flexible and robust manner (Antonakakis and Gabauer, 2017; Antonakakis et al., 2020). On the other hand, the TVP-VAR estimations are superior to those generated by rolling-windows, since: the rolling window size is not set arbitrarily; there is no loss of information in calculating the dynamic measures of connectedness; and it is based on a multivariate Kalman filter, making it less sensitive to the presence of outliers and thus adjusts immediately to events (Antonakakis et al., 2018; Gabauer and Gupta, 2018). Hence, the TVP-VAR has the advantage that can be applied to short data series, which is the case of our research since the period analyzed ranges from January 1, 2020, to April 21, 2021. Second, motivated by the high level of economic policy uncertainty over the COVID-19 outbreak, we investigate the relationship between the different connectedness measures in the Islamic market and the EPU by applying a causality test. We are interested in examining whether EPU is a relevant factor in the connectedness between Islamic stocks and the Coronavirus MCI.

This paper contributes to the existing empirical literature in several ways. We add new insights to the growing literature on the connectedness between financial markets, particularly during episodes of crises as the COVID-19 disease crisis. As far as we know, this is the first research that analyses the dynamic return and volatility connectedness on the Islamic stock market during the ongoing COVID-19 pandemic crisis, by including a pandemic-related sentiment variable such as the Coronavirus MCI by applying the TVP-VAR methodology. First, this research simultaneously investigates not only the isolated effects on the connectedness of the Islamic stock market but also its interrelations by including main sectoral Islamic indices instead of comparing the effects among conventional and Islamic assets as in Umar et al. (2022a) and Shahzad and Naifar (2022), or rather than extending the analysis to country-specific indices as in Mandaci and Cagli (2021). This means that we are dealing with a robust set of ten series of indices values that allow us to study their connectedness and ensure that the main economic and activity sectors are included. Our empirical results confirm the existence of significant spillovers among the returns and volatility of the Dow Jones sectoral indices, indicating a high possibility of systemic risk spillover due to the high level of sectoral connectedness in the Islamic equity market. Our results also show strong pairwise spillovers for both returns and volatility indices, indicating a high integration level. Second, contrary to those studies by Shahzad and Naifar (2022) and Umar et al. (2022a), we use a variable of media reporting about infectious diseases to analyze the effects of the COVID-19 crisis on the Islamic stock market, instead of using economic and macroeconomic variables. Our results suggest that the COVID-19 related media index transmits shocks to Islamic sectoral equity more than it receives, acting then as a net transmitter. This finding suggests the existence of another channel of risk transmission deals with the investor’s sentiments rather than with the occurrence of the COVID-19 disease itself. Our findings are somewhat in line with those in Adekoya et al. (2022), who show that Islamic sectoral indices present a large degree of connectedness during the COVID-19 crisis. Third, and in contrast to the wavelet approach applied in Umar and Gabareva (2021), and the Diebold and Yilmaz (2012) methodology employed in Haddad et al. (2020), we apply the TVP-VAR approach of Antonakakis and Gabauer (2017) which is more adequate to short periods as is the case of this research. Our findings confirm the existence of strong linkages among specific sectors during the pandemic period. Fourth, this research devotes special attention to the role of EPU on the connectedness of Islamic sectoral equities and the related-sentiment MCI variable. To the best of our knowledge, while it has been widely recognized that EPU plays a key role in affecting financial markets and asset prices, only a few papers examine its influence on Islamic assets. Our empirical results about the relationship between EPU and the different connectedness measures of the sectoral equities and the pairwise spillover with the MCI indicate that EPU has predictive power on the net connectedness between the Islamic sectoral equities and the Coronavirus MCI. These findings are in line with those in Pititi and Hadhari (2019), who find a significant relationship between EPU and the returns and volatility spillovers of nine Dow Jones Islamic Market indices.

Our findings have important implications for both researchers and investors operating in the Islamic equity markets. This study is an interesting tool that helps investors to understand how shocks spread across sectors of Islamic equities. In this way, our results identify the industrial, consumer goods, and consumer services as the leading sectors in the system. Therefore, investor attention and decisions should be made based on these sectoral indices’ evolution. In fact, the systematically important sector’s performance can

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2 See, for instance, Gubareva and Umar (2020); Ali et al. (2022); Umar et al. (2021a, 2021b); Zhao et al. (2021); Aharon et al. (2021, 2022); Umar et al. (2022a, 2022c); Esparcia et al. (2022); Zaremba et al., 2022; or Gubareva et al. (2021), among others.
generate useful signals to investors so that they can rebalance their portfolio choices accordingly against systemic risk.

The remainder of the paper is organized as follows. Section 2 presents a review of the literature related to this study. Section 3 describes the data and econometric framework. Section 4 provides the empirical results and discussions. Finally, Section 5 concludes.

2. Literature review

2.1. Crises and Islamic assets

The literature on the performance of Islamic investments has experienced rapid growth over the last three decades. Islamic assets follow specific Sharia principles such as the prohibition of interest, the prohibition of investing in excessive risky assets, and the ban on investment in over-leveraged companies. The bulk of the literature is based on the comparative performance of conventional investments and investments that follows Islamic principles (Sensoy et al., 2015; Umar and Suleman, 2017). This increasing interest comes mainly because Islamic financial assets are viewed as alternative assets to traditional ones due to the advantages of Shariah-compliant that these stocks present against conventional ones (Haddad et al., 2020).

In particular, there is a strand of the literature that examines the effects of worldwide episodes of crises on Islamic investments (e.g., Al-Khazali et al., 2014; Nazlioglu et al., 2015; Alam and Rajjaque, 2016; Hammoudeh et al., 2016; Kenourgios et al., 2016; Hkiri et al., 2017; Mensi et al., 2017; Al-Yahyaee et al., 2020; Haddad et al., 2020; Salisu and Sikiru, 2020; Umar et al., 2020, 2022d). These studies mainly employ traditional economic and macroeconomic variables to identify and quantify the impact of the crises. For instance, Al-Khazali et al. (2014) analyzed the performance of a set of stock indices, including Islamic stock indices, in several regions and found that the European, the US, and the Islamic ones outperformed better than their conventional peers during the Global Financial Crisis (GFC). Nazlioglu et al. (2015) studied the relationship between the Dow Jones Islamic stock market and three international stock markets. They found a transmission effect among the markets analyzed that involve the existence of contagion effects. Other authors as Kenourgios et al. (2016) focused on the effects of the GFC and the Eurozone Debt Crisis EDC on the Islamic equity and bond markets. Their results show a transmission effect between conventional and Islamic equity and bond indices that support the hypothesis of contagion effects. Hkiri et al. (2017) analyzed volatility spillovers between nine Islamic stock indices and their conventional counterparts during a period that included various financial crises. They found evidence that the GFC had a strong impact on cross-market volatility. Other authors as Mensi et al. (2017) examined spillover effects between the Dow Jones Islamic Market index and a set of conventional market indices. They found evidence of increasing dynamic correlations, particularly after the outbreak of the GFC. More recently, Haddad et al. (2020) studied the linkages between Dow Jones Islamic stock market indices and global risk factors during a period that comprises the GFC and the EDC. They found an important connection between Islamic stock markets, which is especially high during the GFC and the EDC periods. In general, the empirical evidence on the effects of the crises on Islamic assets shows that Islamic investments are less affected by crises than conventional investments, and they fared better after such periods (Masih et al., 2018).

The ongoing worldwide crisis derived from the COVID-19 pandemic represents a promising scenario for analyzing its effects on the economy. It entails the worst episode of economic turmoil since the GFC outbreak of 2007–2008, with a destructive power at all levels never seen before (Goodell, 2020). Indeed, since the World Health Organization (WHO) declared the coronavirus pandemic on March 11, 2020, several studies have been conducted to analyze the effects of such unprecedented episodes on financial markets. We find several studies that have been conducted on main international stock markets (e.g., Al-Awadhi et al., 2020; Albuluscu, 2020; Ashraf, 2020; Baker et al., 2020; Haroon and Rizvi, 2020; Zaremba et al., 2022; Zhang et al., 2020), as well as on commodity markets (e.g., Bakas and Triantafyllou, 2020; Salisu et al., 2020a, 2020b; Sharif et al., 2020). The findings show that, to a greater or lesser extent, there is a clear impact derived from the COVID-19 crisis in all markets analyzed.

Concerning the recent literature on the impact of the COVID-19 crisis on investments following Islamic principles, the studies are still scarce. Balcilar et al. (2015) stated that those economic and financial crises caused by infectious diseases are less damaging to the Islamic financial system. It is expected to find evidence of similar patterns of Islamic investments. Among the recent papers, we find that of Ashraf et al. (2020), who provide evidence of the hedging benefits of Islamic equity investments during the COVID-19 crisis. Sherif (2020) studies the impact of the crisis on the Shariah-compliant Dow Jones market index and finds a negative linkage between the crisis and the index. However, the impact differs among the sectors included in the index. More recently, Umar and Gubareva (2021) analyzed the degree to which the media coverage of the COVID-19 pandemic affected the volatility of the Islamic equity indices. They find evidence of periods with a high correlation between the COVID-19 crisis and the financial market volatility. Simultaneously, they find intervals with a low degree of relationship, indicating that these indices allow for diversification benefits and suggest that the Islamic equity indices could serve as a potential safe haven during this worldwide turmoil period.

The methodological approach employed in the prior standing literature that analyzes the effects of past and recent episodes of crises on Islamic investments is wide, including methods such as GARCH models (Al-Khazali et al., 2014; Hkiri et al., 2017; Mensi et al., 2017), SVAR models (Hammoudeh et al., 2016), A-DCC models (Kenourgios et al., 2016), Diebold and Yilmaz (2012) approach (Haddad et al., 2020), or wavelet-based methodologies (Umar and Gubareva, 2021). This paper uses the TVP-VAR approach of Antonakakis and Gabauer (2017) to examine the time-varying connectedness between the sectoral Islamic equity market and the MCI over the COVID-19 pandemic period. This methodology presents several advantages with respect to the Diebold and Yilmaz (2012) approach. It has been used, among others, in Gabauer and Gupta (2018), Adekoya and Oliyide (2021), Antonakakis et al. (2020), Bourli et al., 2021, and Umar et al. (2020) to assess the connectedness in a wide variety of different frameworks.
2.2. Economic policy uncertainty, financial markets, and Islamic assets

Baker et al. (2016) refer to EPU as the uncertainty surrounding the future evolution of economic policies that determine the rules of the game for economic agents. It can be viewed as the risk associated with potential changes in economic policies that market participants are not able to know whether, when, and how will occur. In the presence of EPU, not only companies and consumers but also investors present a conservative behavior avoiding activities that could be affected by such uncertainty (Converse, 2018; Albulescu et al., 2019). Hence, EPU can have direct effects at different economic levels, for example, in financial markets (Pástor and Veronesi, 2012, 2013; Albulescu et al., 2019), and there is a strand of the literature that investigates this linkage (Pástor and Veronesi, 2012, 2013; Arouri et al., 2014; Arouri et al., 2016; Arouri and Roubaud, 2016). Most of the studies agree that EPU has a negative effect on market returns while at the same time contributing to increased market volatility.

In addition, there is an increasing strand of literature that focuses on the relationship between EPU and Islamic markets. For instance, Chau et al. (2014) examined the effect of political uncertainty around Arab civil survey stages on main conventional and Islamic stock market indices. They found evidence of increased volatility of Islamic indices during periods of political instability. Hammoudeh et al. (2014) analyzed the linkages between Islamic indices and EPU and showed that EPU does not have a large impact on indices returns. Similar results can be found in Nazlioglu et al. (2015). Contrary, Hammoudeh et al. (2016) did find evidence of the effects of US EPU on Islamic indices returns. More recently, Ftiti and Hadhri (2019) examined the relationship between Islamic indices and EPU and found a significant relationship between EPU and nine Dow Jones Islamic Market indices. Also, based on Islamic indices, Aziz et al. (2020) investigated volatility spillovers from Global EPU and other macroeconomic factors to the Islamic stock market returns. They found that Global EPU does not have a significant effect on the stock market returns of Islamic stock indices.

Despite the different studies on the relationship between EPU and Islamic markets, the study of the impact of EPU on the connectedness between Islamic indices and the Coronavirus MCI is still under-explored. In this work, we employ the EPU measured by Baker et al. (2016) to examine whether it can be a potential predictor of this connectedness. In this way, we focus mainly on the role of the EPU in predicting the total connectedness, net connectedness, and the pair-wise connectedness between the MCI and the different sectoral indices.

3. Data and econometric framework

3.1. Data

This study uses sectoral indices’ returns and 10-day historical volatility in the Islamic Dow Jones equity index. We analyze ten sectors in the Islamic Dow Jones, including Basic Materials (BM), Consumer Goods (CG), Consumer Services (CS), Financials (Fin), Health Care (HC), Industrial (Ind), Oil-Gas (OG), Technology (Tec), Telecom (Tel), and Utilities (Util). We also use the RavenPack media coverage index MCI. This index estimates the global percentage of worldwide news sources covering the novel Coronavirus. All the data are collected daily, spanning from 01/01/2020 to 04/21/2021, counting 341 observations. The start date is motivated by the RavenPack media coverage index’s availability developed with the beginning of the COVID-19 pandemic crisis. The data relating to the Islamic Dow Jones indices is sourced from Bloomberg, while the MCI is collected manually from the Coronavirus News monitor of the RavenPack data analysis platform.³

Fig. 1 plots the time path of the different return series as well as the MCI during the COVID-19 pandemic period. This figure displays a high variation of returns for all sectors, especially over the first part of the period. Regarding the COVID-19 related media coverage index, the graphical evolution shows an upsurge during the first quarter of the year 2020, which reached its maximum value at the beginning of March 2020, when the World Health Organization declared the COVID-19 a pandemic. This period is characterized by intensive media about the new pandemic and reveals high uncertainty in the world. After, the MCI displays a stable evolution after increasing the number of bad news and taking precautionary health measures globally.

Table 1 contains the different descriptive statistics as well as the preliminary tests of the returns and volatility series. From this table, it appears that the technology index experiences the highest positive average returns value of 0.15%, followed by the consumer goods index of 0.09%. However, the oil-gas index presents the highest negative average returns. The standard deviation, which informs about the risk, ranges between 0.99% and 3.24% for the telecom and the oil-gas indices, respectively. For the 10-day volatility indices, the average returns for almost all sectors close around 0.02%. The standard deviations range between 2.15% and 6.37% for the telecom and oil-gas sectors, respectively.

All sectoral indices’ returns and almost all volatility have negative skewness, indicating a sharp peak that the returns are flatter to the left compared to the normal distribution. The kurtosis reported for each series is higher than 3, the value of a normal distribution, implying that the different sectoral indices’ distributions return compared to a normal distribution. In rigorously testing the returns’ normality, the Jarque-Bera statistics reject all series normality at a 1% significance level. We confirm stationary by employing the Augmented Dickey-Fuller ADF test.

Table 2 presents the pairwise correlation coefficient to have a preliminary idea of the dependence structure between different sectoral Islamic equity indices and the COVID-19-based news. We observe a high positive correlation between the log return data series for almost all sectors. The highest correlations are between the Consumer services and industrial sectors 0.937, followed by the

³ For more details, see https://coronavirus.ravenpack.com/.
Fig. 1. Time series of Islamic Dow Jones sectorial returns for each sector.
Table 1
Descriptive statistics.

|                | BM   | CG   | CS   | Fin  | HC   | Ind  | OG   | Tec  | Tel  | Util | MCI  |
|----------------|------|------|------|------|------|------|------|------|------|------|------|
| **Returns indices** |      |      |      |      |      |      |      |      |      |      |      |
| Mean           | 0.0008 | 0.0008 | 0.0009 | 0.0006 | 0.0006 | 0.0009 | −0.0005 | 0.0014 | 0.0002 | 0.0004 | 67.6928 |
| Median         | 0.0010 | 0.0016 | 0.0022 | 0.0010 | 0.0009 | 0.0017 | −0.0004 | 0.0028 | 0.0002 | 0.0007 | 73.4900 |
| Maximum        | 0.0972 | 0.0571 | 0.0912 | 0.1104 | 0.0580 | 0.0908 | 0.1348 | 0.0846 | 0.0444 | 0.0353 | 82.9500 |
| Minimum        | −0.1036 | −0.0933 | −0.1289 | −0.1373 | −0.0768 | −0.0956 | −0.1885 | −0.1245 | −0.0395 | −0.0566 | 0.0900 |
| Skewness       | 1.0313 | 1.3528 | 1.7510 | 0.5992 | −0.6039 | −0.9498 | −1.1224 | −0.8635 | −0.0704 | −0.8048 | −2.5947 |
| Kurtosis       | 16.2254 | 13.3605 | 20.7151 | 13.5224 | 10.6052 | 13.7910 | 13.0076 | 10.9207 | 8.1766 | 7.8395 | 9.0766 |
| J-B p-value    | 0.0008 | 0.0008 | 0.0009 | 0.0006 | 0.0006 | −0.0005 | 0.0014 | 0.0002 | 0.0004 | 67.6928 |      |

|                |      |      |      |      |      |      |      |      |      |      |      |
| **10-day volatility indices** |      |      |      |      |      |      |      |      |      |      |      |
| Mean           | −0.0001 | −0.0001 | −0.0001 | −0.0002 | −0.0002 | −0.0001 | −0.0002 | −0.0002 | −0.0001 | −0.0002 |      |
| Median         | −0.0004 | 0.0000 | 0.0000 | −0.0002 | −0.0003 | 0.0000 | 0.0008 | 0.0001 | 0.0000 | 0.0000 |      |
| Maximum        | 0.2163 | 0.1708 | 0.1946 | 0.1767 | 0.1263 | 0.1732 | 0.5143 | 0.2059 | 0.1022 | 0.0980 |      |
| Minimum        | −0.1987 | −0.1155 | −0.2905 | −0.2567 | −0.0875 | −0.1489 | −0.2585 | −0.2748 | −0.1585 | −0.1801 |      |
| Skewness       | 0.0231 | 0.0263 | 0.0340 | 0.0364 | 0.0236 | 0.0290 | 0.0572 | 0.0395 | 0.0198 | 0.0205 |      |
| Kurtosis       | 5.1767 | 0.7342 | −1.1631 | −0.4044 | 0.6935 | 0.5941 | 1.6165 | −0.3570 | −0.9048 | −1.8071 |      |
| J-B p-value    | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |      |

This table contains the main descriptive statistics and the results of preliminary tests of the returns and volatility series of the different sectoral indices. BM, CG, CS, Fin, HC, Ind, OG, Tec, Tel, Util, and MCI, refer to Basic Materials, Consumer Goods, Consumer Services, Financials, Health Care, Industrial, Oil-Gas, Technology, Telecom, Utilities, and coronavirus Media Coverage Index, respectively.
financial and industrial sectors 0.910. On the other hand, Table 2 shows a very low correlation between the MCI and the different sectoral returns series, indicating that the Islamic equity indices are not well influenced by the pandemic-based news. In fact, these correlations range from 0.006 and 0.109 for the financial and basic materials sectors, respectively.

### 3.2. Econometric framework

In financial literature, the spillover effect between financial variables is made based on several frameworks. Particularly, the approach proposed by Diebold and Yilmaz (2009, 2012, 2014) remains the most suitable in this context since it allows for measuring the connectedness in both static and dynamic perspectives. In a static framework, this approach is based on the vector autoregressive VAR model estimated on the full sample period. In contrast, in the dynamic spillover context, the VAR model is estimated by a rolling-window method, allowing the spillover effects between variables to be estimated in a time-varying context. However, the time-varying connectedness based on the rolling-window method was largely criticized since it presents some drawbacks. Accordingly, Antonakakis and Gabauer (2017) propose applying the connectedness measures based on the TVP-VAR instead of estimating the VAR model rolling window.

This approach gained intensive attention in modeling the dynamic connectedness between financial assets since the dynamics are not influenced by window size choice. The TVP-VAR connectedness-based approach also presents some additional advantages allowing the improvement of connectedness modeling since there is no loss of information in calculating connectedness dynamics. Second, this approach is based on a multivariate Kalman filter allowing it to be less sensitive to outliers and thus adjust immediately to events (Antonakakis et al., 2018; Gabauer and Gupta, 2018). Third, the TVP-VAR-based connectedness approach has the advantage that it can be employed for low-frequency datasets in addition to high-frequency data generally required in a rolling-window-based approach.

In this study, we analyze the time-varying connectedness between the sectoral Islamic equity market and the MCI over the COVID-19 pandemic period based on the TVP-VAR approach of Antonakakis and Gabauer (2017) and Antonakakis et al. (2020). We consider $Y_t$ that is $(N \times 1)$ vector of N sectoral Islamic equity market returns and MCI. The time-varying VAR model is expressed as follows:

$$Y_t = \Phi_1 Y_{t-1} + u_t; \Omega_{t-1} \sim N(0, S_t)$$

(1)

$$\Phi_1 = \Phi_{1,t-1} + v_{t}; v_t \sim N(0, R_t)$$

(2)

where $Y_{t-1}$ and $u_t$ are two $N \times 1$ vectors denoting the lagged vector of the dependent variable and the error term, respectively. The vector $v_t$ is normally distributed with a time-varying variance-covariance matrix. $\Omega_{t-1}$ is the information set available at $t - 1$. $\Phi_1$ is a parameters matrix with dimensions $N \times Np$, in which all parameters are supposed to be time-varying. Eq. 2 describes the dynamic of the time-varying coefficient matrix as a random walk, and the vector $v_t$ is the error term of this equation, which is supposed normally distributed with a variance-covariance matrix $R_t$, which is $Np \times Np$ and changes over time.

To specify a TVP-VAR- based spillover measures and understand the dynamic of the system using the procedure of Diebold and Yilmaz (2012, 2014), the VAR model should be transformed into a moving average representation (Koop et al., 1996; Pesaran and Shin, 1998) as follows:

$$Y_t = \Phi_1 Y_{t-1} + u_t = A_t u_t$$

(3)

where the matrix $A_t = \begin{bmatrix} A_{1,t} & A_{2,t} & \ldots & A_{Np,t} \end{bmatrix}$ is a $(N \times Np)$ matrix of parameters verifying:

This methodology employs the time-varying VAR TVP-VAR methodology of Koop and Korobilis (2014), combined with the connectedness approach of Diebold and Yilmaz (2014).

| BM  | CG   | CS   | Fin | HC   | Ind  | OG   | Tec  | Tel  | Util | MCI  | BM  |
|-----|------|------|-----|------|------|------|------|------|------|------|-----|
| BM  | 1.000|      |     |      |      |      |      |      |      |      |     |
| CG  | 0.841| 1.000|     |      |      |      |      |      |      |      |     |
| CS  | 0.834| 0.874|1.000|      |      |      |      |      |      |      |     |
| Fin | 0.069| 0.040|0.844| 1.000|      |      |      |      |      |      |     |
| HC  | 0.783| 0.835|0.883| 0.029| 1.000|      |      |      |      |      |     |
| Ind | 0.780| 0.880|0.837| 0.021| 0.841| 1.000|      |      |      |      |     |
| OG  | 0.907| 0.892|0.927| 0.062| 0.888| 0.843| 1.000|      |      |      |     |
| Tec | 0.755| 0.656|0.739| 0.089| 0.728| 0.605| 0.804| 1.000|      |      |     |
| Tel | 0.703| 0.835|0.859| 0.013| 0.848| 0.833| 0.790| 0.600| 1.000|      |     |
| Util| 0.602| 0.545|0.477| 0.091| 0.423| 0.466| 0.567| 0.475| 0.371| 1.000|     |
| MCI | 0.625| 0.612|0.487| 0.043| 0.440| 0.512| 0.584| 0.425| 0.390| 0.651| 1.000|

This table shows the unconditional correlation matrix across the Dow Jones indices returns and the coronavirus MCI. Legend: see Table 1.
\[ A_{ij} = \begin{cases} \sum_{k=1}^{p} \Phi_{ik} A_{i-k} & \text{if } i \neq 0 \\ 0 & \text{if } i = 0 \end{cases} \] (4)

This representation allows decomposing the forecast error variances on the different variables. In this context, the spillover index of Diebold and Yilmaz, 2012 can be built by assessing the fraction of the J-step-ahead error variance in forecasting the \(i^{th}\) variable that is due to shocks to the \(j^{th}\) variable. This is based on the generalized impulse response functions (GIRF) and the generalized forecast error variance decompositions (GFEVD). The GIRF, denoted by \(\Psi_{ij}^{g}(J)\), can be obtained via the following equation:

\[ \text{GIRF}(J, \delta_{ij}, \Omega_{t-1}) = E(Y_{i,t+j}|w_{t}, t = \delta_{ij}, \Omega_{t-1}) - E(Y_{i,t}|\Omega_{t-1}) \] (5)

\[ \Psi_{ij}^{g}(J) = \sum_{p=0}^{J} A_{i-p}^\dagger A_{j} \] (6)

where \(J\) denotes the forecast horizon and \(\delta_{ij}\) is the selection vector equal to 1 on the \(j^{th}\) position, and 0 otherwise.

Also, the GFEVD, denoted by \(\Pi_{ij}^{g}(J)\), can be expressed as:

\[ \Pi_{ij}^{g}(J) = \frac{\sum_{j=1}^{J-1} \Psi_{ij}^{g}(J)}{\sum_{j=1}^{J} \Psi_{ij}^{g}(J)} \] (7)

\[ \Pi_{ij}^{g}(J) \] can be interpreted as the variance share one variable has on others.\(^5\) The GFEVD verifies \(\sum_{i,j=1}^{N} \Pi_{ij}^{g}(J) = 1\) and \(\sum_{i,j=1}^{N} \Pi_{ij}^{g}(J) = N\).

Therefore, the GFEVD, allows the construction of the different connectedness indices as follow:

- **The total connectedness**: This index shows how a shock in one variable spills over to other variables and is defined by:

\[ H_{i}^{g}(J) = \frac{\sum_{j=1}^{N} \Pi_{ij}^{g}(J)}{N} \times 100 \] (8)

- **The directional connectedness from others**: this index measures the shocks that a variable \(i\) receives from variables \(j\). It is defined as:

\[ H_{i-j}^{g}(J) = \frac{\sum_{j=1}^{N} \Pi_{ij}^{g}(J)}{\sum_{j=1}^{N} \Pi_{ij}^{g}(J)} \times 100 \] (9)

- **The directional connectedness to others**: this index measures the shocks that a variable \(i\) transmits to all other variables \(j\). It is defined as:

\[ H_{i-j}^{g}(J) = \frac{\sum_{j=1}^{N} \Pi_{ij}^{g}(J)}{\sum_{j=1}^{N} \Pi_{ij}^{g}(J)} \times 100 \] (10)

- **The net connectedness**: This index is defined as the difference between the two later indices in Eqs. (9) and (10) as follow:

\[ H_{i}^{g}(J) = H_{i-j}^{g}(J) - H_{i-j}^{g}(J) \] (11)

This index examines the net power or influence of each variable \(i\) on the whole variables of the system. If \(H_{i}^{g}(J) > 0\) \(H_{i}^{g}(J) < 0\) the variable \(i\) transmits receives the shocks that it receives transmits and it is called “net transmitter receiver” or drive driven by the network.

4. Results and discussions

Our empirical analysis is carried out on the returns and volatility of the different Islamic Dow Jones Islamic indices and the COVID-19 related MCI. Tables 3 and 4 present the average connectedness measures among the media coverage index and the considered sectors in terms of returns and volatility, respectively.

4.1. Dynamic spillover returns

Table 3 provides the average connectedness measures of the different spillover indices among the Dow Jones Islamic equity sectors’ returns and the media coverage index during the ongoing COVID-19 pandemic. As reported, the total spillover index is 72.3%,

\(^5\) These variance shares are normalized in the sense that each row sums up to 1. This means that all variables together explain 100% of variable \(i\)’s forecast error variance Antonakakis and Gabauer (2017).
such as telecommunications and utilities. This result can be explained by the economic and social disruption triggered by the COVID-19 outbreak. During this period, people and businesses worldwide depended heavily on telecommunications services for information, social distancing, and working from home.

In terms of the net spillover index, the results show that basic materials, consumer goods, consumer services, financial, health care, and industrial sectors are net transmitters of shocks, meaning that the amount of shocks transmitted from each of these indices to the system is greater than the amount of shocks received in the opposite direction. However, the rest of the sectors, including oil-gas, technology, telecom, and utilities, are net receivers of shocks. The fact that the oil-gas sector is a net recipient of shocks may be due to the turmoil induced by the Russia-Saudi Arabia war in 2020. Moreover, the telecom sector receives shocks more than it emits. This result can be explained by the economic and social disruption triggered by the COVID-19 outbreak. During this period, people and businesses worldwide depended heavily on telecommunication services for information, social distancing, and working from home.

Our results are in line with those in Baek et al. (2020), who find that systematic risk has increased for telecoms during the pandemic, and with those of Curto and Serrasqueiro (2021), who show that systematic risk appears to have increased in US defensive industries, such as telecommunications and utilities.

Focusing on the COVID-19 related media coverage index MCI, we observe that own-index spillover explains the highest share of

### Table 3
Connectedness matrix for returns.

|    | BM    | CG    | CS    | OG    | Fin    | HC    | Ind    | Tech   | Tel    | Uti    | MCI    | FROM |
|----|-------|-------|-------|-------|--------|-------|--------|--------|--------|--------|--------|------|
| BM | 17.4  | 12.5  | 12.3  | 9.8   | 10.8   | 10.6  | 14.1   | 9.1    | 6.1    | 7.1    | 0.3   | 92.6 |
| CG | 12.0  | 16.8  | 12.8  | 7.1   | 11.8   | 12.7  | 13.2   | 11.6   | 5.2    | 6.8    | 0.1   | 93.2 |
| CS | 11.6  | 12.7  | 16.6  | 8.8   | 12.7   | 11.5  | 14.4   | 14.4   | 4.5    | 5.0    | 0.1   | 93.4 |
| Fin| 12.6  | 9.5   | 11.9  | 23.2  | 11.2   | 8.0   | 14.3   | 7.7    | 6.2    | 5.1    | 0.3   | 86.8 |
| HC | 10.7  | 12.3  | 13.3  | 8.7   | 17.6   | 12.4  | 13.8   | 12.3   | 4.2    | 4.7    | 0.1   | 92.4 |
| Ind| 11.0  | 13.7  | 12.6  | 8.7   | 12.6   | 18.3  | 12.8   | 12.6   | 4.4    | 5.5    | 0.1   | 91.7 |
| OG | 12.7  | 12.4  | 13.7  | 9.9   | 12.4   | 11.1  | 15.8   | 10.1   | 5.4    | 6.1    | 0.1   | 94.2 |
| Tec| 10.0  | 13.4  | 13.8  | 6.8   | 13.2   | 13.3  | 12.4   | 19.0   | 3.8    | 4.2    | 0.1   | 91.0 |
| Tel| 10.9  | 10.3  | 9.0   | 8.5   | 8.2    | 8.4   | 10.8   | 7.0    | 26.3   | 10.3   | 0.2   | 83.7 |
| Util| 11.7 | 11.5  | 9.2   | 7.2   | 8.8    | 9.3   | 11.3   | 6.8    | 9.5    | 24.5   | 0.2   | 85.5 |
| MCI| 0.2   | 0.1   | 0.1   | 0.2   | 0.1    | 0.1   | 0.2    | 0.1    | 0.1    | 108.7  | 1.3   |      |
| TO | 103.3 | 108.3 | 108.9 | 73.3  | 102.0  | 97.4  | 117.2  | 89.3   | 49.5   | 54.9   | 1.7   | 905.8|
| NET| 10.7  | 15.1  | 15.5  | −13.5 | 9.6    | 5.6   | 23.1   | −1.7   | −34.2  | −30.6  | 0.4   | 72.3 |

Notes: This table presents the average 10-day volatility connectedness results between the Dow Jones Islamic indices and the coronavirus MCI index. The elements in the upper-left of the matrix $11 \times 11$ elements show the pairwise directional connectedness which is 10-day forecast variance error estimated from a TVP-VAR model with optimal lag 1. The total connectedness index is decomposed into two types of measures: receiver denoted by “FROM” and transmitter denoted by “TO”. Then, we obtain the net directional connectedness denoted by “NET” as the difference between directional ‘TO’ and directional ‘FROM’ connectedness. The value in bold on the bottom-right side represents the total net connectedness. Legend: see Table 1.

### Table 4
Connectedness matrix for 10-day volatility.

|    | BM    | CG    | CS    | OG    | Fin    | HC    | Ind    | Tech   | Tel    | Uti    | MCI    | FROM |
|----|-------|-------|-------|-------|--------|-------|--------|--------|--------|--------|--------|------|
| BM | 26.2  | 12.6  | 12.3  | 10.1  | 9.2    | 9.2   | 18.8   | 6.5    | 2.2    | 2.7    | 0.2   | 83.8 |
| CG | 11.4  | 24.2  | 13.1  | 4.6   | 10.5   | 13.7  | 14.8   | 11.8   | 2.5    | 3.2    | 0.2   | 85.8 |
| CS | 10.7  | 12.5  | 23.1  | 5.3   | 15     | 11.2  | 16.3   | 14     | 1      | 0.7    | 0.2   | 86.9 |
| Fin| 14.8  | 7.6   | 8.8   | 40.3  | 10.7   | 5.5   | 14.2   | 5.7    | 1.4    | 0.7    | 0.3   | 69.7 |
| HC | 8.8   | 11    | 15.6  | 6.6   | 24.1   | 11.5  | 14.4   | 14.9   | 1.4    | 1.4    | 0.3   | 85.9 |
| Ind| 9     | 15.2  | 12.8  | 3.6   | 12     | 26.2  | 13.6   | 12.3   | 2.2    | 2.7    | 0.4   | 83.8 |
| OG | 15.2  | 13.1  | 15.1  | 7.6   | 12.4   | 11.1  | 21.3   | 9.3    | 2.3    | 2.3    | 0.2   | 88.7 |
| Tec| 6.6   | 13.2  | 16.2  | 4.2   | 16.7   | 12.7  | 11.9   | 27.2   | 0.6    | 0.4    | 0.3   | 82.8 |
| Tel| 5.3   | 6.7   | 2.7   | 2.9   | 2.2    | 4.9   | 6.5    | 1.8    | 63.6   | 12.9   | 0.5   | 46.4 |
| Util| 6.3  | 8.4   | 2.5   | 1.4   | 2.4    | 7.5   | 6.4    | 4.1    | 13.6   | 59.1   | 0.3   | 50.9 |
| MCI| 0.1   | 0.2   | 0.2   | 0.2   | 0.3    | 0.2   | 0.2    | 0.2    | 0.4    | 107.9  | 2.1   |      |
| TO others| 88.2 | 100.4 | 99.4  | 46.4  | 91.4   | 87.7  | 117.1  | 78.6   | 27.6   | 27.2   | 2.9   | 766.9|
| NET dire con| 4.5  | 14.7  | 12.4  | −23.3 | 5.5    | 28.3  | −4.2   | −18.8  | −23.8  | 0.8    | 59.7 |

Notes: This table presents the average 10-day volatility connectedness results between the Dow Jones Islamic indices and the coronavirus MCI index. The elements in the upper-left of the matrix $11 \times 11$ elements show the pairwise directional connectedness which is 10-day forecast variance error estimated from a TVP-VAR model with optimal lag 1. The total connectedness index is decomposed into two types of measures: receiver denoted by “FROM” and transmitter denoted by “TO”. Then, we obtain the net directional connectedness denoted by “NET” as the difference between directional ‘TO’ and directional ‘FROM’ connectedness. The value in bold on the bottom-right side represents the total net connectedness. Legend: see Table 1.
Moreover, the results emphasize that this sector is a net receiver of shocks, suggesting high adverse effects, which are likely to occur in the future. The evolution of this index shows large variations over the period considered. In addition, the total connectedness index is relatively high throughout the entire period. It reaches its maximum value of 79% at the beginning of March 2020. This period was characterized by an increase in the number of infections and the spread of the new virus at a breakneck speed around the world. Therefore, the bad news accelerated, expressing a state of panic, stress, and highly uncertain conditions. A few days ago, the World Health Organization declared that the COVID-19 is a global pandemic on 03/11/2020.

On the other hand, a more detailed picture is provided in Figs. 3 and 4, which depict the dynamic connectedness “to” and “from” the system, and the net transmission of each sector returns from each sector and from the MCI to the system, respectively. As can be seen in Figs. 3 and 4, the amount of transmitted and received shocks is characterized by a high variation over the study period, indicating a time-varying feature of these indices. Moreover, the results generally show a similar pattern for the net transmitter sectors. Indeed, the basic materials, consumer goods, consumer services, and industrial sectors present a high transmission during the beginning of the period, while a decrease is observed from March 2020 onwards. However, the health care, the oil-gas, and the other net receiver of shocks sectors present a different pattern in which a higher amount of transmitted shocks is observed during March 2020.

Turning to the dynamic spillovers transmitted from the set of variables to each of them, presented in Fig. 4, the results show a very similar pattern of evolution of the amount of shock received by each sectoral index, but with a different magnitude. Indeed, the amount of shock received by this index is low at the beginning of the study period. Subsequently, it increases suddenly, with the onset of the rapid spread of the pandemic and the significant increase in the number of cases worldwide. However, the MCI received a greater amount of shock from the beginning of the study until March 2020 and then approached zero.

The dynamic net spillover indices for the different Islamic equity indices and the MCI are presented in Fig. 5. In this figure, we observe that all sectors keep the same sign throughout the period as a net transmitter or net receiver, except for the technology index and the MCI, in which the net spillover oscillates between negative and positive values. In fact, the MCI is a net recipient of shocks from the beginning of the period until mid-March 2020, when COVID-19 was declared a pandemic.

Fig. 6 plots the connectedness networks among the different sectoral indices and the MCI, where the arrow source indicates the transmitter and the arrowhead the receiver. This figure shows that the telecom, utility, technology, and oil-gas sectoral indices receive shocks from almost all sectors. However, the industrial index appears to be the one that transmits the most to the others. In fact, it transmits shocks to almost all sectors. As for the MCI, the results show that this index does not receive shocks from any sectoral stock index, but it transmits shocks to some sectoral indices, namely basic materials, consumer goods, consumer services, oil-gas, and industrial.

More than the effect of the pandemic on the dynamic spillovers between the MCI and the Islamic indices, the different figures on the return spillovers show a remarkable effect of the recent oil market turmoil, highlighted by the oil price war between Russia and Saudi Arabia during 2020. In fact, the oil-gas sector presents some particularities in terms of shock transmission and reception of shocks. More specifically, a decrease in the number of shocks transmitted and received by this sector is observed over the study period. Moreover, the results emphasize that this sector is a net receiver of shocks, suggesting high adverse effects, which are likely to

![Fig. 2. Total connectedness measure returns.](image-url)
Fig. 3. Dynamic spillover TO the system returns.
Fig. 4. Dynamic spillover FROM the system returns.
Fig. 5. Net dynamic spillover return.
confound the connectedness between energy-based Islamic sector indices that play a role in the dynamic return and volatility connectedness of Islamic equity indices. In this context, Yarovaya et al. (2021) suggest that oil price strongly acts as a predictor of spillovers between conventional and Islamic markets. Furthermore, Karim and Masih (2021) demonstrate that the CBOE crude oil volatility index OVX exerts a persistent negative influence on Islamic stock market returns.

4.2. Dynamic spillover volatility

To verify that the spillover effects are different for Islamic equity market returns and volatility, this study also considers the 10-day volatility indices of the same sectors of Islamic indices related to the MCI. Table 4 presents the connectedness matrix, and Figs. 7, 8, 9, and 10 plot the dynamic total, “to,” “from,” and “net” spillover indices. Starting with the connectedness values in Table 4, which contains the average spillover, the results are generally similar to those in the case of the returns. However, there is a decrease in the total spillover index to 59.7%. This result first justifies the validity of our methodology as the spillover effects are different among returns and volatility and show that the returns of the Islamic sectoral indices have more influential effects in relation to total spillovers than 10-day volatility. Moreover, the rank of each sector in transmitting and receiving shocks remains the same. The industrial sectoral index is still the largest transmitter of the shocks, followed by the consumer goods and consumer services indices, while the utility and telecom sectors transmit shocks the least. In the case of the MCI, we observe an increase in the transmission of shocks of 1.7% for the returns and 2.9% for the 10-day volatility, suggesting that this media coverage index remains a net transmitter of shocks. This finding justifies that the 10-day volatility of Islamic Dow Jones indices is generally more sensitive to media coverage than returns. A plausible
Fig. 8. Dynamic spillover TO the system volatility.
Fig. 9. Dynamic spillover from the system volatility.
Fig. 10. Net dynamic spillover volatility.
explanation for this increase is that pandemic-related media increases uncertainty about the future, leading to increased risk to financial assets.

Regarding the dynamic total connectedness between the 10-day volatility sectoral indices and the MCI, Fig. 7 shows that the spillovers are also vary over time during the pandemic period with less variability. This finding suggests that the decisions of investors and policymakers should be taken from a dynamic perspective and reviewed frequently. The total connectedness reached its maximum value of approximately 70% on December 03, 2020, and its minimum value at the end of the study period.

In order to provide further analysis on the dynamic connectedness, we examine the directional spillover indices to the system from the system, as well as the net directional spillover for each equity sector with the MCI. Fig. 8 indicates that the industrial sector is also dominant in transmitting shocks in a time-varying perspective, while the MCI is the least. On the other hand, the evolution of the spillover received by each sector from the others, presented in Fig. 9, shows that all sectors also exhibit a time-varying character in receiving shocks. The directional net spillover shows a similar sign for all sectors except the technology sector, which alternates between net transmission and shock receivers. The same evolution as in the case of returns is observed for the MCI, which appears as a net receiver of shocks between January and March 2020 epidemic period and becomes a net transmitter between March and April 2021 pandemic period. Moreover, as shown in Fig. 10, the MCI is a net transmitter of shocks, having the minimum transmitted amount of shocks at the end of the period. This result may be explained by the good news related to the vaccination programs.

The spillover network between variables is presented in Fig. 11. As can be seen from this figure, the utility, technology, telecom, and oil-gas sectors are the largest recipients of volatility shocks, while the industrial sector is the largest transmitter. The MCI transmits volatility shocks to six sectors and receives shocks only from the basic materials sector.

It is important to analyze the robustness of our results using an alternative proxy of media sentiment. In particular, Haroon and Rizvi (2020) and Umar et al. (2021a, 2021b) highlight the RavenPack’s Pandemic index PI as a suitable measure to capture the media sentiment for analyzing volatility spillovers. Therefore, we employ the PI as an alternative measure of media sentiment and analyze its impact on connectedness. We report the total connectedness result in Fig. 12. The time-varying pattern of connectedness is similar to the one using the MCI as a proxy of media sentiment. Thus, we complement our results. In addition, we report the net dynamic connectedness with PI as a proxy of media sentiment in Fig. 13. Again, we observe a similar trend as shown by net dynamic connectedness with MCI as an indicator of media sentiment. Overall, we notice that the choice of the proxy does not really affect the overall conclusion drawn from the connectedness analysis.

Our results concerning the connectedness between different sectoral stock indices are in line with the conventional equity markets phenomenon and are consistent with the findings of Chowdhury et al. (2020), who report that Islamic stock markets are deeply connected, especially in the European region. Similarly, Wu et al. (2019) report the dominance of the industrial sector in the system most of the time in the Chinese equity market.

Overall, the main empirical findings of this study concerning returns and volatility are twofold. First, we find a high degree of connectedness and spillover effects between different sectoral Islamic indices. Second, we find a weak connectedness between the different sectoral Islamic indices and the media coverage index related to the COVID-19 crisis, indicating the relevance of the Islamic equity market during this turmoil period. This evidence is consistent with the idea that Islamic equities are more resilient to shocks derived from crises than conventional assets and is in line with previous literature, such as Balcilar et al. (2015), which argue that economic and financial crises caused by infectious diseases are less damaging to the Islamic financial system. Moreover, our results are somewhat in line with those of Ashraf et al. (2020), who show that Islamic equity investments have hedging benefits during the COVID-19 crisis. Also, our findings are in line with those of Sherif (2020), who confirms a negative linkage between the crisis and the Shariah-compliant Dow Jones market index. However, the impact differs among the sectors included in the index. Other previous studies have also highlighted the relevance of Islamic equities in a similar way to our findings (Rizvi and Arshad, 2014; Majdoub and Mansour, 2014; Salisu and Sikiru, 2020; Al-Yahyaee et al., 2020).

4.3. EPU and dynamic connectedness

After obtaining the different dynamic spillover measures, we examine whether the economic policy uncertainty EPU, as measured by Baker et al. (2016), can be a potential predictor of this connectedness. In this way, we mainly focus on the role of the EPU in predicting the total connectedness, net connectedness, and the pair-wise connectedness between the MCI and the different sectoral indices. Moreover, since returns and 10-day volatility provide similar results, we limit our causality analysis to the return series.

The results of Granger causality between EPU and the different connectedness measures are presented in Table 5. As shown, no causality is observed from EPU to the total connectedness. However, the EPU has predictive power on the net connectedness of Basic materials, financial, and utility sectors. On the other hand, the MCI net connectedness cannot be predicted by the EPU, indicating that the economic uncertainty cannot drive the transmission of the media coverage index’s shock transmission during the COVID-19 pandemic. On the other hand, we find that the EPU has predictive power on the pairwise spillover between the MCI and two Islamic sectoral indices such as consumer goods and telecom.

These findings can be explained by the fact that the increased uncertainty due to the new Coronavirus significantly affects investors’ sentiment and therefore has an impact on investors’ decisions regarding asset allocation, risk management, and hedging research against the pandemic. Indeed, the media increased uncertainty about what the epidemic was hiding. Then, the rise of the

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6 We thank an anonymous referee for useful comments for this analysis.
EPU impacted the dependence on the MCI-Islamic stock index connectedness Zhang, 2019. In this context, our findings are in line with previous studies that claimed the existence of a significant effect of EPU on the Islamic equity markets. Indeed, Hammoudeh et al. (2016) show that the US economic uncertainty shock has a significant impact on Islamic stock indices and explains an important portion of their fluctuations. Besides, Ftiti and Hadhri (2019) find a significant causal relationship between the EPU and nine Dow Jones Islamic Market indices. More recently, Aziz et al. (2020) reported that global economic policy uncertainty has a significant spillover effect on the returns of the Turkish Islamic stock index.

5. Conclusion

Examining the connectedness between financial assets is an important issue that investors and policymakers need to make decisions about portfolio design and risk management. Equally important is to investigate the role of sentiment in this connectedness. In this direction, the present paper examines the spillovers between sectoral Islamic equity returns/10-day volatility and a media coverage index. We consider the Dow Jones Islamic stock indices (Basic Materials, Consumer Goods, Consumer Services, Financials, Health Care, Industrial, Oil-Gas, Technology, Telecom, and Utilities) to represent the sectorial Islamic equity market. To develop our study, we use the Diebold and Yilmaz (2009, 2012, 2014) methodology combined with a time-varying VAR model for data covering the current COVID-19 pandemic.
Fig. 13. Net dynamic spillover volatility using RavenPack’s Pandemic index PI as a proxy of media sentiment.
The results show strong dynamic spillovers for both sets of returns and 10-day volatility series of sectoral indices, indicating a high possibility of systemic risk spillover due to the high level of sectoral connectedness in the Islamic equity market. We notice that the industrial, consumer goods, and consumer services sectors are the largest net transmitters of shocks to each other, while the telecom and utility sectors are the least receivers from the other sectors. Noticeable and significant pair-wise spillovers are observed in the spillover network for both returns and 10-day volatility series, indicating a high integration level. Moreover, the results suggest a very weak spillover effect of the Islamic equity sectors and the MCI, indicating that Islamic assets exhibit a strong resilience against the news-based COVID-19 pandemic. Despite its weak connectedness, we find that the COVID-19 related media transmits shocks to Islamic equity sectors more than receives them, making it a net transmitter.

Our empirical results have important implications for portfolio managers and both, Sharia-compliant and conventional investors operating in Islamic equity markets. First, this study is an interesting tool that helps understand how shocks spread across Islamic equity sectors. In fact, the performance of the main sectors can generate useful signals about the performance of the remaining sectors. Therefore, our results can help portfolio managers and investors in designing hedging strategies to minimize risk in their sector investment portfolios or for asset allocation purposes when rebalancing their portfolio choices accordingly against systemic risk. In this way, our results identify the industrial, consumer goods, and consumer services as the leading sectors in the system. Therefore, investors’ attention and decisions should be based on the evolution of these sector indices. In addition, our results are also of interest to policymakers and regulators, who can use these findings to implement measures aimed at monitoring, controlling, and reducing market volatility, especially in times of financial distress. They can adopt strategic decisions and specific actions to reduce market distortions.

CRediT authorship contribution statement

Zaghm Umar: Conceptualization, Methodology, Formal analysis, Data curation, Writing – original draft, Writing – review & editing. Khaled Mokni: Conceptualization, Methodology, Formal analysis, Data curation, Writing – original draft, Writing – review & editing. Ana Escribano: Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing, Funding acquisition.

Declaration of Competing Interest

None.

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