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Research article

A commentary on emerging markets banking sector spillovers: Covid-19 vs GFC pattern analysis

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HIGHLIGHTS

- The GFC and COVID pairwise correlation is similar for most emerging market banking sectors.
- The far east banking sector has a lower correlation compared to its counterparts.
- Investors should follow the pattern from the GFC for any future crises.

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ABSTRACT

The emerging-market banking sector plays a significant role in modern-day banking sector stability. In this study, we have used the dynamic conditional correlation (DCC) version of the Generalised autoregressive conditional heteroscedasticity (GARCH) model to estimate the correlation among Emerging Markets (BANKSEK), Latin America (BANKSLA), Brazil, Russia, India, and China (BRIC) (BANKSBC), Portugal, Ireland, Italy, Greece, and Spain (PIIGS) (BANKSPI) and Far East (BANKSFE). The study covers more than 100, 200 and 300 trading days of the GFC (starting July 8, 2008) and the COVID-19 pandemic (starting January 1, 2020). We have found that generally, in the short-term excluding PIIGS, all banks show similar pairwise correlation, and the pattern holds in the medium and long term. The far east banking sector displays a reduced correlation than their counterparts, even following the same pattern.

1. Introduction

The modern-day financial market has undergone tremendous change due to the rapid nature of growing challenges and subsequent supervision it faces in the contemporary world (Hassan et al., 2020; Baglioni et al., 2019; Fabris, 2018; Leuz, 2018). It can be stated without any doubt that COVID, as a health-driven medical crisis, has fundamentally influenced the basic concept of modern-day investment (Meher et al., 2020; Kinateder et al., 2021). Previously, the Western financial superpowers dominated the financial market and system (Armijo et al., 2020). However, emerging markets and the corresponding ecosystem have played a significant role in recent times, especially in the aftermath of the COVID (Ahmed et al., 2017; ElBannan, 2020; Jeon and Wu, 2020). Unlike the global financial crisis (GFC), COVID has some fundamentally different impacts on the emerging market, as suggested by other authors. In most cases, the emerging markets are producing a better recovery than their western counterparts (Akhtaruzzaman et al., 2021) and adding up the impact of China and India (Blarel, 2012; Dharani et al., 2022; Liu et al., 2019; Wu 2019). It has never been more critical to understand the impact of the emerging nations' financial outlook in the scope of modern-day crises (GFC and COVID).

In the past researchers have investigated various aspects of emerging market financial systems. These topics include many aspects - corporate governance (Ciftci et al., 2019; Kayalvizhi and Thenmozhi, 2018), market structural analysis (Bekiros et al., 2017; Vo, 2017), causes (Melvin and Taylor, 2009). However, the most prominent investigation has always been the contagion or spill over effect in or out of the emerging market financial entities (Daly et al., 2019; Jebran et al., 2017). Past researchers have emphasised this avenue as this has a clear goal of risk management due to unfavourable market movement (Shakila et al.,

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2017). However, none of the studies has compared the spill over effect between different crisis periods, especially in emerging markets.

The knowledge of the pattern differences in various crises periods can significantly reduce investor risk in the current global environment if used in conjunction with other risk-minimising strategies (Kumar et al., 2021; Atif et al., 2022; Hawaldar et al., 2017). In this regard, in this study, we propose to investigate the market correlations between different emerging market banking sector participants in both GFC and COVID periods. By doing this, we will understand how these correlates with each other in severe stress scenarios. At the same time, by contrasting their movement in the different stress scenarios, we can observe how investors can safely invest in these extraordinary situations (Hawaldar et al., 2020; Kumar et al., 2018; Shaikh et al., 2022).

To achieve the objectives of the study, in this paper, we have investigated five prominent emerging market banking sectors represented by their corresponding indices collected from Thomson Reuters DataStream. They are Emerging Markets (BANKSEK), Latin America (BANKSLA), Brazil, Russia, India, and China – BRIC (BANKSBC), Portugal, Ireland, Italy, Greece, and Spain – PIIGS (BANKSPI) and Far East (BANKSFE). We calculate the pairwise Dynamic Conditional Correlation (DCC) GARCH correlation for the sample and compare the GFC with the COVID period to achieve our objective.

Although the banks in the emerging markets showed resistance to the COVID-19 pandemic, it is not above the disruptions caused by the pandemic (Blarel, 2012; ElBannan, 2020; Korzeb and Niedziółka, 2020). In our result, we have found a strong correlation among the markets other than far east/Latin and far east/pigs, and the findings also coincide with the (ElBannan, 2020; Korzeb and Niedziółka, 2020; S. Liu et al., 2020; Rebucci et al., 2020). However, the correlation chart for 100, 200, and 300 days draws a clear picture in pairwise correlation for these markets. In the short term (100 days), we can see some apparent discrepancies between the correlation of GFC and COVID (Hassan et al., 2021; Kinateder et al., 2021). As we move towards more maturity, in 300 days, markets correlate identically. However, pairwise correlation in the Latin market is the only case where we can observe differences (Güloğlu et al., 2016; Pretorius, 2002).

The rest of the paper is structured as follows. Section 2 presents data sources and methodology; section 3 present results of the study and section 4 provides conclusion.

2. Data and methodology

2.1. Data and preliminary analysis

The sample data were collected from Thompson Reuters Data stream daily closing price, P_t, of BANKSEK, BANKSLA, BRIC (BANKSBC), PIIGS (BANKSPI) and BANKSFE to compute continuously compounded 1-trading day returns, i.e., $R_t = ln(P_t) - ln(P_{t-1})$.Given our understanding of the past literature, other authors have used these five groups to analyse the non-western banking sector. Other authors who used these sorts of groupings are BANKSEK (Bui et al., 2021; Tian et al., 2021), Latin America (BANKSLA) (Cantú et al., 2020; Nagels, 2021), BRIC (BANKSBC) (Karagiannis et al., 2014), Portugal, Ireland, Italy, Greece, and Spain – PIIGS (BANKSPI) (Miguélez et al., 2019) and Far East (BANKSFE) (Miguélez et al., 2019). The researchers applied the Dynamic Conditional Correlation (DCC) Generalised Autoregressive Conditional Heteroskedasticity (GARCH) models. These are the critical econometric models to measure the financial time series volatility and explain the co-movement of the time series data (Alkan and Ç i ç ek, 2020; Dong et al., 2020; Hassan et al., 2021).

The volatility pattern shows significant similarity with the previous author in this field (Choudhury and Daly, 2021; Kinateder et al., 2021), as described in Table 1. The statistics include mean, median, standard deviation, kurtosis, skewness, and count.

Overall, we can observe a steady pattern among our sample variables during the examined period. The Emerging Markets (EMERG afterwards in this paper), Latin America (LATIN afterwards in this paper), and Brazil, Russia, India, and China – BRIC (BRIC afterwards in this paper) showed similar mean return for our 15 years sample. However, Portugal, Ireland, Italy, Greece, and Spain – PIIGS (PIIGS afterwards in this paper) and Far East (FAR EAST afterwards in this paper) showed a negative return from the previous day. The standard deviation of these returns is similar to PIIGS, described through the Eurozone crisis (Dyson, 2017; Wasserfallen et al., 2019). Jarque Bera's p-value reaffirms our assumption. We can also observe a significant kurtosis for the LATIN market, which should be a direct side effect of the political and financial instability in the region for the last decade (Brinks et al., 2019; Viana et al., 2019). The skewness is negative for all classes as expected; however, the skewness of LATIN is significantly higher than the rest of the cohort as the reason described before. Next, Table 2 reports the pairwise Pearson correlations and associated two tailed p-values for each pair of variables for the sample period of March 21, 2006, to March 19, 2021. Overall, we can see a high correlation for the entire sample.

Table 2 reports the Pearson correlation and associated p-value for the continuously compounded 1-trading day returns, i.e., *the study sample's* $R_t = ln(P_t) - ln(P_{t-1})$. The variables are (with DataStream code) one trading day return of BANKSEK, BANKSLA, BRIC (BANKSBC), PIIGS (BANKSPI) and BANKSFE for the sample period of March 21, 2006, to March 19, 2021.

Figure 1 displays the continuously compounded 1-trading day returns, i.e., $R_t = ln(P_t) - ln(P_{t-1})$ of the sample of the study. The variables are (with DataStream code) one trading day return of BANKSEK, BANKSLA, BRIC (BANKSBC), PIIGS (BANKSPI) and BANKSFE for the sample period of March 21, 2006, to March 19, 2021.

Table 1. Descriptive statistics.

	EMERGING	*LATIN*	*BRIC*	*PIIGS*	*FAR EAST*
Mean	0.0001	0.0001	0.0001	-0.0005	-0.0001
Standard Error	0.0002	0.0003	0.0002	0.0004	0.0002
Median	0.0007	0.0003	0.0006	0.0000	0.0000
Standard Deviation	0.0125	0.0184	0.0155	0.0223	0.0132
Sample Variance	0.0002	0.0003	0.0002	0.0005	0.0002
Kurtosis	12.4295	22.1701	12.0229	12.0552	10.8907
Skewness	-0.4873	-1.5252	-0.0681	-0.3250	-0.0987
Jarque-Bera	14655.6669	61449.4825	13279.9719	13441.2130	10160.4844
p-Value	0.0000	0.0000	0.0000	0.0000	0.0000
Range	0.2058	0.3835	0.2496	0.4255	0.2358
Minimum	-0.0928	-0.2538	-0.1062	-0.2395	-0.1207
Maximum	0.1130	0.1297	0.1434	0.1860	0.1151
Count	3914	3914	3914	3914	3914

Table 2. Pairwise Pearson correlation analysis.

		EMERGING	LATIN	BRIC	PIIGS	FAR EAST
EMERGING	*Pearson Stat*	1	.735**	.950**	.589**	.739**
	P-value (2-tailed)		0.000	0.000	0.000	0.000
LATIN	*Pearson Stat*	.735**	1	.701**	.523**	.331**
	P-value (2-tailed)	0.000		0.000	0.000	0.000
BRIC	*Pearson Stat*	.950**	.701**	1	.523**	.742**
	P-value (2-tailed)	0.000	0.000		0.000	0.000
PIIGS	*Pearson Stat*	.589**	.523**	.523**	1	.344**
	P-value (2-tailed)	0.000	0.000	0.000		0.000
FAR EAST	*Pearson Stat*	.739**	.331**	.742**	.344**	1
	P-value (2-tailed)	0.000	0.000	0.000	0.000	

To illustrate our sample further, we have plotted the 15 years returns in Figure 1 for all our sample variables. The figure clearly shows that around 2008, all the plots had their highest deviation in both directions, and this is due to the Global Financial Crisis as explained by many authors in our field (Batten et al., 2019; Dungey et al., 2017; Kinateder et al., 2021). However, it is interesting to observe that the volatility during the COVID period is significantly lower than the GFC counterpart from a visual point of view.

To choose the period for the Global Financial Crisis (GFC) and COVID, we have followed.

Hassan et al. (2021); Kinateder et al. (2021). These authors used the Chicago Board Options Exchange's (CBOE) Volatility Index (VIX) to

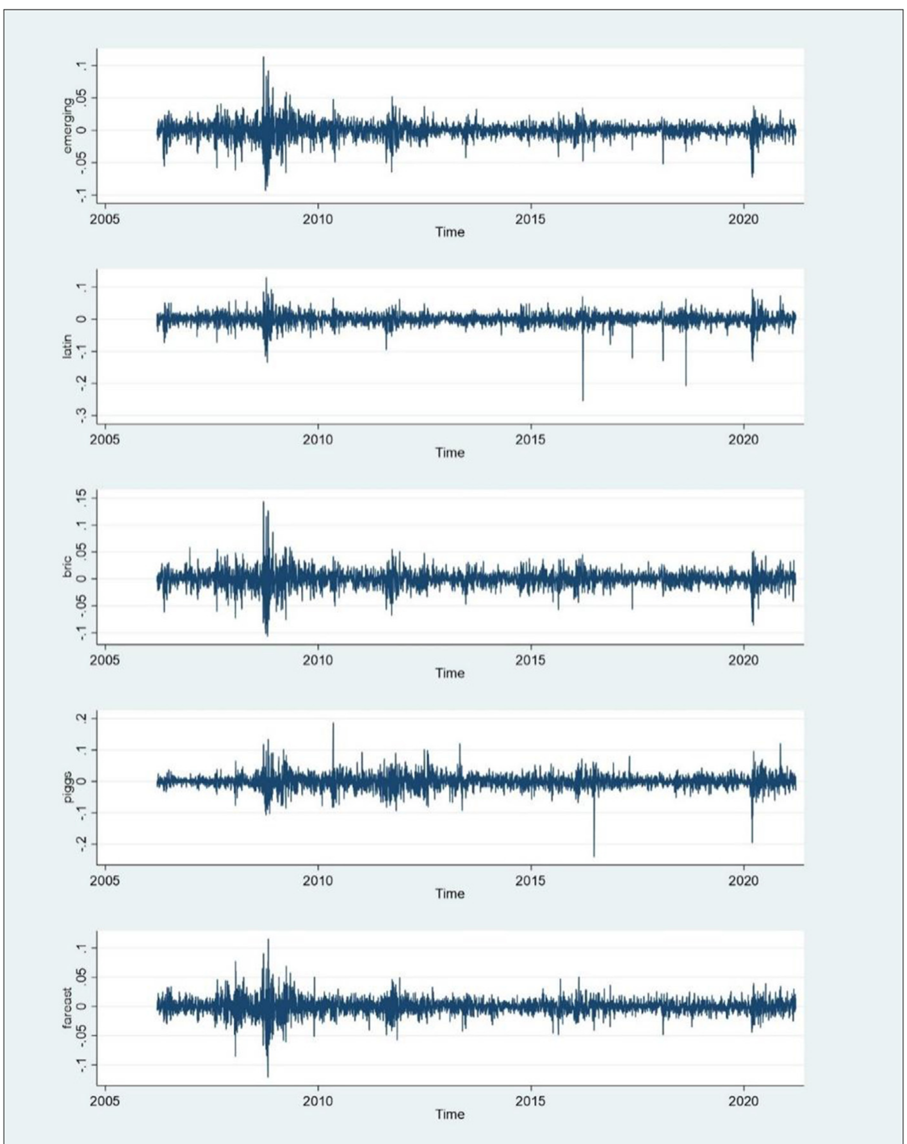

Figure 1. Sample overview.

Table 3. DCC GARCH condition correlation.

		LATIN	BRIC	PIIGS	FAR EAST
EMERGING	DCC Correlation	0.7312***	0.9429***	0.5493***	0.6848***
	Std. Err.	0.0144	0.0064	0.0332	0.0133
LATIN	DCC Correlation		0.7072***	0.4383***	0.2894***
	Std. Err.		0.0867	0.0756	0.0212
BRIC	DCC Correlation			0.4495***	0.7005***
	Std. Err.			0.0480	0.0148
PIIGS	DCC Correlation				0.2963***
	Std. Err.				0.0368

pinpoint the GFC and COVID period in their respective samples for the first 100 days. We have echoed the VIX fluctuation procedure to further pinpoint our 200 and 300 working days in our sample. Following their starting point for the first 100 days, we have selected July 8, 2008, for the GFC starting point and January 1, 2020, for the COVID starting point. From this point, we have taken 100, 200, and 300 working financial days data for our subsample observation period.

2.2. Methodology

The researchers used the dynamic conditional correlation (DCC) version of the Generalised autoregressive conditional heteroscedasticity (GARCH) model to estimate the correlation among the variables. In this regard, past authors have heavily used GARCH based models (Arouri et al., 2011, 2012). The DCC-GARCH model measures the volatility in the financial market during turmoil such as crises or pandemics (Adekoya and Oliyide, 2021; Mensi et al., 2021). The study employed the bivariate GARCH model because the GARCH model captures the error terms of the return processes (Hou and Li, 2016; Kollias et al., 2013). Thus, the recent studies on bivariate or multivariate analysis (for example Kumar et al. (2021) & Bagchi (2017) have applied the MGARCH model DCC of Engle (2002). The DCC of Engle (2002) is the extended MGARCH model constant conditional correlation (CCC) of Bollerslev (1990). The general form of the MGARCH CCC model of Bollerslev (1990) is presented in Eqs. (1) and (2).

$$\boldsymbol{y_t} = E(\boldsymbol{y_t} \,|\boldsymbol{F}_{t-1}) + \boldsymbol{\varepsilon_t} \tag{1}$$

$$\mathbf{Var}(\boldsymbol{\varepsilon_t F}_{t-1}) = \boldsymbol{\Omega_t} \tag{2}$$

Where Ω_t becomes the positive definite and symmetric conditional covariance matrix and F_{t-1} is the σ- area quantified by all the available information till time $t-1$.In a bivariate CCC model, Ω_t

$$\begin{aligned}\boldsymbol{\Omega_t} &= \begin{pmatrix} \boldsymbol{\sigma_{a,t}} & 0 \\ 0 & \boldsymbol{\sigma_{b,t}} \end{pmatrix} \begin{pmatrix} 1 & \boldsymbol{\rho} \\ \boldsymbol{\rho} & 1 \end{pmatrix} \begin{pmatrix} \boldsymbol{\sigma_{a,t}} & 0 \\ 0 & \boldsymbol{\sigma_{b,t}} \end{pmatrix} \\ &= \begin{pmatrix} \boldsymbol{\sigma^2_{a,t}} & \boldsymbol{\rho.\sigma_{a,t}.\sigma_{b,t}} \\ \boldsymbol{\rho.\sigma_{a,t}.\sigma_{b,t}} & \boldsymbol{\sigma^2_{b,t}} \end{pmatrix}\end{aligned} \tag{3}$$

The first and the third matrix in Eq. (3) are matrices of diagonal elements of conditional standard deviations of the logged returns of

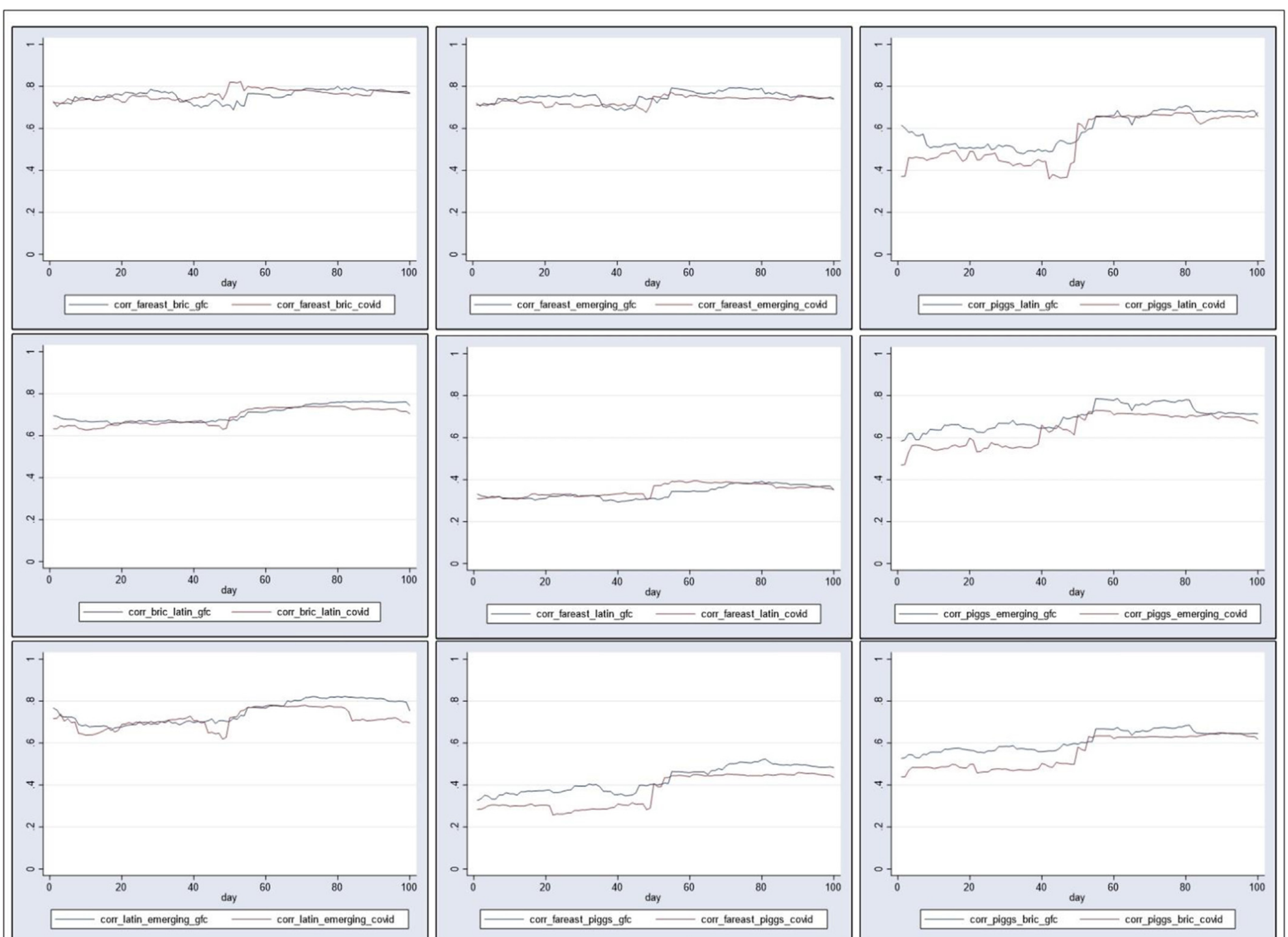

Figure 2. GFC VS COVID: 100 Days.

series $\boldsymbol{a}$ and series $\boldsymbol{b}$. In the same equation, the second matrix is the conditional correlation matrix. The conditional correlation between the return series of $\boldsymbol{a}$ and $\boldsymbol{b}$ is shown as $\boldsymbol{\rho}$ in the above equation. The conditional variances of series $\boldsymbol{a}$ and $\boldsymbol{b}$ are presented as first and second elements in the resultant matrix of the decomposed matrices. The off-diagonal elements are the rho times the conditional standard deviations of $\boldsymbol{a}$ and $\boldsymbol{b}$ series in the resultant matrix. The ${\sigma_{a,t}}^2$ and ${\sigma_{b,t}}^2$ in $\boldsymbol{\Omega_t}$ are given by the univariate GARCH (1.1) for series$\boldsymbol{a}$ and $\boldsymbol{b}$. This CCC model is extended by Engle (2002) to the DCC MGARCH model, where the constant conditional correlation $\boldsymbol{\rho}$ becomes time-varying conditional correlationρ_t. The covariance matrix $\Omega_t = D_tR_tD_t$, where the $D_tR_tD_t$ is the decomposed matrices of the covariance matrix $\boldsymbol{\Omega_t}$. The conditional standard deviations of the logged return of series a and b are vectors, and the D_t *and* D_t are the diagonal matrices. The conditional standard deviation computation process is identical to the CCC model of MGARCH, using univariate GARCH (1,1) models. Matrix R_t is the time-varying conditional correlation matrix. The off-diagonal elements of R_t are time-varying conditional correlation ρ_t between return series of a and b. In the original work of Engle (2002) the conditional correlation matrix R_t is presented as Equation 4 and Equation 5.

$$\boldsymbol{R_t} = (\boldsymbol{diag}(\boldsymbol{Q_t}))^{-\frac{1}{2}}\boldsymbol{Q_t}(\boldsymbol{diag}(\boldsymbol{Q_t}))^{-\frac{1}{2}} \tag{4}$$

$$\boldsymbol{Q_t} = \boldsymbol{S}(1-\boldsymbol{\alpha}-\boldsymbol{\beta}) + \boldsymbol{\alpha}(\boldsymbol{\varepsilon_{CF,t-1}\varepsilon_{TE,t-1}}) + \boldsymbol{\beta Q_{t-1}} \tag{5}$$

The Q_t in Eq. (5) is a time-varying covariance matrix of the standardised error terms. The dynamic correlations of $\varepsilon_{a,t}\varepsilon_{b,t}$ is shown as S, and the sum of α *and* β is less than one and indicates that Q_t is greater than 0, if $\alpha = \beta = 0$, Q_t in the above equation, it is identical to CCC.

3. Result

3.1. Baseline Generalized autoregressive conditional heteroskedasticity (GARCH) model's conditional correlation

The study results from our baseline Generalised autoregressive conditional heteroskedasticity (GARCH) model's conditional correlation show a high connectedness pattern that other prominent authors in our field also echo (Ahmad et al., 2018; Ahmed et al., 2017; McIver and Kang, 2020). Table 3 presents the result of conditional correlation calculated by Equation.5 $\boldsymbol{Q_t} = \boldsymbol{S}(1-\boldsymbol{\alpha}-\boldsymbol{\beta}) + \boldsymbol{\alpha}(\boldsymbol{\varepsilon_{CF,t-1}\varepsilon_{TE,t-1}}) + \boldsymbol{\beta Q_{t-1}})$ for the study period from March 21, 2006, to March 19, 2021. Other than the Far east sample, all pair wise DCC correlations show high cohesiveness. The fluctuating oil markets can explain the results in the Far East in our sample period (Caldara et al., 2019; J. Liu et al., 2019), where the banking sector and the economy are connected to oil markets (Nasir et al., 2019; Vohra, 2017).

3.2. GFC VS COVID: first 100 days pattern analysis – short term

Both GFC and COVID have been devastating for the global baking industry (Atif et al., 2022; Karim et al., 2021; Naeem et al., 2021). The emerging markets banking sector is not different from the rest when it

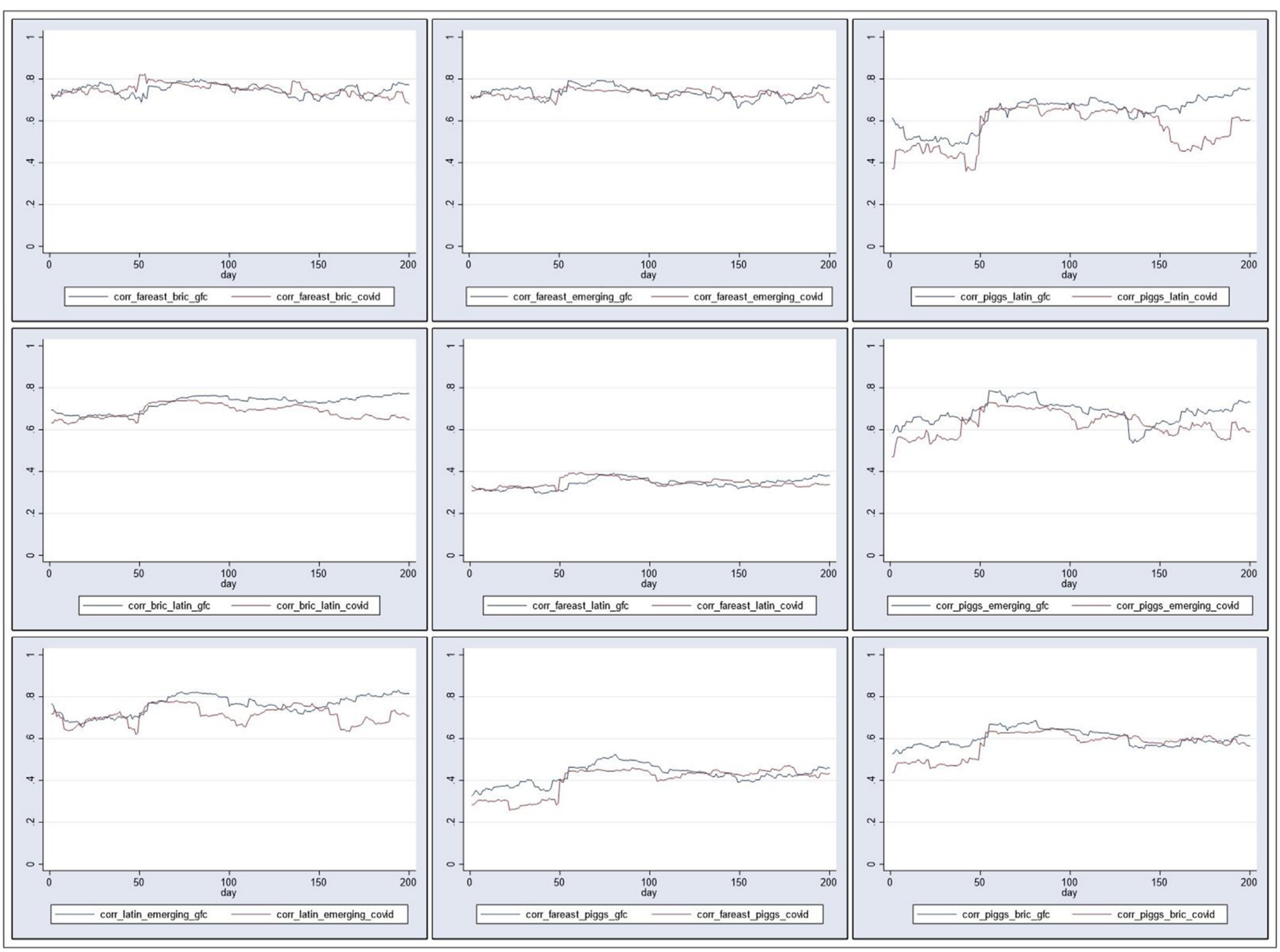

Figure 3. GFC VS COVID-19: 200 Days.

comes to the impact of these crises (Bretas and Alon, 2020; McIver and Kang, 2020). This part examines the primary effect of these events on the market by looking into our sample's first 100 days' impact on pairwise correlation. In this regard, Figure 2 plots the pairwise DCC-GARCH (1,1) correlation in one-day return (i.e., $R_t = ln\ (P_t)$ - $ln\ (P_{t-1})$) of BANKSEK, BANKSLA, BRIC (BANKSBC), PIIGS (BANKSPI) and BANKSFE over 100 trading days of the GFC (July 8, 2008, to November 24, 2008) and the COVID-19 pandemic (January 1, 2020, to May 19, 2020). Each cell of the figure demonstrates a correlation between two series during the GFC and the COVID-19 pandemic, represented by blue and red lines, respectively. For example, the top left corner cell shows the correlation between the Far East (BANKSFE)and Brazil, Russia, India, and China – BRIC (BANKSBC) indexes during the GFC and the COVID-19 pandemic.

Figure 2 displays the pairwise DCC-GARCH (1,1) correlation in one-day return over 100 trading days of the GFC (July 8, 2008, to November 24, 2008) and the COVID-19 pandemic (January 1, 2020, to May 19, 2020).

Figure 2 plots the pairwise DCC-GARCH (1,1) correlation in one-day return (i.e., R_t= $ln\ (P_t)$ - $ln\ (P_{t-1})$) of BANKSEK, BANKSLA, BRIC (BANKSBC), PIIGS (BANKSPI) and BANKSFE over 100 trading days of the GFC (July 8, 2008, to November 24, 2008) and the COVID-19 pandemic (January 1, 2020, to May 19, 2020). Each cell of the figure demonstrates a correlation between two series during the GFC and the COVID-19 pandemic, represented by blue and red lines, respectively. For example, the top left corner cell shows the correlation between the Far East (BANKSFE)and Brazil, Russia, India, and China – BRIC (BANKSBC) indexes during the GFC and the COVID-19 pandemic.

The primary observation out of the figure resonates a distinguished similarity in-between the GFC and COVID in this short-term period. As expected by other authors, both show similar banking sector correlations following our result (Hassan et al., 2021), excluding PIIGS, where we can see a gap between the COVID and GFC in the first half of the figures. The correlation in COVID is lower than the GFC counterpart. This anomaly can be explained by the early COVID market condition of the underlying countries. Given the significant health concerns among those countries at the beginning of COVID (Ke et al., 2020; Yuan et al., 2020), the market reacted negatively compared to the GFC in the first 50 days.

3.3. GFC VS COVID: first 200 days pattern analysis

Using Figure 3, we plotted the pairwise DCC-GARCH (1,1) and correlation in one-day return of BANKSEK, BANKSLA, BRIC (BANKSBC), PIIGS (BANKSPI) and BANKSFE for more than 200 trading days of the GFC (from July 8, 2008, to April 13, 2009) and the COVID-19 pandemic (from January 1, 2020, to October 6, 2020). Following the previous section, each cell of the figure demonstrates a correlation between two series during the GFC and the COVID-19 pandemic, represented by blue and red lines, respectively. Again, we can see a remarkable similarity between the pairwise correlation of our sample. In 200 days, both crises started showing a similar pattern.

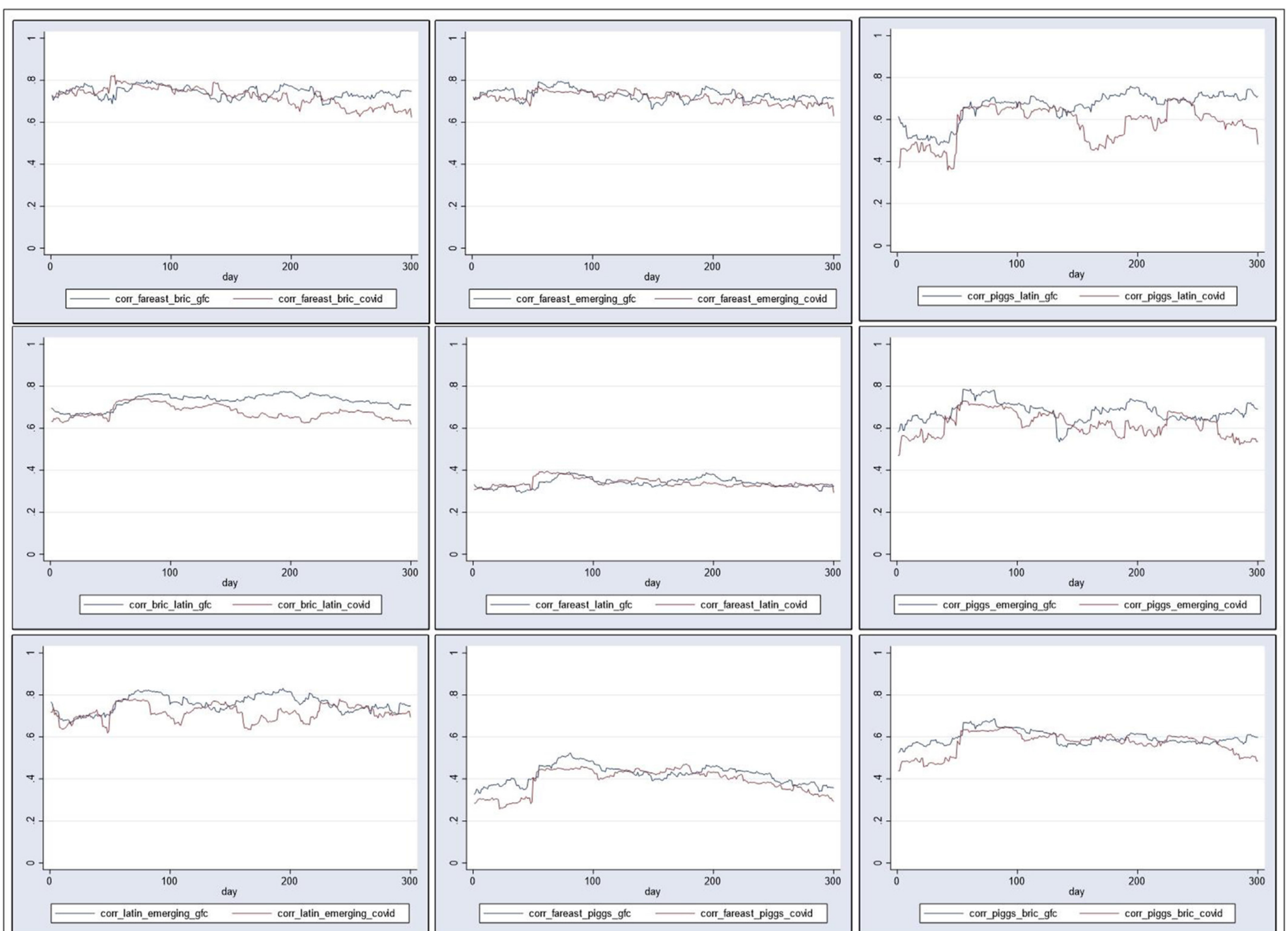

Figure 4. GFC VS COVID: 300 Days.

term. The results obtained in the study have severe implications for the governments, policymakers, and portfolio managers in the selected emerging markets. To manage the risk accurately, portfolio managers need to access the covariance between different markets correctly. This makes the DCC values obtained in the study more appealing because it forecasts the covariation between the different emerging markets studies in the paper.

Figure 3 below, plots the pairwise DCC-GARCH (1,1) correlation in one-day return (i.e., $R_t = ln\ (P_t)$ - $ln\ (P_{t-1})$) of BANKSEK, BANKSLA, BRIC (BANKSBC), PIIGS (BANKSPI) and BANKSFE over 200 trading days of the GFC (July 8, 2008, to April 13, 2009) and the COVID-19 pandemic (January 1, 2020, to October 6, 2020). Each cell of the figure demonstrates a correlation between two series during the GFC and the COVID-19 pandemic, represented by blue and red lines, respectively. For example, the top left corner cell shows the correlation between the Far East (BANKSFE)and Brazil, Russia, India, and China – BRIC (BANKSBC) indexes during the GFC and the COVID-19 pandemic.

Figure 3 plots the pairwise DCC-GARCH (1,1) and correlation in one-day for more than 200 trading days of the GFC (from July 8, 2008, to April 13, 2009) and the COVID-19 pandemic (from January 1, 2020, to October 6, 2020).

3.4. GFC VS COVID: first 300 days pattern analysis

The researcher analysed the long-term effect by analysing Figure 4. In Figure 4, the researchers plot the pairwise DCC-GARCH (1,1) correlation in one-day return (i.e., Rt = ln (Pt) - ln (Pt-1)) BANKSEK, BANKSLA, BRIC (BANKSBC), PIIGS (BANKSPI) and BANKSFE over 300 trading days of the GFC (July 8, 2008, to August 31, 2009) and the COVID-19 pandemic (January 1, 2020, to February 23, 2021). As expected, the banking sector correlation among the emerging markets showed a similar pattern between both crises. However, the correlation related to the far east is significantly lower than the other pairs. This directly impacts the region's banking sector (Alqahtani et al., 2019; Nusair and Al-Khasawneh, 2018).

At this point, we do not report on the residuals following (Kinateder et al., 2021). However, the model's residuals showed acceptable AIC, BIC and log-likelihood criteria and negligible autocorrelation.

Figure 4 plots the pairwise DCC-GARCH (1,1) correlation in one-day return (i.e., $R_t= ln\ (P_t)$ - $ln\ (P_{t-1})$) of BANKSEK, BANKSLA, BRIC (BANKSBC), PIIGS (BANKSPI) and BANKSFE over 300 trading days of the GFC (July 8, 2008, to August 31, 2009) and the COVID-19 pandemic (January 1, 2020, to February 23, 2021). Each cell of the figure demonstrates a correlation between two series during the GFC and the COVID-19 pandemic, represented by blue and red lines, respectively. For example, the top left corner cell shows the correlation between the Far East (BANKSFE)and Brazil, Russia, India, and China – BRIC (BANKSBC) indexes during the GFC and the COVID-19 pandemic.

Figure 4 plots the pairwise DCC-GARCH (1,1) correlation in one-day return (i.e., $R_t = \ln (P_t) - \ln (P_{t-1})$) over 300 trading days of the GFC (July 8, 2008, to August 31, 2009) and the COVID-19 pandemic (January 1, 2020, to February 23, 2021).

4. Conclusion

GFC and COVID, at a very core, restricted our fundamental understanding of the financial market stability and connectedness. After the GFC, many financial experts predicted that this is low, and there is no chance of having a lower point. However, COVID has proved them wrong. What started as a medical crisis now has converted into a full-blown financial meltdown, especially in the financial sector. As a core of the financial sector, the banking sector is not above the impact, especially in emerging banks. Emerging market banks have defining characteristics compared to the rest of the world, where they must play a significant role in local economic sustainability. Thus, how they impact and work together plays a significant role in their performance. From that point of view, our paper is the first paper that has looked at the spill over behaviour between the emerging market banking sectors and compared the GFC vs COVID relationship among them in different time horizons. From an investor's point of view, it opens many avenues of a safe investment. Even in the short term, there might be some changes in the pattern of pairwise correlation, especially with PIIGS; both cases are the same in the long term. This suggests that all crises will similarly impact the emerging market banking sector, especially in the medium to long term. The results obtained in the study have severe implications for the governments, policymakers, and portfolio managers in the selected emerging markets. To manage the risk accurately, portfolio managers need to access the covariance between different markets correctly. This makes the DCC values obtained in the study more appealing because it forecasts the covariation between the different emerging markets studies in the paper.

Declarations

Author contribution statement

Mustafa Raza Rabbani: Conceived and designed the experiments; Performed the experiments; Contributed analysis tools or data; Wrote the paper.

Umar Kayani: Contributed analysis tools or data; Wrote the paper.

Hana Saeed Bawazir, Iqbal Thonse Hawaldar: Analyzed and interpreted the data.

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Data availability statement

Data available at Bloomberg.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

References

Adekoya, O.B., Oliyide, J.A., 2021. How COVID-19 drives connectedness among commodity and financial markets: evidence from TVP-VAR and causality-in-quantiles techniques. Resour. Pol. 70 (October), 101898.

Ahmad, W., Mishra, A.V., Daly, K.J., 2018. Financial connectedness of BRICS and global sovereign bond markets. Emerg. Mark. Rev. 37, 1–16.

Ahmed, S., Coulibaly, B., Zlate, A., 2017. International financial spillovers to emerging market economies: how vital are economic fundamentals? J. Int. Money Finance 76, 133–152.

Akhtaruzzaman, M., Boubaker, S., Sensoy, A., 2021. Financial contagion during COVID–19 crisis. Finance Res. Lett. 38, 101604.

Alkan, B., Çiçek, S., 2020. Spillover effect in financial markets in Turkey. Cent. Bank Rev. 20 (2), 53–64.

Alqahtani, A., Klein, T., Khalid, A., 2019. The impact of oil price uncertainty on GCC stock markets. Resour. Pol. 64, 101526.

Armijo, L.E., Tirone, D.C., Chey, H., 2020. The monetary and financial powers of states: theory, dataset, and observations on the trajectory of American dominance. New Polit. Econ. 25 (2), 174–194.

Arouri, M.E.H., Jouini, J., Nguyen, D.K., 2011. Volatility spillovers between oil prices and stock sector returns: implications for portfolio management. J. Int. Money Finance 30 (7), 1387–1405.

Arouri, M.E.H., Jouini, J., Nguyen, D.K., 2012. On the impacts of oil price fluctuations on European equity markets: volatility spillover and hedging effectiveness. Energy Econ. 34 (2), 611–617.

Atif, M., Rabbani, M.R., Bawazir, H., Hawaldar, I.T., Chebab, D., Karim, S., AlAbbas, A., 2022. Oil price changes and stock returns: fresh evidence from oil-exporting and oil-importing countries. Cogent Econ. Finan. 10 (1), 2018163.

Baglioni, A., Monticini, A., Peel, D., 2019. The Impact of the ECB Banking SupervisionAnnouncements on the EU Stock Market.

Batten, J.A., Kinateder, H., Szilagyi, P.G., Wagner, N.F., 2019. Hedging Stocks with Oil. Energy Economics, p. 104422.

Bekiros, S., Boubaker, S., Nguyen, D.K., Uddin, G.S., 2017. Black swan events and safe havens: the role of gold in globally integrated emerging markets. J. Int. Money Finance 73, 317–334.

Blarel, N., 2012. India: the Next Superpower?: India's Soft Power: from Potential to Reality?.

Bretas, V.P.G., Alon, I., 2020. The impact of COVID-19 on franchising in emerging markets: an example from Brazil. Global Bus. Organ. Excell. 39 (6), 6–16.
Brinks, D.M., Levitsky, S., Murillo, M.V., 2019. Understanding Institutional Weakness: Power and Design in Latin American Institutions. Cambridge University Press.
Bui, D.-T., Nguyen, C.P., Su, T.D., 2021. Asymmetric impacts of monetary policy and business cycles on bank risk-taking: evidence from Emerging Asian markets. J. Econ. Asymmetries 24.
Caldara, D., Cavallo, M., Iacoviello, M., 2019. Oil price elasticities and oil price fluctuations. J. Monetary Econ. 103, 1–20.
Cantú, C., Claessens, S., Gambacorta, L., 2020. How do bank-specific characteristics affect lending? New evidence-based on credit registry data from Latin America. J. Bank. Finance.
Choudhury, T., Daly, K., 2021. Systemic Risk Contagion within US States. Studies in Economics and Finance.
Ciftci, I., Tatoglu, E., Wood, G., Demirbag, M., Zaim, S., 2019. Corporate governance and firm performance in emerging markets: evidence from Turkey. Int. Bus. Rev. 28 (1), 90–103.
Daly, K., Batten, J.A., Mishra, A.V., Choudhury, T., 2019. Contagion risk in the global banking sector. J. Int. Financ. Mark. Inst. Money 63, 101136.
Dharani, M., Hassan, M.K., Rabbani, M.R., Huq, T., 2022. Does the covid-19 pandemic affect faith-based investments? Evidence from global sectoral indices. Res. Int. Bus. Finance 101537.
Dong, X., Li, C., Yoon, S.-M., 2020. Exogenous shocks, dynamic correlations, and portfolio risk management for the Asian emerging and other global developed and emerging stock markets. Appl. Econ. 52 (43), 4745–4764.
Dungey, M., Matei, M., Luciani, M., Veredas, D., 2017. Surfing through the GFC: systemic risk in Australia. Econ. Rec. 93 (300), 1–19.
Dyson, K., 2017. Playing for High Stakes: the Eurozone Crisis. The European Union in Crisis, pp. 54–76.
ElBannan, M.A., 2020. Does catering behavior persist? Evidence on dividend sentiment in emerging financial markets. Int. Rev. Econ. Finance 69, 350–373.
Fabris, N., 2018. Challenges for modern monetary policy. J. Cent. Bank Theor. Pract. 7 (2), 5–24.
Güloğlu, B., Kaya, P., Aydemir, R., 2016. Volatility transmission among Latin American stock markets under structural breaks. Phys. Stat. Mech. Appl. 462, 330–340.
Hassan, M.K., Rabbani, M.R., Ali, M.A., 2020. Challenges for the Islamic Finance and banking in post COVID era and the role of Fintech. J. Econ. Cooperat. Develop. 43 (3), 93–116.
Hassan, M Kabir, Djajadikerta, H.G., Choudhury, T., Kamran, M., 2021. Safe havens in Islamic financial markets: COVID-19 versus GFC. Global Finance J. 100643.
Hawaldar, I.T., Rajesha, T.M., Sarea, A.M., 2020. Causal nexus between the anamolies in the crude oil price and stock market. Int. J. Energy Econ. Pol. 10 (3).
Hawaldar, I.T., Rohit, B., Pinto, P., Rajesha, T.M., 2017. The impact of oil price crisis on financial performance of commercial banks in Bahrain. Banks Bank Syst. 12 (4), 4–16.
Hou, Y., Li, S., 2016. Information transmission between US and China index futures markets: an asymmetric DCC GARCH approach. Econ. Modell. 52, 884–897.
Jebran, K., Chen, S., Ullah, I., Mirza, S.S., 2017. Does volatility spillover among stock markets varies from normal to turbulent periods? Evidence from emerging markets of Asia. J. Finan. Data Sci. 3 (1–4), 20–30.
Jeon, B.N., Wu, J., 2020. Emerging Market Finance: New Challenges and Opportunities. Emerald Publishing Limited.
Karagiannis, S., Panagopoulos, Y., Vlamis, P., 2014. The response of retail bank rates to money market rates in the BRIC economies: an application of the disaggregated gets model. Emerg. Mark. Finance Trade 50 (2), 153–168.
Karim, S., Akhtar, M.U., Tashfeen, R., Raza Rabbani, M., Rahman, A.A.A., AlAbbas, A., 2021. Sustainable banking regulations pre and during coronavirus outbreak: the moderating role of financial stability. Econ. Res. Ekonomska Istraživanja 1–18.
Kayalvizhi, P.N., Thenmozhi, M., 2018. Does quality of innovation, culture and governance drive FDI?: evidence from emerging markets. Emerg. Mark. Rev. 34, 175–191.
Ke, R., Sanche, S., Romero-Severson, E., Hengartner, N., 2020. Fast Spread of COVID-19 in Europe and the US Suggests the Necessity of Early, strong and Comprehensive Interventions. MedRxiv.
Kinateder, H., Campbell, R., Choudhury, T., 2021. Safe haven in GFC versus COVID-19: 100 turbulent days in the financial markets. Finance Res. Lett. 101951.
Kollias, C., Papadamou, S., Siriopoulos, C., 2013. European markets' reactions to exogenous shocks: a high-frequency data analysis of the 2005 London bombings. Int. J. Financ. Stud. 1 (4), 154–167.
Korzeb, Z., Niedziólka, P., 2020. Resistance of commercial banks to the crisis caused by the COVID-19 pandemic: the case of Poland. Equilibrium Quart. J. Econ. Econ. Pol. 15 (2), 205–234.
Kumar, K.A., Pinto, P., Hawaldar, I.T., Spulbar, C., Birau, R., 2021. Crude oil futures to manage the price risk of natural rubber: empirical evidence from India. Agric. Econ. Czech 67, 423–434.
Kumar, K.R.N., Hawaldar, I.T., Mallikarjunappa, T., 2018. Windows of opportunity and seasoned equity offerings: an empirical study. Cogent Econ. Finan. 6 (1), 1–18.
Leuz, C., 2018. Evidence-based policymaking: promise, challenges and opportunities for accounting and financial markets research. Account. Bus. Res. 48 (5), 582–608.
Liu, J., Ma, F., Tang, Y., Zhang, Y., 2019. Geopolitical risk and oil volatility: a new insight. Energy Econ. 84, 104548.
Liu, S., Xu, Q., Jiang, C., 2020. The systemic risk of China's commercial banks during financial turmoils in 2010-2020: a MIDAS-QR based CoVaR approach. Appl. Econ. Lett. 1–10.
McIver, R.P., Kang, S.H., 2020. Financial crises and the dynamics of the spillovers between the US and BRICS stock markets. Res. Int. Bus. Finance 54, 101276.
Meher, B.K., Hawaldar, I.T., Mohapatra, L., Sarea, A.M., 2020. The impact of COVID-19 on price volatility of crude oil and natural gas listed on multi commodity Exchange of India. Int. J. Energy Econ. Pol. 10 (5), 1–10.
Melvin, M., Taylor, M.P., 2009. The global financial crisis: causes, threats and opportunities. Introduction and overview. J. Int. Money Finance 28 (8), 1243–1245.
Mensi, W., Hamed Al-Yahyaee, K., Vinh Vo, X., Hoon Kang, S., 2021. Dynamic spillover and connectedness between oil futures and European bonds. N. Am. J. Econ. Finance 56, 101342.
Miguélez, E., Spiteri, J., Grima, S., 2019. Establishing the contributing factors to the resurrection of Piigs banks following the crisis: a panel data analysis. Int. J. Econ. Bus. Admin. 7 (1), 3–34.
Naeem, M.A., Rabbani, M.R., Karim, S., Billah, M., 2021. Religion vs Ethics: hedge and haven properties of Sukuk and green bonds for stock markets pre-and during COVID-19. Int. J. Islam. Middle E Finance Manag.
Nagels, N., 2021. Gender, the World Bank, and conditional cash transfers in Latin America. Int. Fem. J. Polit.
Nasir, M.A., Al-Emadi, A.A., Shahbaz, M., Hammoudeh, S., 2019. Importance of oil shocks and the GCC macroeconomy: a structural VAR analysis. Resour. Pol. 61, 166–179.
Nusair, S.A., Al-Khasawneh, J.A., 2018. Oil price shocks and stock market returns of the GCC countries: empirical evidence from quantile regression analysis. Econ. Change Restruct. 51 (4), 339–372.
Pretorius, E., 2002. Economic determinants of emerging stock market interdependence. Emerg. Mark. Rev. 3 (1), 84–105.
Rebucci, A., Hartley, J.S., Jiménez, D., 2020. An Event Study of COVID-19 central Bank Quantitative Easing in Advanced and Emerging Economies. National Bureau of Economic Research.
Shaikh, S.P., Hassan, M.K., Atif, M., Rabbani, M.R., 2022. Do Implied Volatilities of Stock and Commodities Markets Affect Bond, Conventional and Shariah Indices Differently? Evidence by OVX, GVZ and VIX. Eurasian Economic Review, Forthcoming.
Shakila, B., Pinto, P., Hawaldar, I.T., 2017. Semi-monthly effect in stock returns: new evidence from Bombay Stock Exchange. Invest. Manag. Financ. Innovat. 14 (3), 1–13.
Tian, S., Park, D., Cagas, M.A., 2021. Bond market development and bank stability: evidence from emerging markets. Res. Int. Bus. Finance 58.
Viana, D.B.C.C., Caixe, D.F., Ponte, V.R.M.R., 2019. Moderating effect of economic instability in the relationship between concentration of control and market value: empirical evidence in Latin America. BBR. Brazil. Bus. Rev. 16, 400–415.
Vo, X.V., 2017. Determinants of capital structure in emerging markets: evidence from Vietnam. Res. Int. Bus. Finance 40, 105–113.
Vohra, R., 2017. The impact of oil prices on GCC economies. Int. J. Bus. Soc. Sci. 8 (2), 7–14.
Wasserfallen, F., Leuffen, D., Kudrna, Z., Degner, H., 2019. Analysing European Union decision-making during the Eurozone crisis with new data. Eur. Union Polit. 20 (1), 3–23.
Wu, S., 2019. China: How Science Made a Superpower. Nature Publishing Group.
Yuan, J., Li, M., Lv, G., Lu, Z.K., 2020. Monitoring transmissibility and mortality of COVID-19 in Europe. Int. J. Infect. Dis. 95, 311–315.