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.

ARTICLE INFO

Keywords:
DCC Garch
Emerging market
Banking sector

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; Dhariani 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).
2017). However, none of the studies has compared the spillover 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 Niedziolka, 2020). In our result, we have found a strong correlation among the markets other than far east/Latin and far east/PIIGS, and the findings also coincide with the (ElBannan, 2020; Korzeb and Niedziolka, 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 presents 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) (Miguelez et al., 2019) and Far East (BANKSFE) (Miguelez 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 Çiçek, 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 assumptions. 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 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                     | 1.7551   | 6649.4825 | 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     |

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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

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

Figure 1. Sample overview.
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).

\[
y_t = E(y_t | F_{t-1}) + \epsilon_t
\]

(1)

\[
\text{Var}(\epsilon_t F_{t-1}) = \Omega_t
\]

(2)

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

\[
\Omega_t = \left( \begin{array}{cc} \sigma_{a_a} & 0 \\ 0 & \sigma_{b_b} \end{array} \right) \left( \begin{array}{cc} 1 & \rho \\ \rho & 1 \end{array} \right) \left( \begin{array}{cc} \sigma_{a_a} & \sigma_{a_b} \\ \sigma_{a_b} & \sigma_{b_b} \end{array} \right)
\]

(3)

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

|                  | 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  |            |          |          |

Table 3. DCC GARCH condition correlation.
series \(a\) and series \(b\). In the same equation, the second matrix is the conditional correlation matrix. The conditional correlation between the return series of \(a\) and \(b\) is shown as \(\rho\) in the above equation. The conditional variances of series \(a\) and \(b\) 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 \(a\) and \(b\) in the resultant matrix. The conditional variances of series \(a\) and \(b\) are presented as first and second elements in the resultant matrix of the decomposed matrices.

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The sum of \(\alpha\) and \(\beta\) 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 Generalised 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 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; Naeeem et al., 2021). The emerging markets banking sector is not different from the rest when it...
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).

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) 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. 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. GFC VS COVID: 300 Days.
of the GFC, many financial experts predicted that this is low, and there is no financial meltdown, especially in the financial sector. As a core, financial market stability and connectedness. After the financial crisis in 2008, to February 23, 2021. Each cell of the figure demonstrates a correlation between two series 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 researchers 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., \( R_t = \ln (P_t) - \ln (P_{t-1}) \)) of BANKSEK, BANKSLA, BRIC (BANKSBC), PIIGS (BANKSPI) and BANKSFSE 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 (Kinatened 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 BANKSFSE 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., \( R_t = \ln (P_t) - \ln (P_{t-1}) \)) of BANKSEK, BANKSLA, BRIC (BANKSBC), PIIGS (BANKSPI) and BANKSFSE 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 covariance 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.

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

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

Funding statement

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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.

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