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Article

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Volatility spillover among the sectors of emerging and developed markets: a hedging perspective

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ABSTRACT

This study empirically investigates the volatility spillover among the sectors of emerging markets, that is, India and China and developed markets, that is, the United Kingdom (UK) and the United States (US). Focusing on financial services, auto, oil and gas, Information Technology (IT), healthcare and real estate sectors, the research employs the BEKK GARCH and GO-GARCH models to analyze the daily data. Results reveal that the own market's conditional volatility is primarily responsible for the volatility spillover in every sector. Further, the study also found evidence of major cross-market volatility spillover in the oil and gas, IT, healthcare and real estate sectors of emerging and developed markets. Specifically, the US IT sector dominated other markets' IT sectors. The hedge ratio indicates that hedging between sectors of the emerging and developed markets is the cheapest, contrasting with the higher cost for hedging solely with the emerging or developed markets sectors. Investors are advised to monitor and rebalance their portfolios based on the volatility and dynamics of developed market sectors for optimum return. Additionally, the study found that the BEKK model is better for risk-return optimization.

IMPACT STATEMENT

Assessing the volatility spillovers among markets and sectors reveals the level of capital market integration. The evolving interconnections and volatilities present diverse challenges for investors, portfolio managers, and regulators. This underscores the importance of close and continuous monitoring of sector-specific developments in both emerging and developed markets. Such vigilance enables investors and risk managers to rebalance portfolios and hedge positions more effectively and promptly. Importantly, these findings have varied implications for stakeholders across the financial landscape.

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Introduction

Economists are particularly interested in the stock market and its relationship with the macroeconomy; however, a country's economy has built with different sectors, which are highly related to the sectoral Gross Domestic Product (GDP) contribution to that sector. A sector is an economic area where organizations engage in similar economic activities, merchandise, or resources. Splitting an economy into multiple sectors allows stakeholders to analyze its underlying economic activity, indicating whether the sectoral economy is growing or shrinking. The financial market, sometimes called the capital market, is also fragmented into multiple submarkets, alternatively called investment sectors, to replicate real economy sectors. The financial market is vulnerable to variations in a country's economic situation because the financial market stimulates capital inflow. Building a single proxy to evaluate the complete financial market is difficult, and most researchers focus on a specific sector. In recent years, investors have become more interested in understanding sectoral volatility. They are more concerned than ever about

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the rewards and risks associated with sector-specific investment. The flow of information to a specific sector, which is closely related to sectoral index volatility, influences investors' decision-making. The movement of these sectoral stock indices is tied directly to the direction of the actual sectoral economy. Meanwhile, several real examples have demonstrated the co-movement between the macroeconomy sectors and financial markets. For example, events such as the onset of the global financial crisis in 2008 (Maxfield & Magaldi De Sousa, 2015; Nidhiprabha, 2011) and the COVID-19 pandemic precipitated a real economic recession (S. Y. Choi, 2021) have a significant impact on the financial market sectors.

Investors always keep track of sectoral indices for decision-making and portfolio modification. The sectoral index is continuously scrutinized for risk-return characteristics (Dhal, 2009). Investors prefer equities in sectors that offer the best returns and the least risk. The best return can be achieved if an investor identifies a linkage among different financial market sectors (Patra & Poshakwale, 2008). Therefore, understanding the interdependence among various capital market sectors may be helpful for investors and traders. Owing to the rapid growth of the global financial market, the developed and emerging equity sector has become the most attractive avenue for investment for retail investors, institutional investors, and foreign investors. Consequently, the country's stock market has seen a massive increase in value and volume, providing many opportunities to earn high returns. From an investment standpoint, it is important to investigate the structural relationships among sectors of different markets. A comprehensive understanding of the volatility spillover could be significant for developing a conducive and appropriate international sectoral investment strategy. It enables one to comprehend the evolution and progression of such linkages and intersectoral changes over time (Kaur et al., 2012). Owing to the significant ramifications for many parties involved, the sectoral relationship has been a central issue in the finance literature in the last decade.

The motivation to explore sector interrelationships in emerging and developed markets arises from a desire to understand the complex dynamics shaping the global economic landscape. This exploration offers valuable insights into factors influencing economic growth, resilience, and stability, allowing for a nuanced examination of connections between financial and non-financial sectors. Changes in one market's sector can have ripple effects across sectors of other markets. Moreover, the study aids in identifying distinctive patterns, vulnerabilities, and opportunities in both emerging and developed markets, enabling informed decision-making for investors, policymakers, and businesses. Delving into these interrelationships aims to comprehensively understand the forces shaping the economic trajectories of both types of economies, contributing to the broader discourse on global economic dynamics.

Generally, it is believed that benchmark indices of the different markets, specifically developed and emerging markets, are interlinked (Baumöhl et al., 2018; Gamba-Santamaria et al., 2019; Habiba et al., 2020; Li & Giles, 2015); however, there is lack of studies conducted on the volatility spillover among the sectoral indices of the developed and emerging markets. Examining the interactions among sectors in both emerging and developed markets warrants attention. A potential imbalance in research focus, often leaning towards developed markets, creates a knowledge gap in understanding the challenges and prospects in the interplay of sectors within emerging and developed markets. The oversight of variations in sectoral relationships across diverse regions emphasizes the importance of considering regional nuances. To bridge this gap, the study endeavours to explore the transmission of volatility across sectors within emerging and developed capital markets.

It is indeed worth mentioning that the equity market of emerging countries has long departed from the path of economic progress. The emerging Indian and Chinese capital markets and developed United Kingdom (UK) and United States (US) capital markets were selected to fulfil the purpose of the study. So, here, one key question arises: why did the study select these markets? First, the study discusses the motivation behind selecting the Indian and Chinese markets for the study. When we speak about emerging markets, two main countries come to mind: India and China. With a current valuation of approximately \$3.5 trillion, India possesses the world's fifth-largest economy. In contrast, China is the second-largest global economy. According to the International Monetary Fund (IMF), the combined contributions of these two countries are anticipated to constitute approximately half of the global growth in 2023 (Thomas Helbling & Srinivasan, 2023). The world's largest developing markets have risen swiftly in recent decades, yet real-world examples have shown that market volatility has remained high over the years (Jin & Guo, 2021). India has initiated a production-linked incentive program valued at \$26

billion. This program attracts companies to establish manufacturing operations across 14 sectors, encompassing electronics, automobiles, pharmaceuticals, and medical devices (Ministry of Commerce & Industry, 2023). India's growing influence falls considerably short of replicating the economic miracle initiated by China decades ago. Conversely, China has undergone a strong recovery from the substantial downturn following the COVID-19 outbreak (Ch Das, 2022; Liu et al., 2020). In Q3 2023, the Chinese economy grew by 4.9% year-on-year, exceeding the market's 4.4% forecast. This positive performance fuels optimism for reaching the annual target of around 5% for 2023 (Bloomberg, 2023). Furthermore, all know that the capital market is always linked to underlying economic activities. Global big players, such as foreign institutional investors, regularly invest in the Indian capital market because of better returns. China's strict capital controls and the growth of its capital market have been separated and poorly understood by the rest of the world (Petry, 2020). However, as China becomes more linked to the global financial system, movements in its capital market have a growing influence on global markets, whether directly or indirectly (Isha Agarwal et al., 2019). Prior studies found interrelationships between developed and emerging markets (Agrawal, 2016; Belaid et al., 2023; Mensi et al., 2021). Second, the rationale for choosing the UK and US as developed markets is outlined. With a GDP reaching 2.23 trillion British pounds in 2022, the UK stands among the world's largest economies. Furthermore, its Q3 2023 GDP was 1.8% higher than the pre-pandemic level in Q4 2019 (Clark, 2023). Nevertheless, since 2008, the US economy has grown twice as fast as the UK's. Post-COVID, the UK faces stagnation, while the US shows robust growth. Notably, despite faster growth, the US experiences rapidly decreasing inflation, whereas the UK contends with high inflation, finding itself in a challenging situation with the worst aspects of both scenarios. Ranked sixth globally, the UK is a key player in the international economic landscape. Its economic strength is driven by vital sectors such as tourism, manufacturing, retail, and financial services. The US saw a strong economic recovery after the great recession, creating millions of jobs and witnessing rising wage growth. Before the COVID-19 pandemic, economic growth was driven by substantial expansion in healthcare. Technological advancements, including artificial intelligence and machine learning, drove growth across sectors. Noteworthy contributions to the economy over the last decade also came from industries like construction, retail, and non-durable manufacturing. It is known that Europe's developed countries, specifically the UK, strongly correlate with the US stock market movement (Longin & Solnik, 2001). Nowadays, international investors see the global market as a basket of assets containing both emerging and developed markets. They consider emerging markets for higher returns and developed markets for safeguarding investments in case of crisis. Therefore, this study tests the integration of sectoral indices of developed and emerging capital markets.

As mentioned earlier, a country's capital markets are segregated into different sectors, each representing one index that tracks the sector's performance. The study focuses on six sectors: financial services, auto, oil and gas, Information Technology (IT), healthcare and real estate, which were selected for their significance. First, the financial services sector is crucial as the prosperity of a country's population is closely linked to its strength, contributing to economic growth and effective risk management for companies within the industry. Financial services sectors are globally interconnected through transactions, investments, and capital flows. Developments in one country's financial sector can have global ripple effects due to investments in each other's financial markets. Interdependence is fueled by foreign direct investments (FDI), portfolio investments, and cross-border lending. Second, the auto sector plays a pivotal role in the economies of various developed and emerging countries. In India, for instance, the auto sector constitutes 7.1% of the GDP for 2021–2022, standing as the largest manufacturing sector and representing 49% of the manufacturing GDP (Abodh Kumar, 2023). Additionally, the auto sector's consumption of materials such as aluminium, rubber, steel, plastics, glass, and iron contributes to the growth of other sectors. The auto sector heavily depends on global supply chains, with components manufactured in various countries. Disruptions in one part of the world can impact global automaker production. The global economy's health, influenced by factors like GDP growth, consumer confidence, and interest rates, affects global automobile demand, creating cascading effects during economic downturns or upswings. Third, the energy market is significantly shaped by the prominence of oil and gas, serving as primary fuel sources on a global scale. Both economically and geopolitically, the oil and gas sector plays a pivotal role in current global affairs. The oil and gas sector operates globally, with interconnected markets for crude oil, natural gas, and refined products. One country's production or consumption changes can

impact global prices and supply. Fourth, the IT sector's significance lies in boosting productivity, streamlining business processes, and promoting efficient growth in today's competitive environment. It not only influences a country's economic growth but also makes the government more accessible and efficient. For instance, the remarkable expansion of IT companies in India over the last two decades has significantly reshaped the country's global perception. IT companies depend on global supply chains for hardware and software development. Disruptions in one part of the world can impact the entire IT ecosystem, with developments in one country's IT sector causing ripple effects across global markets. Fifth, the healthcare sector holds paramount importance globally, and occurrences like pandemics or widespread health crises can profoundly influence healthcare stocks. Investigating volatility spillover is essential to comprehend how disruptions in one market's healthcare sector can reverberate and impact markets worldwide, particularly during health emergencies. The healthcare industry is intricately connected through global supply chains, encompassing pharmaceuticals, medical devices, and essential components. Analyzing volatility spillover offers valuable insights into the repercussions of supply chain disruptions on healthcare stocks and markets across diverse markets. Finally, the real estate sector is a vital economic indicator, particularly responsive to interest rate shifts. Examining volatility spillovers aids in evaluating the impact of interest rate fluctuations in one market on real estate investments and property values across different markets. Comprehending volatility spillover is instrumental in assessing how substantial infrastructure developments in one market can resonate, influencing property values and investment prospects in other markets.

The study considers both financial and non-financial sectors to meet its objectives. This comprehensive approach provides insights into the economy by considering indicators like stock market performance and banking activities, offering a nuanced understanding of a nation's fiscal health. Non-financial sectors like manufacturing, IT, oil and gas, healthcare and real estate offer a broader perspective on economic well-being. Investors can mitigate risk through diversification across both financial and non-financial assets. A balanced portfolio can include assets from financial and non-financial sectors to enhance overall resilience.

The authors have contributed to the existing literature in different ways. First, this study examines the volatility spillover among sectoral indices of emerging and developed capital markets using the Baba–Engle–Kraft–Kroner (BEKK) model, which has proven to be better than other econometric methodologies (Belasri & Ellaia, 2017; Musunuru, 2014; Sarwar et al., 2019). Additionally, the study employed the Generalized Orthogonal – Generalized Autoregressive Conditional Heteroskedasticity (GO-GARCH) model to examine short- and long-term persistence in volatility spillover. One advantage of using the GO-GARCH model is that it addresses the limitations of the BEKK model. The study also computed the hedge ratios. Furthermore, this study goes beyond by comparing the optimal hedge ratios derived from the BEKK model with those obtained from GO-GARCH. This comparative analysis contributes to a more comprehensive comprehension of how optimal hedge ratios exhibit variations across distinct multivariate GARCH specifications.

Therefore, this study is important because it provides a comprehensive empirical assessment of volatility spillover among sectoral indices of India, China, the UK, and the US, especially when investors look for investment options in these markets that guarantee hedging and diversification opportunities. Our study question is: Are sectoral indices of emerging and developed markets connected? Furthermore, the study examines whether hedging and diversification opportunities exist among the sectors of the emerging and developed markets.

The remainder of this article is organized as follows: “Literature Review” is discussed in the second section, “Data and Methodology” are discussed in the third section, and “Results and Discussion” is included in the fourth section. The final section presents the “Conclusion” Section.

Literature review

Numerous recent discussions have focused on the spillover effect of volatility among sectoral indices and broad market index, sectoral index and commodities, and the performance of sectoral index during an uncertainty. Prior studies have investigated the stock market's reactions to various circumstances, such as the impact of COVID-19 on sectoral indices. Different studies by Ashri et al. (2021), Curto and

Serrasqueiro (2022), Fernandes et al. (2021), Shahzad et al. (2021) assessed the impact of the corona crisis on the different sectoral indices and found that Covid does have an impact on the sectoral indices. Kyriazis (2021) found that the movement of sectoral indices is also linked to COVID-19 deaths. Economic events create havoc in the investment universe, so investors use gold as a shield to protect them against sharp drops during turmoil. Ahmad et al. (2021) investigate the effect of implied volatility in the US equity sector and gold. Kumar (2014) finds significant unidirectional return spillovers from gold to the capital market sector. Trabelsi et al. (2021) found that gold prices largely depend on the Bombay Stock Exchange (BSE) sector index performance. Furthermore, gold returns can assist in anticipating the expected performance of consumer durables, fast moving consumer goods (FMCG), and oil and gas stock indices. This research suggests that stock and gold portfolios provide better hedging and diversification. Other commodities, such as crude oil, are the lifeblood that keeps the economy running, and the economic sectors are impacted by the price movements of crude oil, whether directly or indirectly. Tiwari et al. (2021) empirically examine the spillover and systematic risk management between the oil prices and returns of the sectoral indices of the BSE. The results showed that all sectoral indices are affected by oil price movements, and industry, power, and energy have higher persistence in the dependence structure among all sectors. Malik and Rashid (2017), Wang and Wang (2019), Zhu et al. (2021) investigated volatility spillovers between the sector index and crude oil. Hamdi et al. (2019) employ quantile regression analysis (QRA) to investigate the volatility spillover between oil prices and sectoral indices in the Gulf Cooperation Council (GCC) countries. The authors found that the transportation and telecommunication sectors are reactive to the oil price shock. Purankar and Singh (2020) assessed the volatility spillover between Indian commodities and equity indices using the Dynamic Conditional Correlation (DCC) approach.

Studies have also been conducted on the traditional and sectoral indices. Hedi Arouri and Khuong Nguyen (2010) use several econometric tools to investigate short-term relationships in Europe at the aggregate and sectoral levels. Apart from traditional indices, studies have been conducted on Islamic stock indices with sectoral indices. Investors want to know if the Islamic equity market is immune to global financial turbulence so that they may diversify their portfolios and hedge against unanticipated dangers. Billah et al. (2022) investigated the spillover from developed markets on the sectoral Sukuk returns of Islamic markets. Mensi et al. (2017) examined the spillover between 10 Dow Jones Islamic and conventional sector indices. Conditional relationships are confirmed for all sector index pairs except telecommunications and utilities. Ng et al. (2017) explore the return and volatility spillover between sectoral indices and the FTSE Bursa Malaysia Emas Shariah (FBMS) index using an asymmetric version of the BEKK-GARCH model.

From finding diversification opportunities among the different assets, the studies also focused on finding opportunities for portfolio diversification in the capital market but considering different sectors. Costa et al. (2022) tested the connectedness among sectoral indices of the US. Further studies by Balli et al. (2014, 2016); Balli et al. (2013) have attempted to determine whether the sectoral indices of developed markets are reactive to domestic and global shocks similarly or not. Hachicha et al. (2022) investigated the time-varying optimal hedging ratios for both the Dow Jones Islamic and conventional emerging stock market with oil, gold, and the VSTOXX, along with four sectoral Credit Default Swaps (CDS) indices. The study employed the DCC, Asymmetric DCC (ADCC) and GO-GARCH models. Zghal et al. (2018) estimate time-varying correlations to explore the potential of CDS as a hedge and safe haven for European stock sectors.

It is not just finding portfolio diversification opportunities in one market; investors can also consider other markets and benefit from global sectoral movement. Choi et al. (2021) measure the dynamic volatility spillover and interconnectedness across 11 sector indices of the Australian capital market. Notably, among the 11 sectors, the financial sector is the primary source of volatility connectivity. The study also uses the DCC model to derive conditional correlations among the European, UK, and US stock markets and their respective industrial sectors. Kouki et al. (2011) investigated volatility spillover among the five major sectors of developed markets and found a cross-border relationship among the sectors. Antoniou et al. (2007) employ MGARCH to evaluate volatility transmission and find that the UK's capital market is better connected to European capital markets. Hammoudeh et al. (2009) calculated hedge ratios and found that sectors of the GCC that hedge long holdings with short positions are lower than those in the

US stock sectors. One of the studies by Bissoondoyal-Bheenick et al. (2018) found that the US market sector dominates the Chinese sector, but emerging markets such as China (Zhang et al., 2019) and India are capable of dominating global markets. Jin et al. (2020) use the DCC, ADCC and GO-GARCH models to determine the effectiveness of global sectors as potential hedges for equities in both emerging and developed markets.

The existing literature extensively covers relationships between broad indices, commodities, and sector indices. However, a notable gap exists in exploring volatility spillover among sectoral indices in emerging and developed capital markets. This study fills this research gap by investigating the volatility spillover among India, China, the UK, and the US sectoral indices, focusing on major sectors: financial services, auto, oil and gas, IT, healthcare and real estate. Additionally, the study calculates optimal hedge ratios among these market sectoral indices.

Data and methodology

Data

To investigate the volatility spillover among sectors of emerging and developed capital markets, the study selected the sectoral indices, presented in Table 1. The sectoral indices include the closing value from 1 January 2015 to 29 December 2023. The log return of each sectoral index series is calculated using the formula $R_t = \ln(P_t/P_{t-1})$. These calculated log return series are considered for further analysis.

Table 2 provides the descriptive statistics of the sectoral indices of all markets. During the study period, the financial services sector of all the markets generated positive returns except China. Except for the UK auto index, all auto indices gave positive returns, whereas the Chinese oil and gas index gave a negative return during the period. In the case of the IT sector, all the markets generate positive returns. The US healthcare and Indian real estate index generated the highest positive return; however, the real estate index of China and the UK gave a negative return during the study period. The sectoral indices of all four markets are negatively skewed. Skewness indicates that the series deviates significantly from the normal distribution. Kurtosis confirms that all sectoral indices are leptokurtic. The significant Jarque-Bera value confirmed the rejection of the normality. ADF and PP tests confirm the stationarity of the data series. The significant coefficient value of the ARCH LM and LB Q^2 test indicates that all series have heteroscedasticity and serial correlation properties at lag five.

Methodology

The study uses two different models to examine the volatility spillover and hedge ratios of sectoral indices of emerging and developed markets. These models are the BEKK and GO-GARCH proposed by Engle and Kroner (1995) and Van Der Weide (2002). BEKK directly models the conditional covariance matrix, allowing for time-varying correlations between the squared return shocks. GO-GARCH assumes that the shocks in the model are orthogonal, meaning that they are uncorrelated. This can be particularly useful when modelling relationships between different financial assets. There are two motivations for using these two models; first, the study can compare the results and conclude which model best fits the data. The second use of both models helps in testing the robustness of the findings; if both models produce similar results, it enhances the reliability of the research.

Table 1. Sectoral indices.

Sectors	India ¹	China ²	UK ²	US ³
Financial Services	Nifty Financial Services	FTSE China A 600 Financials	FTSE 350 Financial Services	Dow Jones US Financials
Auto	Nifty Auto	FTSE China A 600 Automobile & Parts	FTSE 350 Automobiles & Parts	Dow Jones Automobiles
Oil and Gas	Nifty Oil and Gas	FTSE China A 600 Oil & Gas	FTSE 350 Oil & Gas	Dow Jones US Oil & Gas
IT	Nifty IT	FTSE China A 600 Technology	FTSE 350 Technology	Dow Jones US Technology
Healthcare	Nifty Healthcare	FTSE China A 600 Healthcare	FTSE 350 Healthcare	Dow Jones US Healthcare
Real Estate	Nifty Realty	FTSE 350 Real Estate	SSE Real Estate	Dow Jones US Real Estate

Table 2. Descriptive Statistics.

Stat	Sectors	India	China	UK	US
Mean	Financial Services	0.00047	−0.00014	0.00012	0.00027
	Auto	0.00036	0.00012	−0.00072	0.00063
	Oil and Gas	0.00051	−0.00012	0.000083	0.000019
	IT	0.00051	0.000049	0.00031	0.00069
	Healthcare	0.00027	0.00018	0.000052	0.00031
Std. Dev	Real Estate	0.00060	−0.00013	−0.000101	0.000068
	Financial Services	0.01389	0.01455	0.01398	0.01343
	Auto	0.01404	0.01854	0.02731	0.02664
	Oil and Gas	0.01338	0.01588	0.01914	0.01967
	IT	0.01301	0.02192	0.01459	0.01535
Skewness	Healthcare	0.01178	0.01182	0.01666	0.01106
	Real Estate	0.01896	0.01814	0.01380	0.01330
	Financial Services	−1.16253	−0.39597	−0.73037	−0.85424
	Auto	−0.59406	−0.47891	−0.20307	−0.16533
	Oil and Gas	−1.08055	−0.60533	−0.53866	−0.85795
Kurtosis	IT	−0.44766	−0.361899	−0.4914	−0.53846
	Healthcare	−0.26346	−0.18442	−0.44967	−0.57497
	Real Estate	−0.56058	−0.38938	−0.90230	−1.58277
	Financial Services	19.82468	9.45101	13.08661	22.50893
	Auto	13.84184	6.43397	11.15875	9.68953
Jarque-Bera	Oil and Gas	14.43332	7.53677	19.17624	18.5943
	IT	9.29719	33.3666	36.46319	11.13563
	Healthcare	8.23232	6.15307	6.12806	12.8641
	Real Estate	7.35749	7.98908	17.47829	29.90241
	Financial Services	26768.14*	3919.781*	9638.602*	35587.22*
ADF	Auto	11038.23*	1179.348*	6192.011*	4162.562*
	Oil and Gas	12563.18*	2045.872*	24388.56*	22838.5*
	IT	3754.009*	85614.64*	103996.4*	6249.352*
	Healthcare	2566.137*	935.1456*	983.0018*	9151.372*
	Real Estate	1878.547*	2365.949*	19753.25*	68086.82*
PP	Financial Services	−12.7742*	−10.2971*	−11.2861*	−9.8498*
	Auto	−16.4893*	−16.2684*	−16.0914*	−15.413*
	Oil and Gas	−13.4633*	−35.2345*	−10.436*	−10.46*
	IT	−17.1267*	−18.0584*	−17.277*	−14.8576*
	Healthcare	−31.4777*	−47.9685*	−11.8431*	−28.2707*
L-B Q ² Stat (5)	Real Estate	−44.1449*	−9.9482*	−17.3824*	−14.8624*
	Financial Services	−45.9991*	−46.7781*	−46.058*	−51.4806*
	Auto	−46.1646*	−45.4519*	−45.7179*	−47.901*
	Oil and Gas	−47.1243*	−47.2039*	−44.6644*	−48.0223*
	IT	−47.8084*	−45.6539*	−46.61*	−53.2197*
LM Test (5)	Healthcare	−45.053*	−47.9756*	−45.3351*	−50.9725*
	Real Estate	−44.3118*	−45.227*	−44.2683*	−48.9112*
	Financial Services	125.93*	106.95*	186.72*	117.05*
	Auto	108.60*	139.02*	29.01*	256.81*
	Oil and Gas	46.868*	106.21*	86.95*	148.83*
	IT	193.37*	134.78*	40.04*	129.63*
	Healthcare	58.504*	97.76*	142.19*	171.82*
	Real Estate	74.35*	87.93*	63.33*	163.56*
	Financial Services	116.40*	98.70*	166.87*	108.58*
	Auto	105.53*	126.67*	27.55*	222.79*
	Oil and Gas	42.84*	100.07*	82.60*	149.30*
	IT	173.15*	138.08*	42.814*	116.42*
	Healthcare	54.12*	95.22*	135.11*	153.35*
	Real Estate	66.85*	80.02*	56.42*	152.68*

Notes: (*) indicate the significance at 1%, Unit root test: Augmented Dickey-Fuller (ADF) Phillips-Perron (PP) test, Serial correlation test: Ljung-Box test in squared residual at lag five and ARCH test: Lagrange Multiplier test at lag five.

Source: Author's calculation.

BEKK model

This study employed the multivariate BEKK model to test the volatility spillover among the sectoral indices. The BEKK model is a generalized form of the univariate model, which directly estimates the variance and co-variance and ensures that conditional variance is positive (McCullough et al., 2018). The BEKK model extensively examines the volatility spillover between the two markets or assets. To estimate the volatility, below the BEKK MGARCH model has been formed:

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B \quad (1)$$

Specifically, bivariate BEKK is presented as follows.

$$\begin{bmatrix} H_{11,t} & H_{12,t} \\ H_{21,t} & H_{22,t} \end{bmatrix} = C'C + \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}' \begin{bmatrix} \epsilon_{1,t-1}^2 & \epsilon_{1,t-1}\epsilon_{2,t-1} \\ \epsilon_{2,t-1}\epsilon_{1,t-1} & \epsilon_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix} \\ + \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}' \begin{bmatrix} H_{11,t-1} & H_{12,t-1} \\ H_{21,t-1} & H_{22,t-1} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \quad (2)$$

Where C is the lower triangular matrix, C makes H_t positive-definite. From Eq. (2), the conditional variance of the first and second series are represented by $H_{11,t}$ and $H_{22,t}$. Whereas conditional co-variance of the first and second series are represented by $H_{12,t}$ and $H_{21,t}$ (Vardar et al., 2018). A and B are the parameter matrices of the order $k \times k$. In Eq. (2), diagonal coefficients of matrix A (α_{11} and α_{22}) and matrix B (b_{11} and b_{22}) measure the effect of past shock (ARCH) and past volatility (GARCH) on the conditional volatility of the asset, respectively (Gyamerah et al., 2022; Sahoo & Kumar, 2022). The off-diagonal coefficients matrix A (α_{12} and α_{21}) and matrix B (b_{12} and b_{21}) capture the impact of past shocks and volatility of one asset on the other asset.

GO-GARCH model

The GO-GARCH is designed to capture volatility clustering, a phenomenon observed in financial time series where periods of high volatility tend to cluster together. The GO-GARCH model is defined as follows:

$$r_t = m_t + \varepsilon_t \quad (3)$$

In Eq. (3), asset return is denoted as r_t expressed as a function of the conditional mean m_t . It encompasses the error term ε_t and an AR(1) term. In this context, the model entails the transformation of $r_t - m_t$ into a set of unobservable dependent factors, f_t (Abakah et al., 2023). Consequently, the error term is defined as:

$$\varepsilon_t = Af_t \quad (4)$$

In Eq. (4), A represents a mixing matrix that can be further decomposed into an orthogonal matrix U and an unconditional covariance matrix Σ . So, $A = \Sigma^{1/2}U$ (Basher & Sadorsky, 2016). The rows in matrix A correspond to the assets, and the columns represent the factors (f) (Sarwar et al., 2019); can be expressed as follows:

$$f_t = H_t^{1/2}z_t \quad (5)$$

In Eq. (5), the mean and variance of the random variable z_t are set to 0 and 1, respectively. h_{it} is the factor conditional variances estimated through a GARCH process. Additionally, the unconditional distribution of factors f satisfies $E(f_t) = 0$ and $E(f_t f_t') = 1$ (Raza et al., 2019). The conditional means of the asset returns are modelled by combining the three Eqs. (3)–(5) as:

$$r_t = m_t + AH_t^{1/2}z_t \quad (6)$$

Finally, the conditional covariance matrix of the return series ($r_t - m_t$) is as Eq. (7):

$$\Sigma_t = AH_t A' \quad (7)$$

The GO-GARCH model is based on two primary assumptions. First, matrix A remains time-invariant. Second, H_t is a form of a diagonal matrix. Across all the models under consideration, the mean equation adheres to the AR(1) process, reflecting the characteristics of volatility clustering, autocorrelation, and fat tails commonly observed in financial series.

Hedge ratio

Hedging against purchasing the first asset can be achieved by selling the second asset to produce the best hedge ratio. The following formula estimates the hedge ratio for two assets, S and F (Mensi et al., 2013).

$$\beta_{SFt} = \frac{h_{SFt}}{h_{FFt}} \quad (8)$$

The hedge ratio between the two assets, S and F , is denoted by β_{SFt} . The conditional covariance between assets S and F is expressed by h_{SFt} (Sahoo & Kumar, 2023; Thenmozhi & Maurya, 2020) and h_{FFt} represents the conditional variance of asset F .

Results and discussion

Table 3 shows the results of the BEKK model. The significant diagonal elements of matrix A and B indicate that previous shocks and volatility influenced current volatility. However, the off-diagonal elements of the coefficient matrix A and B suggest cross-market shocks and volatility. First, we discuss volatility spillovers in the financial services sector. The significant coefficient values of A(India, India), A(China, China), A(UK, UK), and A(US, US) indicate that the past shock in the financial services index of India, China, the UK, and the US affected the current volatility. The significant off-diagonal elements A(China, India) and A(China, US) suggest that the shock of the Chinese financial services index impacted the volatility of India's and the US financial services index. The outbreak of the COVID-19 pandemic in 2019 and its global spread in 2020 led to widespread market turbulence. As the virus originated in China, the initial shock affected Chinese financial markets, leading to increased volatility in the China financial services index. However, Bissoondoyal-Bheenick et al. (2017) reported contrasting results, where they found spillover from US financial services to Chinese financial services. The diagonal element of the coefficient matrix B indicates that all market's financial indices are affected by their past volatility.

The second section discusses the spillover in the auto sector. The significant coefficient values of A(China, US) and A(UK, China) suggest that the shock from the auto index of China and the UK impacted the current volatility of the auto index of the US and China, respectively. The significant coefficient values of A(India, US) and A(US, India) suggest that the bi-directional shock spillover between Indian and US indices. Fluctuations in worldwide automotive demand have the potential to impact the auto industries of both the US and India. The volatility arising from changes in consumer preferences, market demand, or global economic conditions has the capacity to transmit across these two markets.

The third section interprets the coefficients of volatility spillovers in the oil and gas sector. The past shocks of all markets' oil and gas indices significantly impacted their current volatility. The historical shock in the US's oil and gas index has played a substantial role in the present volatility of India's and China's oil and gas index. Furthermore, the past volatility of the oil and gas index impacted the current

Table 3. BEKK results.

Descriptive statistics	Financial services	Auto	Oil and gas	IT	Healthcare	Real estate
A(India, India)	0.23478*	0.34529*	0.26939*	0.13332*	0.04612	0.19843*
A(India, China)	0.02758	0.02128	-0.02233	-0.06501	-0.12249*	-0.01072
A(India, UK)	0.01853	-0.04284	-0.00488	-0.33008*	0.00496	0.00586
A(India, US)	0.05192	-0.07141**	0.017826	-0.08796*	-0.02075	0.01045
A(China, India)	0.03876**	0.02197	0.03025	0.03846*	0.05870**	0.06397*
A(China, China)	0.17361*	0.15469*	0.18059*	0.22725*	0.04710**	0.22528*
A(China, UK)	0.05976**	0.02795	0.01897	-0.08608*	-0.03933**	0.03286*
A(China, US)	0.05277**	0.02967*	0.02410	-0.02066	-0.03046	0.04118*
A(UK, India)	0.01846	-0.00698	0.05201*	0.05815*	0.04192*	0.01222
A(UK, China)	-0.01955	0.01853**	0.00031	0.19470*	-0.01889	-0.02282
A(UK, UK)	0.28208*	0.13851*	0.19553*	-0.07967**	0.19140*	0.33809*
A(UK, US)	0.00772	-0.03508**	0.02255	-0.00885	-0.02121	-0.02965*
A(US, India)	-0.0121	0.03238*	0.10444*	-0.04616	0.16096*	0.06215
A(US, China)	-0.00625	0.01109	0.03620*	-0.05361**	0.10776*	0.01527
A(US, UK)	-0.10583	0.08643*	-0.00094	-0.01654	0.07824*	-0.09651*
A(US, US)	0.36012*	0.23407*	0.24221*	0.29084*	0.32299*	0.30240*
B(India, India)	0.95979*	0.90051*	0.71986*	0.74388*	0.79058*	0.90858*
B(India, China)	-0.01333	-0.00717	-0.03267**	0.03465	0.65703*	-0.01217
B(India, UK)	-0.00972	0.03039	0.06742**	0.43163*	-0.02649	0.02253**
B(India, US)	-0.00857	0.02971	-0.00811	-0.05133	0.02939	-0.02765**
B(China, India)	-0.00557	-0.00005	0.01095	-0.02781*	-0.70582*	-0.01208
B(China, China)	0.98121*	0.98644*	0.98360*	0.96174*	0.56911*	0.96566*
B(China, UK)	-0.01368	-0.00294	-0.0092	0.03301*	-0.02822	-0.0152*
B(China, US)	-0.00313	-0.00451	-0.0014	0.00633	-0.08853*	-0.00614
B(UK, India)	0.00732	0.00085	0.01337	0.19975*	0.02799	0.01294
B(UK, China)	0.01344	-0.00869*	0.00529	-0.05664	0.00030	0.00388
B(UK, UK)	0.90059*	0.97601*	0.93270*	0.32088*	0.98443*	0.88755**
B(UK, US)	-0.00361	-0.00167	-0.04601*	-0.2324*	0.01099**	0.03684
B(US, India)	-0.00855	-0.00382	-0.01262	0.09897*	0.19321*	-0.01613
B(US, China)	-0.00494	-0.00015	-0.00852**	0.02650	0.00480	-0.00165
B(US, UK)	0.07808	-0.01476*	0.04547*	0.22862*	-0.01826	0.06839*
B(US, US)	0.89825*	0.97259*	0.99594*	1.01347*	0.95557*	0.92850*

Notes: (*) and (**) indicate the significance at 1% and 5% level.

Source: Author's calculation.

volatility of the oil and gas indices in all four markets. The past volatility of India's oil and gas index affected the current volatility of the UK's oil and gas index. Oil and gas, being commodities traded on a global scale, have the potential to impact numerous countries through price fluctuations and market conditions. India has broadened its export markets for refined petroleum products in the past year, benefiting from discounted Russian oil after the Ukraine war. Despite the UK taking a leading role in imposing sanctions on Russia, including a ban on importing Russian oil, the UK is now acquiring Russian oil through India. The volatility of the US oil and gas index impacted the volatility of the UK oil and gas index. One major reason is that US oil and gas production has increased dramatically over the last decade. The US competes with Russia and Saudi Arabia to lead global crude oil production (Gross, 2018).

The fourth section discusses the results of the IT sector. The past shock of the UK IT index significantly impacted the IT sector volatility of the emerging markets. The IT sector depends on intricate global supply chains. A shock in the UK IT index potentially disturbed supply chain dynamics, impacting the functioning of IT companies in India and China, thereby exerting an influence on sector volatility. The volatility of the US IT index influenced the volatility of the other emerging and developed market IT index volatility. The US serves as a centre for technological innovation and research. Progress and breakthroughs in the US IT sector mirror technological advancements, creating a ripple effect on the volatility of IT indices in other markets.

This section presents the results of the healthcare sector. The current volatility of the Indian healthcare index is influenced by the past shock and volatility in the UK and US healthcare index. Furthermore, the current volatility of all markets' healthcare indices is impacted by their past volatility. The Indian healthcare sector holds a crucial position in the worldwide pharmaceutical market. Fluctuations in the healthcare indices of major pharmaceutical consumers like the UK and the US can influence demand, supply chains, and pricing dynamics. Global health events, such as the COVID-19 pandemic, have had a significant influence on healthcare stocks across the globe. During health crises, shocks and heightened volatility in the UK and US healthcare indices may contribute to increased uncertainty and market volatility in the Indian healthcare index.

Finally, the past shock in China's real estate index influenced the current volatility of the real estate index of India, the UK, and the US. The contraction of China's real estate sector is poised to exert a notable influence on heavy industries and real estate sectors in other countries. For example, over the twelve months leading to March 2023, expenditures by Chinese entities on residential real estate in the US more than doubled compared to the preceding year, underscoring the perception of the US market as a secure haven by capital holders in China (Vince, 2023). Investments from China in the real estate sector transcend national boundaries. If these investors find themselves compelled to sell assets in China to offset domestic losses swiftly, it could adversely affect real estate markets in various countries.

The parameter estimates of the GO-GARCH are reported in Table 4. As the GO-GARCH model calculates factors, it does not yield standard errors. In each considered sector, the long-run persistence (β) surpasses the short-run persistence (α). Furthermore, the sum of α and β is less than 1 in all sectors; this indicates that the volatility process is mean reverting. Finally, the study presents the results of the diagnostic tests of both BEKK and GO-GARCH models in Table 5. The insignificant coefficient of the L-B test fails to reject the null hypothesis of no serial correlation in the data series in all the sectors under consideration; this indicates the stability of both models.

Hedge ratio

The results of the hedge ratios of different pairs of markets of sectoral indices are presented in Table 6. The hedge ratios of the BEKK model are discussed and compared with the GO-GARCH model. First, start with hedge ratios calculated from BEKK in the financial services sector. The mean value of the computed hedge ratio between the US and China is 0.11. This signifies that a \$1 investment in the US financial services sectoral index can be hedged against selling in the Chinese financial services sectoral index for 11 cents, and it is the cheapest hedge among all pairs of the financial services sector. This may be due to the fact that the financial sector in each country provides an extensive selection of products and services that differ from one another in a variety of ways. However, the expensive hedge in the financial services sector is between the UK and the US, where \$1 buying in the UK's financial services index can

Table 4. GO-GARCH estimates.

Sectors	Parameter	F1	F2	F3	F4
Financial services	ω	0.02013	0.02241	0.01155	0.07393
	α	0.07364	0.14825	0.07338	0.15363
	β	0.904	0.83091	0.91892	0.77447
	skew	-0.01074	-0.23041	0.09007	-0.01056
	shape	1.37732	1.29433	0.63363	1.75376
Auto	ω	0.00521	0.00329	0.02674	0.00296
	α	0.06699	0.03748	0.08137	0.05526
	β	0.93071	0.96005	0.88887	0.94373
	skew	-0.04784	-0.04923	-0.12747	0.03349
	shape	1.21186	0.85837	1.65184	0.98818
Oil and gas	ω	0.05150	0.00654	0.00460	0.01567
	α	0.06306	0.06643	0.05684	0.07749
	β	0.87823	0.92693	0.94104	0.90699
	skew	-0.18305	-0.0948	0.02646	0.09227
	shape	1.83649	1.61097	0.90450	2.98145
IT	ω	0.01249	0.01631	0.02766	0.16366
	α	0.11943	0.09127	0.05004	0.11609
	β	0.87547	0.89540	0.92003	0.70156
	skew	-0.24954	0.04016	0.04311	0.06732
	shape	1.45798	0.85256	1.40893	0.88577
Healthcare	ω	0.06751	0.00297	0.07889	0.01975
	α	0.07768	0.06014	0.07630	0.09555
	β	0.85252	0.93885	0.84587	0.88305
	skew	-0.0496	-0.0529	0.027853	0.218724
	shape	1.90721	1.80448	1.53660	2.02581
Real estate	ω	0.01152	0.09600	0.01935	0.06710
	α	0.09510	0.08923	0.08293	0.14102
	β	0.89331	0.81329	0.89916	0.78708
	skew	-0.23109	-0.117	0.09506	0.03133
	shape	1.97095	1.41593	0.91220	1.58439

Notes: The GO-GARCH model is computed utilizing a multivariate affine negative inverse Gaussian (MANIG) distribution. Each model incorporates a constant and an AR(1) term in the mean equation. It is customary to display the rotation matrix (U) and the mixing matrix (A); these details are omitted here for space. Nevertheless, they can be made available upon request.

Table 5. Diagnostic tests.

Sectors	Financial Services		Auto		Oil and Gas		IT		Healthcare		Real Estate	
	BEKK	GO-GARCH	BEKK	GO-GARCH	BEKK	GO-GARCH	BEKK	GO-GARCH	BEKK	GO-GARCH	BEKK	GO-GARCH
Markets	Q(5)	Q(5)	Q(5)	Q(5)	Q(5)	Q(5)	Q(5)	Q(5)	Q(5)	Q(5)	Q(5)	Q(5)
India	6.83588	4.10014	0.93260	2.21529	1.77649	3.31128	5.91669	2.14772	0.79881	1.12054	3.6239	5.99495
China	2.65829	1.99359	3.25561	2.82777	2.38698	2.55757	1.26180	1.61151	5.43762	7.89972	1.4155	1.00528
UK	1.92218	8.51321	5.53564	4.28627	4.85646	5.34542	3.43448	4.96228	8.12736	6.46535	9.7719	8.04923
US	6.63209	8.24340	6.17655	4.23971	4.50961	4.82564	2.42760	5.79611	4.63627	3.50131	3.4555	5.98293

Notes: Q(5) is the Ljung-Box test on the residual at lag 5.

be a hedge against selling 58 cents in the US financial services sectoral index. Let us compare both models' hedge ratios. It is evident that the hedge ratios are higher in the GO-GARCH model than in the BEKK model.

In the case of hedging in the auto sector, the China/UK pair is the cheapest, where a \$1 long position in China can be a hedge against the 4 cents short position in the UK auto index. The second and third cheapest hedge is between the UK/China and China/US pairs. The most expensive hedge in the auto index is between the UK/India and US/India pair. Like the financial services sector, in the auto sector, the mean value of the hedge ratio is comparatively higher in GO-GARCH than BEKK. In case of hedging in the oil and gas sector, the most expensive hedge is between the US and the UK, where a \$1 buying in the US oil and gas index can be a hedge against 62 cents in the UK index. The cheapest hedge in the oil and gas sector is the \$1 long position in India that can be hedged against the short position in China and the US for 7 cents individually. A hedge between India and the US is the cheapest oil and gas sector hedge. India's power and position in the global energy ecosystem, as well as India's encouraging geology, open information accessibility, and supportive policy regime, attract foreign investors to invest in India's power and petroleum growth. In the case of the IT sector, the cheapest hedge is between the UK and China, where the \$1 long position in the Indian IT index can be hedged against the 4 cents short position in the Chinese IT index. The costliest hedge is between the IT index of the UK/US, indicated by the mean value of 0.38. In the healthcare sector, the cheapest and costliest hedge

Table 6. Hedge ratios.

Pairs	Model	Stat	Financial services	Auto	Oil and Gas	IT	Healthcare	Real Estate
India/China	BEKK	Mean	0.19	0.11	0.07	0.06	0.15	0.11
		HE(%)	7	7	4	3	6	1
	GO-GARCH	Mean	0.22	0.18	0.13	0.11	0.21	0.14
		HE(%)	11	6	2	3	5	2
India/UK	BEKK	Mean	0.31	0.10	0.13	0.15	0.08	0.33
		HE(%)	19	6	7	11	3	10
	GO-GARCH	Mean	0.35	0.14	0.17	0.26	0.11	0.40
		HE(%)	19	6	6	9	3	9
India/US	BEKK	Mean	0.28	0.10	0.08	0.15	0.18	0.24
		HE(%)	10	3	7	4	3	3
	GO-GARCH	Mean	0.29	0.13	0.15	0.25	0.24	0.28
		HE(%)	12	4	6	4	4	4
China/India	BEKK	Mean	0.24	0.17	0.10	0.13	0.16	0.10
		HE(%)	3	4	2	1	6	1
	GO-GARCH	Mean	0.23	0.25	0.15	0.27	0.22	0.12
		HE(%)	5	4	2	0	5	2
China/UK	BEKK	Mean	0.20	0.04	0.12	0.09	0.05	0.14
		HE(%)	2	0	1	1	1	0
	GO-GARCH	Mean	0.21	0.09	0.13	0.17	0.06	0.15
		HE(%)	4	2	2	1	2	2
China/US	BEKK	Mean	0.19	0.09	0.13	0.20	0.42	0.11
		HE(%)	2	3	1	1	14	0
	GO-GARCH	Mean	0.19	0.15	0.14	0.24	0.49	0.14
		HE(%)	3	4	2	1	13	1
UK/India	BEKK	Mean	0.36	0.39	0.27	0.18	0.14	0.16
		HE(%)	16	5	3	8	3	7
	GO-GARCH	Mean	0.38	0.51	0.32	0.30	0.20	0.19
		HE(%)	15	6	6	8	2	9
UK/China	BEKK	Mean	0.17	0.06	0.18	0.04	0.10	0.06
		HE(%)	4	0	2	0	1	3
	GO-GARCH	Mean	0.19	0.15	0.17	0.08	0.16	0.09
		HE(%)	6	1	3	2	2	3
UK/US	BEKK	Mean	0.58	0.28	0.59	0.38	0.16	0.40
		HE(%)	32	8	44	13	0	21
	GO-GARCH	Mean	0.50	0.35	0.57	0.41	0.21	0.48
		HE(%)	29	8	43	14	2	21
US/India	BEKK	Mean	0.24	0.35	0.21	0.21	0.14	0.10
		HE(%)	7	1	5	0	6	9
	GO-GARCH	Mean	0.28	0.42	0.34	0.30	0.20	0.13
		HE(%)	10	3	6	3	4	7
US/China	BEKK	Mean	0.11	0.15	0.19	0.09	0.31	0.05
		HE(%)	4	1	3	1	15	4
	GO-GARCH	Mean	0.17	0.22	0.20	0.11	0.34	0.09
		HE(%)	7	2	4	2	16	5
US/UK	BEKK	Mean	0.42	0.24	0.62	0.37	0.06	0.35
		HE(%)	35	7	45	13	3	26
	GO-GARCH	Mean	0.43	0.28	0.62	0.43	0.10	0.41
		HE(%)	35	8	45	12	4	23

Source: Author's calculation.

between China/UK and China/US, respectively. In the real estate sector, an expensive hedge is between the UK and the US, and the cheapest is between the US and China. The study also finds that the hedging effectiveness (HE) of the BEKK model is very near to the GO-GARCH model. Overall, the HE is higher in financial services than in the other sectors. The results suggest that considering only developed or only emerging market indices does not result in efficient hedging.

Conclusion

This study assesses volatility spillover among sectoral indices of emerging and developed markets, specifically focusing on India, China, the UK, and the US. Analyzing cross-country volatility spillover is crucial for understanding financial market integration and promoting economic cooperation. From the financial perspective and intercountry investment opportunities, any policy-related developments in the sectors of developed markets significantly affect the capital markets of both developed and emerging countries. Significant spillover was found in the oil and gas; possible reason is that India, China, and the UK are major oil and gas importing countries, so they are more prone to the global shocks and demand and

supply of oil and gas. The significant volatility spillover in the IT sector may stem from the dynamic and fast-paced nature of the technology industry. Factors such as continuous innovations, regulation shifts, and market sentiment fluctuations contribute to increased volatility. Moreover, the interconnected global supply chains and interdependencies within the technology sector could magnify the influence of shocks or developments in one country, impacting others in the process. Evidence of the global health pandemic exposed the healthcare sectors to global shocks. Innovation in the healthcare sector and the global demand and supply of pharmaceutical raw materials and products make this sector more vulnerable. The collapse of China's real estate sector made this sector more volatile; however, this scenario created an opportunity for real estate investors to invest in other developed or emerging markets.

Furthermore, the GO-GARCH model presents evidence of volatility persistence. The hedge ratio, crucial for building hedging strategies, indicates that hedging between emerging and developed markets is the cheapest, whereas hedging between only developed or emerging markets is the costliest hedge. Here, the study wants to answer one question: which model is better, whether BEKK or GO-GARCH? By investigating the results of volatility and hedging, the study finds that the BEKK model is better than the other one in minimizing the hedging risks. The study aids investors in developing an ideal portfolio by considering prior shocks and volatility. It is advised to the investors about investments in sectoral indices of the Indian market. The sectoral index of India is less affected by the volatility of the other markets, and it also does not significantly impact other countries' sectoral indices. Some of the underlying possibilities are why global investors visit India for portfolio diversification. Strong economic trends backed by the financial, IT, healthcare and real estate sectors, with trade policy reforms, proactive FDI policies for infrastructure development, and outstanding human capital abilities, make India an excellent investment avenue.

Evaluating sector index volatility provides insights into financial health, and analyzing volatility spillovers among markets and industries indicates the degree of capital market integration. Changing interconnections and volatilities offer a variety of intriguing challenges for investors, portfolio managers, and regulators. This finding implies that portfolios and risk managers should closely and constantly monitor sector-specific improvements in emerging and developed markets to rebalance their portfolios and hedge positions more effectively and on time. The finding has different implications for the different stakeholders.

Implication for the investors

Investors can use the study's insights to customize their investment strategies, considering the increased vulnerability of oil and gas, IT, healthcare and real estate sectors to cross-border spillover effects. Understanding the cost dynamics associated with hedging strategies provides investors with the tools to enhance risk management practices for exposures in both emerging and developed markets. International investors, portfolio managers, and hedge funds can follow this study while diversifying or hedging among emerging and developed capital market sectors. Financial institutions can enhance their risk management practices by acknowledging the high volatility of certain sectors to global shocks.

Implication for the policy makers

Policymakers obtain valuable insights into the potential repercussions of global shocks on their domestic economies, underscoring the importance of coordinated policies to mitigate cross-border spillover effects. Adjustments in the economic sectors of developed markets may have significant implications for emerging markets, shaping investment opportunities.

Finally, the study presents the limitations and scope for future research. The current study is limited to the six sectors and two developed and emerging markets each. Future studies can consider additional major sectors by taking additional markets. Furthermore, "Sustainable Sectors" is one of the emerging topics to be researched by considering both emerging and developed markets. The studies can also consider the impact of sustainable factors on the volatility of sectoral indices in different markets.

Authors' contribution

Dr. Satyaban Sahoo: Writing- Original draft, Data Collection, Data Analysis, Editing. Dr. Sanjay Kumar: Supervision, Reviewing and Validation.

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Data availability statement

Data are available on request.

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