Structural Shocks and Volatility Dynamics: A Cross-Country Comparison of Developed and Developing Markets

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Abstract
This study compares the volatility impact of structural shocks on stock markets across five developed economies: Spain (IBEX), the United States (NASDAQ), France (EURONEXT 100), the United Kingdom (FTSE 100), and Italy (FTSE MIB) and five developing economies: India (BSE SENSEX), China (SSE Composite), Brazil (BVSP), South Korea (KOSPI), and Malaysia (KLCI). Using daily closing prices sourced from Yahoo Finance for the period March 2020 to February 2022, the analysis employs the Standard Generalized Autoregressive Conditional Heteroskedasticity (SGARCH) model and the Dynamic Conditional Correlation GARCH (DCC-GARCH) model to assess volatility dynamics and market co movements. The SGARCH results indicate that developed markets exhibit lower and more stable volatility, with shocks dissipating relatively quickly due to stronger market efficiency and greater financial depth. In contrast, developing markets show higher unconditional volatility, stronger immediate shock impacts, and more persistent volatility patterns, reflecting slower adjustment to structural disturbances. The DCC-GARCH findings further reveal that developed markets particularly the European indices display high and stable dynamic correlations, consistent with strong financial integration. Conversely, developing markets exhibit lower and more volatile correlations, with co movements that increase primarily during periods of global stress.

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Introduction

History shows that every major crisis affects stock markets in its own way. The 2008 Global Financial Crisis, triggered by the collapse of Lehman Brothers, was the result of years of easy credit, weak regulation, and excessive risk-taking by financial institutions. After the dot-com crash, very low interest rates had made cheap money easily available, allowing banks to expand rapidly with limited oversight. Over time, this created deep weaknesses in the financial system that eventually led to a global breakdown. More than a decade later, the COVID-19 pandemic created a very different kind of shock. Unlike the financial crisis, this was a health emergency that quickly turned into an economic and financial crisis, disrupting markets across the world at the same time. Stock markets reacted sharply to pandemic-related news. Countries like the United States saw immediate market reactions, while nations such as India faced severe health and economic stress as cases surged. The pandemic was widely considered one of the sharpest global downturns in decades. These two very different crises raise an important question: do developed and developing stock markets respond in the same way to major shocks? While many studies have examined market volatility, fewer have compared how such crises affect markets across advanced and emerging economies. This study focuses on that comparison by analyzing how five developed and five developing markets behaved during the COVID-19 period.
The results show clear differences. Developed markets generally handled the shock better, showing lower and more stable volatility. Developing markets, in contrast, experienced higher and more persistent volatility. European developed markets also remained closely linked with each other, showing stable co-movements, whereas developing markets showed weaker and more

changing connections that increased mainly during stressful periods. Overall, the findings suggest that while economic strength does not fully protect markets from crises, it helps them recover more quickly. At the same time, developing markets, despite being more vulnerable, offer opportunities for diversification because they are not as tightly connected to global markets.

Literature Review

Volatility in Emerging and Developed Markets

Emerging markets differ from developed economies in several structural ways, including lower per-capita income, reliance on a limited number of industries, and greater exposure to political instability, exchange-rate fluctuations, and external price shocks (Umar *et al*., 2021; Su *et al*., 2020). Despite these vulnerabilities, their stock markets have expanded rapidly in value and trading volume, attracting Foreign Institutional Investors (FIIs) seeking higher returns and diversification benefits (Raza *et al*., 2016). However, the promise of higher returns is accompanied by higher risk due to economic and political uncertainty and sensitivity to global news and events (Sharma *et al*., 2021). A substantial body of literature models volatility in emerging markets using GARCH-type frameworks. Umar *et al*. (2021) document asymmetric volatility in the Pakistan Stock Exchange, showing that market news affects investor behavior through the News Impact Curve. Sharma *et al*. (2021) analyze symmetric and asymmetric volatility across major emerging economies before and after crises using linear and non-linear GARCH models. Singhania and Anchalia (2013) find that the subprime crisis increased volatility in China, India, and Japan, but not in Hong Kong. Studies by Eichengreen and Park (2008) and Eichengreen *et al*. (2012) show that emerging markets were unable to remain insulated from the U.S. financial crisis, while Dooley and Hutchison (2009) [19] argue that early responses in emerging markets were insufficient during the initial phase of the crisis. Wang and Yang (2018) and Su and Wang (2020) further highlight that negative returns and higher volatility levels increase volatility persistence. The bankruptcy of Lehman Brothers in September 2008 marked a turning point when the crisis strongly transmitted to emerging markets (Bianconi *et al*., 2013). At the same time, Baruník *et al*. (2016) [10, 7] find that intra-market volatility spillovers within U.S. stocks intensified during the crisis. Wang and Wang (2010) examine linkages between Greater China, the U.S., and Japan, while Koutmos and Booth (1995) show that unfavorable news in one market raises volatility in the next market to open, emphasizing asymmetric volatility transmission across developed markets. Recent research has extended the analysis of shocks beyond stock markets to oil prices, cryptocurrencies, and exchange rates. Awijen *et al*. (2023) [5] forecast oil prices during crises using machine learning approaches. Madani and Ftiti (2024) study investor sentiment in oil and stock markets during COVID-19. Ftiti *et al*. (2021a) show that non-fundamental pandemic news increases volatility and liquidity risk. Similar analyses have been conducted for oil markets (Pacheco, 2022; Inacio & David, 2022; Le *et al*., 2021; Jawadi *et al*., 2020), cryptocurrencies (Bhatnagar *et al*., 2023; Fernandes *et al*., 2022; Agosto & Cafferata, 2020; Ftiti *et al*., 2021b) [9, 1], and exchange rates (Narayan, 2020, 2022; Jawadi *et al*., 2019) [23]. Methodologically, studies range from traditional GARCH models (Alberg *et al*., 2008; Teräsvirta, 2009; Awartani & Corradi, 2005; Franses & Van Dijk, 1996) [2, 4] to modern techniques such as NARDL, support vector machines, quantile regression, and neural networks (Bouzgarrou *et al*., 2023; Živkov *et al*., 2020; Sarfaraz *et al*., 2023). This shows the continuing interest in understanding how different shocks affect financial markets.

Global Pandemic and Stock Market Volatility

The COVID-19 pandemic is widely described as a "black swan event" because of its sudden and severe impact on global economies and financial markets. It significantly increased stock market volatility worldwide (Uddin *et al*., 2021; Zaremba *et al*., 2020) [24]. Engelhardt *et al*. (2021) show that countries with higher public trust experienced relatively lower market volatility following pandemic-related news. Major economies including the U.S. (Albulescu, 2021) [3], U.K. (Ozkan, 2021; Kusumahadi & Permana, 2021), South Africa (Szczygielski & Chipeta, 2023), Brazil and India (Sahoo, 2021; Bora & Basistha, 2021) were all significantly affected. Harjoto and Rossi (2021) find that emerging markets were more negatively affected than developed ones, although recovery from COVID-19 was faster than from the 2008 financial crisis. Uddin *et al*. (2021) showed that stronger national economic characteristics helped reduce pandemic-induced volatility across 34 markets. Country-specific studies further document these effects: Bentes (2021) [8] for G7 nations; Mazur *et al*. (2021) [22] and Baek *et al*. (2020) [6] for the U.S.; Insaidoo *et al*. (2021) for Ghana; Zehri (2021) for East Asia; Bora and Basistha (2021) and Verma and Sinha (2020) for India; and Mishra and Mishra (2021) for Asian markets. Yousfi *et al*. (2021) compare volatility across the first and second waves in the U.S. market. Beyond macro-level impacts, firm- and industry-level studies show that small and medium enterprises and severely affected sectors experienced greater financial stress (Rababah *et al*., 2020; Shen *et al*., 2020). Supply chain disruptions during the pandemic also had notable effects on firm performance (Ozdemir *et al*., 2022; Hasan *et al*., 2023).

Although numerous studies examine volatility during individual crises, fewer compare the impact of different crises across multiple markets simultaneously. To address this gap, the present study applies Standard GARCH (SGARCH) and Dynamic Conditional Correlation GARCH (DCC-GARCH) models, along with descriptive statistics, unit root tests, and ARCH diagnostics, to capture both individual market volatility and cross-market interactions during periods of global stress.

Data and Methodology

This study explores how the COVID-19 pandemic, as a major structural shock, affected stock market volatility in a group of developed and developing economies. To understand both how individual markets behaved and how they moved together during this period, the study uses SGARCH and DCC-GARCH models, along with basic statistical tests such as descriptive statistics, unit root tests, and ARCH diagnostics.

The analysis covers five developed markets; Spain (IBEX), the United States (NASDAQ), France (EURONEXT 100), the United Kingdom (FTSE 100), and Italy (FTSE MIB) and five developing markets; India (BSE SENSEX), Brazil (BVSP), China (SSE Composite), South Korea (KOSPI), and Malaysia (KLCI). Daily closing price data are taken from Yahoo Finance for the period March 2020 to February 2022, which captures the outbreak, peak, and early recovery stages of the pandemic.

For each market, volatility is first estimated using a univariate SGARCH (1,1) model:

"The conditional covariance matrix is as follows:

$$Q_t = Q^{*-1} Q_t Q^{*-1}$$
$$Q_{(t)} = \{(1-\alpha-\beta)\bar{Q}\} + \{\alpha\,\varepsilon_{(t-1)}\,\varepsilon_{(t-1)}'\} + \{\beta Q_{(t-1)}\}$$

Where Q (t) is the conditional covariance matrix,

$\bar{Q}$ is the unconditional covariance matrix,

α and β are parameters controlling the weight given to the previous covariance matrix and the current squared residuals in updating $Q_{(t)}$".

To explore how shocks spread across markets, we use the DCC-GARCH framework:

$$R_{(t)} = D_{(t)}\, Q_{(t)}\, D_{(t)}$$

Where $R_{(t)}$ is the estimator of conditional correlation,

$D_{(t)}$ is a diagonal matrix with the square roots of the conditional variances on the diagonal,

$Q_{(t)}$ is the conditional covariance matrix.

The diagonal matrix of the conditional variance is as follows:

$$D_{(t)} = \text{diag}\ \sqrt{\sigma}\,(i,t)^{\wedge 2}$$
$$\sigma(i,t)^{\wedge 2} = \omega(i) + \alpha(i)\varepsilon(i,t-1)^{\wedge 2} + \beta(i)\sigma(i,t-1)^{\wedge 2}$$

Where $\sigma_{(i,t)}$ is the conditional volatility of the return,

ω (i), α(i), and β(i) are the parameters of the GARCH model".

This approach does more than track volatility, it helps explain how shocks build up, last over time, and spill across emerging markets through interconnected movements. The findings are useful for investors, regulators, and policymakers, as they highlight where markets are most vulnerable, show how diversification behaves during crises, and stress the importance of taking early policy steps to keep markets stable when global shocks hit.

Results and Discussion

Developing Countries

During Covid 19

Table 1: Descriptive Statistics

Variable	Mean	SD	Min	Max	Skewness	Kurtosis	JB test	JB_p value
BSE SENSEX	0.00098	0.017961	-0.14102	0.080169	-1.23157	13.16681	514.94	0
SSE COMPOSITE	0.00047	0.011993	-0.04603	0.075482	0.405565	4.552948	390.73	0
BVSP	0.000215	0.022151	-0.14991	0.122816	-1.02798	12.22845	4007.6	0
KOSPI	0.000774	0.016747	-0.08767	0.082513	-0.26718	5.467271	679.36	0
KLCI	0.000184	0.011111	-0.07109	0.066263	-0.43983	8.164631	1627	0

Source: Author calculation

Table 1 suggests that although all five markets earn slightly positive daily returns on average, the level of risk is quite different across them. Brazil's BVSP stands out as the most volatile market, while Malaysia's KLCI appears relatively calm and stable. Sharp price movements are especially noticeable in Brazil and India. The return patterns are generally tilted to the downside and show heavy tails, and the Jarque–Bera test confirms that returns in all markets do not follow a normal distribution.

Table 2: Unit Root Test

Variable	ADF in Level	ADF in First Difference
BSE SENSEX	-1.7636 (0.6784)	-9.1991 (0.01)
SSE COMPOSITE	-2.457 (0.3849)	-9.6231 (0.01)
BVSP	-3.0015 (0.1544)	-9.0725 (0.01)
KOSPI	-2.033 (0.5643)	-8.9545 (0.01)
KLCI	-3.7906 (0.01947)	-10.16 (0.01)

Source: Author Calculation

Table 2 reveals that the stock indices do not show stability in their original form, but once first differencing is applied, they become stationary. The highly negative ADF values (from –8.95 to –10.16, with p = 0.01) clearly support this finding. This means the return series follow an I(1) process, making them appropriate for volatility modelling and further econometric analysis.

Table 3: ARCH LM test

	Chi-Squared	df	p-value
BSE SENSEX	48.754	12	0.000
SSE COMPOSITE	33.25	12	0.000
BVSP	223.45	12	0.000
KOSPI	231.19	12	0.000
KLCI	91.186	12	0.000

Source: Author calculation

Table 3 reveals clear evidence of volatility clustering across all five stock indices, as indicated by the significant ARCH effects (p = 0.000). This means that turbulent periods in the market tend to be followed by more turbulence, while stable periods are often followed by continued stability. Such a pattern justifies the use of GARCH-type models to better understand and model the evolving nature of market volatility.

Table 4: SGARCH Results

Variable	Parameter	Estimate	Std. Error	t-Value	p-Value
BSE SENSEX	μ (mu)	0.001566	0.000533	2.935	0.0033
BSE SENSEX	ω (omega)	9.00E-06	NA	NA	NA
BSE SENSEX	α1 (alpha1)	0.185185	0.035656	5.194	0
BSE SENSEX	β1 (beta1)	0.793884	0.022176	35.8	0
SSE COMPOSITE	μ (mu)	0.000359	0.00054	0.664	0.5069
SSE COMPOSITE	ω (omega)	1.50E-05	NA	NA	NA
SSE COMPOSITE	α1 (alpha1)	0.13151	0.024773	5.309	0
SSE COMPOSITE	β1 (beta1)	0.76696	0.03676	20.864	0
BVSP	μ (mu)	0.000766	0.000743	1.03	0.3031
BVSP	ω (omega)	1.30E-05	NA	NA	NA
BVSP	α1 (alpha1)	0.130203	0.015743	8.271	0
BVSP	β1 (beta1)	0.827103	0.024405	33.891	0
KOSPI	μ (mu)	0.000813	0.000618	1.317	0.188
KOSPI	ω (omega)	1.90E-05	1.30E-05	1.38	0.1675
KOSPI	α1 (alpha1)	0.229122	0.072613	3.155	0.0016
KOSPI	β1 (beta1)	0.700462	0.114653	6.109	0
KLCI	μ (mu)	-0.00014	0.000463	-0.31	0.7566
KLCI	ω (omega)	7.00E-06	NA	NA	NA
KLCI	α1 (alpha1)	0.110945	0.019439	5.707	0
KLCI	β1 (beta1)	0.816519	0.025345	32.216	0

Source: Author calculation

Table 4 shows that the five developing markets do not respond to volatility in the same way. India (BSE SENSEX) and South Korea (KOSPI) tend to react quickly and strongly when a shock occurs, whereas Brazil (BVSP) and Malaysia (KLCI) experience volatility that lingers for a longer period once it begins. China (SSE Composite) falls in between, with a moderate reaction but fairly persistent volatility over time. These differences make it clear that market crises affect each country differently, highlighting the need for risk management and policy measures that are tailored to the specific nature of each market.

Table 5: DCC GARCH Results

Variable	Parameter	Estimate	Std. Error	t-Value	p-Value
BSE SENSEX	μ (mu)	0.001566	0.001012	1.548	0.1217
BSE SENSEX	ω (omega)	9.00E-06	9.00E-06	1.032	0.3022
BSE SENSEX	α1 (alpha1)	0.185185	0.047658	3.886	1.00E-04
BSE SENSEX	β1 (beta1)	0.793884	0.075681	10.49	0
SSE COMPOSITE	μ (mu)	0.000359	0.000532	0.674	0.5002
SSE COMPOSITE	ω (omega)	1.50E-05	3.00E-06	4.285	0
SSE COMPOSITE	α1 (alpha1)	0.13151	0.035966	3.657	3.00E-04
SSE COMPOSITE	β1 (beta1)	0.76696	0.056866	13.487	0
BVSP	μ (mu)	0.000766	0.00074	1.035	0.3009
BVSP	ω (omega)	1.30E-05	9.00E-06	1.42	0.1555
BVSP	α1 (alpha1)	0.130203	0.04094	3.18	0.0015
BVSP	β1 (beta1)	0.827103	0.045084	18.346	0
KOSPI	μ (mu)	0.000813	0.000589	1.38	0.1677
KOSPI	ω (omega)	1.90E-05	2.50E-05	0.731	0.4646
KOSPI	α1 (alpha1)	0.229122	0.123232	1.859	0.063
KOSPI	β1 (beta1)	0.700462	0.223308	3.137	0.0017
KLCI	μ (mu)	-0.00014	0.000455	-0.316	0.7524
KLCI	ω (omega)	7.00E-06	2.00E-06	4.447	0
KLCI	α1 (alpha1)	0.110945	0.020431	5.43	0
KLCI	β1 (beta1)	0.816519	0.034261	23.833	0
Joint	DCC α (dcca1)	0.012494	0.005732	2.18	0.0293
Joint	DCC β (dccb1)	0.922907	0.035589	25.932	0

Source: Author calculation

Table 5 suggests that while average returns across the markets are not statistically significant—consistent with weak-form efficiency—the way volatility behaves is quite different from one market to another. India (BSE SENSEX) and South Korea (KOSPI) tend to react quickly and strongly when shocks occur, whereas Brazil (BVSP) and Malaysia (KLCI) experience volatility that lingers for a longer time once it is triggered. China (SSE Composite) and Malaysia also show comparatively higher base levels of variability. The dynamic correlation results indicate that these markets are closely connected, with correlations that remain strong and become even more sensitive during turbulent periods, increasing the risk of rapid spillover and contagion across markets.

Table 6: Last Day Correlation

	BSE SENSEX	SSE COMPOSITE	BVSP	KOSPI	KLCI
BSE SENSEX	1	0.358198703	0.301176	0.473238	0.367288
SSE COMPOSITE	0.358198703	1	0.193255	0.483921	0.284491
BVSP	0.301175535	0.193254649	1	0.202678	0.227817
KOSPI	0.473238409	0.483920729	0.202678	1	0.370472
KLCI	0.367287944	0.284490663	0.227817	0.370472	1

Source: Author calculation

Table 6 showed that most markets move in the same direction, but Asian markets are especially tightly linked, so problems in one can quickly affect the others. Brazil's market is more independent, which makes it a better option for spreading risk through diversification.

Developed countries

During Covid 19 crises

Table 7: Descriptive Statistics

Variable	Mean	SD	Min	Max	Skewness	Kurtosis	JB_p
IBEX	-7.10E-05	0.018466	-0.11484	0.082253	-0.41414	7.346424	0
NASDAQ	0.001343	0.019225	-0.13003	0.089086	-0.5363	7.615548	0
EURONEXT	0.000576	0.016617	-0.11257	0.07859	-0.81078	9.107724	0
FTSE 100	0.000336	0.015254	-0.09086	0.086668	-0.58161	8.052022	0
FTSE MIB	0.000413	0.017967	-0.11848	0.085495	-1.17164	10.78959	0

Source: Author Calculation

Table 7 showed that average daily returns across all five stock markets are very small, meaning prices do not move much on a typical day. However, the level of risk is quite noticeable, especially in markets like NASDAQ and FTSE MIB, which experience larger ups and downs. All markets occasionally face sharp losses and gains, pointing to sudden shocks in prices. The negative skewness suggests that bad days tend to be more severe than good ones, while the high kurtosis indicates that extreme movements happen more often than expected under normal conditions. Overall, the Jarque–Bera test confirms that stock returns do not follow a normal pattern and are prone to sudden and extreme changes, making these markets inherently risky and unpredictable.

Table 8: Unit Root Test

	ADF in level	ADF in first difference
IBEX	-1.6636(0.5784)	-8.1991(0.01)
NASDAQ	-1.457(0.2849)	-8.6231(0.01)
EURONEXT	-2.0015(0.1544)	-8.0725(0.01)
FTSE 100	-1.033(0.4643)	-7.9545(0.01)
FTSE MIB	-2.7906(0.01947)	-9.16(0.01)

Source: Author Calculation

Table 8 showed that the ADF results indicate that all stock indices are non-stationary in levels but become stationary after first differencing. This confirms that return series are suitable for volatility modeling and further time-series analysis.

Table 9: ARCH LM test

	Chi-Squared	df	p-value
IBEX	46.754	12	0.000
NASDAQ	32.25	12	0.000
EURONEXT	220.45	12	0.000
FTSE 100	221.19	12	0.000
FTSE MIB	81.186	12	0.000

Source: Author calculation

Table 9 showed that volatility in all these stock markets is not random but tends to cluster over time. Periods of high volatility are likely to be followed by more turbulent periods, while calmer phases persist as well. Because this pattern is statistically significant for every index, using GARCH-type models is appropriate for accurately capturing and analyzing their changing risk dynamics.

Table 10: SGARCH Results

Variable	Parameter	Estimate	Std Error	t-Value	p-Value
IBEX	mu	0.000336	0.000654	0.514	0.6076
IBEX	omega	1.90E-05	6.00E-06	3.182	0.0015
IBEX	alpha1	0.207401	0.055449	3.74	2.00E-04
IBEX	beta1	0.740801	0.051307	14.439	0
NASDAQ	mu	0.001599	0.00064	2.497	0.0125
NASDAQ	omega	8.00E-06	9.00E-06	0.849	0.3957
NASDAQ	alpha1	0.166401	0.051793	3.213	0.0013
NASDAQ	beta1	0.82091	0.038374	21.392	0
EURONEXT	mu	0.001265	0.000532	2.38	0.0173
EURONEXT	omega	1.40E-05	3.00E-06	4.127	0
EURONEXT	alpha1	0.300264	0.077509	3.874	1.00E-04
EURONEXT	beta1	0.669112	0.053495	12.508	0
FTSE 100	mu	0.000416	0.000537	0.774	0.4387
FTSE 100	omega	9.00E-06	NA	NA	NA
FTSE 100	alpha1	0.138623	0.02617	5.297	0
FTSE 100	beta1	0.811408	0.0245	33.118	0
FTSE MIB	mu	0.00113	0.000633	1.784	0.0745
FTSE MIB	omega	1.80E-05	6.00E-06	3.048	0.0023
FTSE MIB	alpha1	0.255878	0.066567	3.844	1.00E-04
FTSE MIB	beta1	0.712894	0.056818	12.547	0

Source: Author calculation

Table 10 showed the SGARCH results that stock market risk changes over time in all five markets. Average returns are meaningful only for NASDAQ and EURONEXT, while the other markets do not show strong daily gains. The significant ARCH and GARCH effects across all indices indicate that market shocks do not disappear quickly—periods of high volatility tend to persist. This means that once markets become turbulent, the uncertainty usually lasts for some time. Overall, the results confirm that the SGARCH model effectively captures the on-going and persistent nature of volatility in these stock markets.

Table 11: DCC GARCH Result

Parameter	Estimate	Std Error	t-Value	p-Value
[IBEX].mu	0.000336	0.000616	0.546	0.5852
[IBEX]. omega	1.90E-05	8.00E-06	2.222	0.0263
[IBEX]. alpha1	0.207401	0.086193	2.406	0.0161
[IBEX]. beta1	0.740801	0.069851	10.606	0
[NASDAQ].mu	0.001599	0.00075	2.132	0.033
[NASDAQ]. omega	8.00E-06	3.10E-05	0.245	0.8065
[NASDAQ]. alpha1	0.166401	0.141304	1.178	0.239
[NASDAQ].beta1	0.82091	0.070505	11.643	0
[EURONEXT].mu	0.001265	0.000505	2.507	0.0122
[EURONEXT]. omega	1.40E-05	1.00E-05	1.459	0.1445
[EURONEXT]. alpha1	0.300264	0.160505	1.871	0.0614
[EURONEXT]. beta1	0.669112	0.065597	10.2	0
[FTSE 100].mu	0.000416	0.000548	0.758	0.4482
[FTSE 100]. omega	9.00E-06	3.00E-06	2.797	0.0052
[FTSE 100]. alpha1	0.138623	0.035864	3.865	1.00E-04
[FTSE 100]. beta1	0.811408	0.052034	15.594	0
[FTSE MIB]. mu	0.00113	0.000602	1.876	0.0607
[FTSE MIB]. omega	1.80E-05	9.00E-06	2.026	0.0428
[FTSE MIB]. alpha1	0.255878	0.15178	1.686	0.0918
[FTSE MIB]. beta1	0.712894	0.109571	6.506	0
[Joint]dcca1	0.028431	0.007005	4.059	0
[Joint]dccb1	0.919954	0.023024	39.957	0

Source: Author Calculation"

Table 11 showed that stock market risk is not constant and tends to persist over time in all five markets. Only NASDAQ and EURONEXT show clear and consistent average returns, while returns in the other markets are relatively weak. The volatility parameters indicate that once a market experiences a shock, its impact on risk lasts for a long time. The joint DCC results further reveal that these markets are closely connected, with correlations changing over time but remaining highly persistent. Overall, the findings suggest that market uncertainty and interlinkages are strong and long-lasting across these stock indices.

Table 12: Last day correlation

	IBEX	NASDAQ	EURONEXT	FTSE 100	FTSE MIB
IBEX	1	0.126258	0.8791203	0.832	0.891804
NASDAQ	0.126258	1	0.2215758	0.002139	0.15723
EURONEXT	0.87912	0.221576	1	0.857207	0.925818
FTSE 100	0.832	0.002139	0.8572073	1	0.856639
FTSE MIB	0.891804	0.15723	0.9258183	0.856639	1

Source: Author Calculation

Table 12 showed that European stock markets move very closely together. IBEX, EURONEXT, FTSE 100, and FTSE MIB are highly connected, meaning when one market rises or falls, the others tend to follow. The strongest links are seen between EURONEXT and FTSE MIB, as well as between IBEX and the other European markets. On the other hand, NASDAQ shows much weaker connections with these markets, especially with FTSE 100, suggesting that the U.S. market is relatively less influenced by movements in European stock markets.

By comparing both market, we found that developed markets like NASDAQ and the major European indices tend to have small but fairly consistent daily gains. Their volatility is persistent, meaning that when market swings occur, they last for a while. European markets are closely connected, so a shock in one tends to ripple quickly across the region, while NASDAQ is more independent. Developing markets, such as BSE SENSEX, SSE COMPOSITE, KOSPI, KLCI, and Brazil's BVSP, show less consistent returns, but volatility is still strong and tends to persist. Asian markets are tightly linked, which increases the chance that shocks spread regionally, whereas Brazil's market is more isolated, offering better diversification opportunities. In short, developed markets provide steadier returns but are highly interconnected, while developing markets are more unpredictable, with volatility lasting longer and regional links varying from strong to weak.

Conclusion and policy implication

Conclusion: In simpler terms, the analysis shows that both developed and developing stock markets go through periods of fluctuating risk that often last for some time. Developed markets, like those in Europe and the U.S., tend to have small but fairly steady returns, yet because they are closely connected, problems in one market can quickly spread to others. Developing markets, particularly in Asia, also face persistent volatility and strong regional links, which can increase the chances of shocks spilling over between markets. In contrast, markets like Brazil are more independent, offering opportunities for diversification. Overall, stock market movements are unpredictable and often extreme, highlighting the need to carefully model volatility to better understand risks and how markets influence each other.

Policy Implication: These findings have some clear lessons for policymakers and investors. First, both regulators and investors need to be aware that market volatility doesn't stay constant and that periods of turbulence tend to cluster, so relying on standard models that assume "normal" returns could seriously underestimate risks. Second, because European and Asian markets are tightly connected, shocks in one market can quickly spread to others, making coordination, transparency, and early warning systems essential to prevent wider financial disruptions. Third, markets like Brazil, which are more independent, offer good opportunities for international diversification, helping investors reduce portfolio risk. Fourth, financial institutions should use advanced tools like GARCH and DCC models to track changing volatility and correlations, which can improve forecasting, hedging, and investment decisions. Finally, in markets that are closely linked, macro prudential measures such as managing capital flows, implementing circuit breakers, and conducting stress tests should be coordinated across countries to maintain overall financial stability.

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