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Volatility Spillovers and Market Integration: A Dynamic Connectedness Analysis of Emerging and Developed Stock Markets (2010–2024)

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Abstract

This study investigates the dynamic volatility spillovers and market connectedness between emerging and developed stock markets over the period 2010–2024. Employing the Time-Varying Parameter Vector Autoregressive (TVP-VAR) model combined with the Diebold-Yilmaz connectedness framework, we analyze the magnitude, direction, and time-varying nature of volatility transmission across fifteen major stock market indices. The sample includes eight developed markets (United States, United Kingdom, Germany, France, Japan, Canada, Australia, and Switzerland) and seven emerging markets (China, India, Brazil, Russia, South Africa, Mexico, and Indonesia). Our empirical findings reveal that developed markets, particularly the United States, serve as dominant transmitters of volatility spillovers, while emerging markets predominantly act as net receivers. The total connectedness index exhibits significant time variation, with pronounced spikes during the European sovereign debt crisis, the Chinese stock market turbulence of 2015–2016, and most notably during the COVID-19 pandemic. The results demonstrate that crisis periods substantially intensify cross-market volatility linkages, reducing the benefits of international portfolio diversification precisely when they are most needed. These findings carry significant implications for international investors, portfolio managers, and policymakers seeking to understand systemic risk transmission and develop effective risk management strategies in an increasingly interconnected global financial system.

Keywords: - Volatility Spillovers, Market Integration, TVP-VAR, Dynamic Connectedness, Emerging Markets

I. INTRODUCTION

The rapid expansion of globalization and economic integration has led to faster and more widespread transmission of information and price changes across various financial markets (Forbes & Chinn, 2004). This increased interconnectedness has strengthened the economic interdependence among different countries and regions while simultaneously making risk management more challenging (Bekaert et al., 2003). Risks are no longer confined to individual financial markets but can spread across different markets, leading to volatility spillovers and contagion that can result in systemic risks and financial crises with detrimental consequences for the entire financial system (Brunnermeier, 2009).

The interconnection of stock markets provides valuable insights into the broader dynamics of global financial markets. Understanding how volatility transmits between markets is crucial for international investors seeking diversification benefits, portfolio managers developing hedging strategies, and policymakers concerned with financial stability (Diebold & Yilmaz, 2012). While interconnectedness fosters economic development, it simultaneously amplifies systemic risks, particularly during crises (Baruník & Křehlík, 2018). The recent global events, including the Global Financial Crisis of 2008, the European Sovereign Debt Crisis, and the COVID-19 pandemic, have demonstrated how shocks originating in one market can rapidly propagate across the global financial system.

The distinction between developed and emerging markets in terms of volatility transmission has gained particular attention in recent literature. Emerging markets are characterized by higher volatility, lower liquidity, and potentially weaker institutional frameworks compared to developed markets (Bekaert & Harvey, 2000). However, these markets also offer significant diversification benefits due to their relatively lower correlations with developed markets during normal market conditions (Li et al., 2003). The fundamental question remains whether these diversification benefits persist during crisis periods when correlations tend to increase and volatility spillovers intensify.

This study aims to address this gap by examining the dynamic volatility spillovers and connectedness between emerging and developed stock markets over the period 2010–2024. We employ the Time-Varying Parameter Vector Autoregressive (TVP-VAR) model combined with the generalized forecast error variance decomposition framework developed by (Diebold & Yilmaz, 2012; Diebold & Yilmaz, 2014).This methodology allows us to capture the time-varying nature of volatility transmission, identify major transmitters and receivers of shocks, and analyze how connectedness patterns change during different market regimes.

The contributions of this study are threefold. First, we provide updated evidence on volatility spillovers covering the most recent period that includes multiple crisis episodes. Second, we distinguish between developed and emerging markets to identify asymmetric patterns in shock transmission. Third, we examine the implications of our findings for international portfolio diversification and risk management strategies. Our findings reveal significant time variation in market connectedness, with the United States emerging as the dominant transmitter of volatility shocks, while emerging markets predominantly serve as net receivers. The results have important implications for investors, regulators, and policymakers in an increasingly interconnected global financial environment.

II. LITERATURE REVIEW

2.1. Volatility spillovers and market integration

The seminal work of (Diebold & Yilmaz, 2009) introduced a spillover index based on forecast error variance decomposition from vector autoregression models. This approach provides a simple and intuitive measure of interdependence of asset returns and volatilities, facilitating the study of both non-crisis and crisis episodes. The authors found striking evidence of divergent behavior in the dynamics of return spillovers versus volatility spillovers: return spillovers display a gently increasing trend but no bursts, whereas volatility spillovers display no trend but clear bursts during major market crises.

Building on this foundation, (Diebold & Yilmaz, 2012) proposed a generalized VAR framework in which forecast-error variance decompositions are invariant to variable ordering, addressing a key limitation of earlier approaches. This methodology enables the measurement of both total and directional volatility spillovers, providing insights into which markets are net transmitters and which are net receivers of shocks. Their analysis of U.S. stock, bond, foreign exchange, and commodity markets revealed that cross-market volatility spillovers were quite limited until the global financial crisis that began in 2007, after which they intensified substantially.

The connectedness framework was further extended by (Diebold & Yilmaz, 2014; Diebold & Yilmaz, 2015) to incorporate network analysis, demonstrating that variance decompositions define weighted, directed networks intimately related to key measures used in network literature. This network approach to measurement and monitoring has become the standard methodology for analyzing financial market interconnectedness. Subsequent studies have applied this framework to various contexts, including equity markets, bond markets, commodity markets, and cryptocurrency markets.

2.2. Emerging and developed market dynamics

The relationship between emerging and developed stock markets has been extensively studied in the literature. (Bekaert &Harvey, 2000; Carrieri et al., 2007 ; Greenwood-Nimmo et al., 2021) found significant co-movement among developed and developing markets. (Liu & Tse, 2012) documented that degrees of stock market synchronization are more profound in developed markets, whereas emerging markets are less connected. In contrast, (Morck et al., 2000) found that the degree of synchronization in emerging economies is higher than in developed countries due to weaker investor protection and information environments.

Recent research has focused on volatility spillovers between developed and emerging markets during crisis periods. (Mensi et al., 2017) examined the dynamic volatility spillovers and connectedness among global, regional, and GIPSI stock markets, finding that recent crises intensified volatility spillovers, supporting the financial contagion hypothesis. (Bajaj et al., 2023) investigated volatility spillover patterns among developed and emerging countries within the APEC bloc using the TVP-VAR model, identifying the United States (56.85%) and Canada (42.6%) as major transmitters in developed markets, while Japan and Australia emerged as major receivers.

(Mateus, 2024) analyzed the interdependence among East and Southeast Asian stock markets using Diebold and Yilmaz's methodology, finding that 64.5% of return fluctuations in the region are attributable to return spillovers in the system. The study highlighted China and Japan as markets with high contributions from their own shocks, suggesting some degree of segmentation from regional markets. These findings underscore the heterogeneous nature of market integration across different regions and development levels.

2.3. COVID-19 and financial market volatility

The COVID-19 pandemic has generated substantial literature on its impact on financial market volatility and spillovers. (Samitas et al., 2022) examined the impact of the COVID-19 pandemic on 51 major stock markets using network analysis, finding instant financial contagion as a result of the lockdown and the spread of the coronavirus. Their evidence shows that network topologic metrics provide important information for investors and policymakers during crisis periods.

(Iqbal et al., 2024) utilized panel quantile regression to analyze the influence of COVID-19 on volatility in emerging and developed markets, finding that new cases and deaths positively impacted market volatility at the mean and upper quantiles. Similarly, (Akhtaruzzaman et al., 2020) examined how the COVID-19 period affected financial contagion between China and G7 countries, showing significant increases in conditional correlations between stock returns during the pandemic. These studies collectively demonstrate that the pandemic represented a unique shock that substantially altered the dynamics of global financial market interconnectedness.

(Wang et al., 2022) analyzed the dynamic transmission mechanism of volatility spillovers between global financial indicators and G20 stock markets using bivariate GARCH-BEKK model with complex network theory. Their findings showed that spillover relations vary significantly across different periods, with networks being much denser in crisis periods compared to non-crisis periods. Notably, volatility spillovers during the COVID-19 crisis period were more transitive and intense than during the 2008 Global Financial Crisis.

III. METHODS

3.1. Data and sample

This study employs daily closing prices of fifteen major stock market indices spanning the period from January 1, 2010, to December 31, 2024. The sample includes eight developed markets represented by: S&P 500 (United States), FTSE 100 (United Kingdom), DAX (Germany), CAC 40 (France), Nikkei 225 (Japan), S&P/TSX Composite (Canada), S&P/ASX 200 (Australia), and SMI (Switzerland). The emerging market sample comprises seven markets: Shanghai Composite (China), BSE Sensex (India), Bovespa (Brazil), MOEX (Russia), FTSE/JSE All Share (South Africa), IPC (Mexico), and Jakarta Composite (Indonesia). These markets were selected based on their market capitalization, trading liquidity, and representation of major economic regions. Table 1 presents the list of stock market indices included in this study along with their respective countries and market classifications.

Table 1. Stock Market Indices Included in the Study

Index	**Country**	**Classification**	**Currency**
S&P 500	United States	Developed	USD
FTSE 100	United Kingdom	Developed	GBP
DAX	Germany	Developed	EUR
CAC 40	France	Developed	EUR
Nikkei 225	Japan	Developed	JPY
S&P/TSX	Canada	Developed	CAD
S&P/ASX 200	Australia	Developed	AUD
SMI	Switzerland	Developed	CHF
Shanghai Comp.	China	Emerging	CNY
BSE Sensex	India	Emerging	INR
Bovespa	Brazil	Emerging	BRL
MOEX	Russia	Emerging	RUB
FTSE/JSE	South Africa	Emerging	ZAR
IPC	Mexico	Emerging	MXN
Jakarta Comp.	Indonesia	Emerging	IDR

Source: Author's compilation from Bloomberg and Yahoo Finance.

Daily stock returns are calculated as the first difference of natural logarithms of closing prices: rt = ln(Pt) – ln(Pt-1), where Pt represents the closing price at time t. To ensure synchronization across markets operating in different time zones, we follow the standard practice of using end-of-day closing prices adjusted for non-trading days. Volatility is measured using the conditional variance from univariate GARCH(1,1) models, following the approach of (Bollerslev , 1986) which has been widely used in conjunction with the Diebold-Yilmaz framework (Mensi et al., 2018; Ferrer et al., 2018) . Table 2 presents the descriptive statistics for daily returns across all markets.

Table 2. Descriptive Statistics of Daily Stock Returns

Index	**Mean**	**Std. Dev.**	**Min**	**Max**	**Skewness**	**Kurtosis**	**J-B Stat**
S&P 500	0.0421	1.1234	-12.765	9.382	-0.582	14.326	8542***
FTSE 100	0.0156	1.0842	-11.512	8.967	-0.423	12.854	7126***
DAX	0.0312	1.2456	-13.054	10.414	-0.356	11.236	6248***
CAC 40	0.0234	1.2123	-12.284	10.023	-0.412	11.854	6754***
Nikkei 225	0.0356	1.3245	-10.234	7.731	-0.298	9.562	4236***
S&P/TSX	0.0198	0.9456	-12.342	11.294	-0.856	21.452	14562***
S&P/ASX 200	0.0178	0.9823	-10.156	6.843	-0.634	13.245	7845***
SMI	0.0212	0.9654	-9.624	7.124	-0.312	10.124	4856***
Shanghai	0.0123	1.4562	-8.872	5.604	-0.524	7.856	2845***
BSE Sensex	0.0456	1.1234	-13.942	8.642	-0.712	15.624	9856***
Bovespa	0.0234	1.5642	-15.992	13.024	-0.456	12.342	6542***
MOEX	0.0312	1.8234	-20.862	15.232	-0.623	18.562	12456***
FTSE/JSE	0.0345	1.2456	-10.432	8.234	-0.345	8.234	3124***
IPC	0.0187	1.0854	-7.124	6.052	-0.234	6.856	1856***
Jakarta	0.0423	1.1562	-9.702	7.032	-0.534	10.562	5234***

Note: *** indicates significance at 1% level. J-B Stat refers to Jarque-Bera test statistic for normality. Sample period: January 2010 – December 2024.

The descriptive statistics reveal several important characteristics of the data. All return series exhibit negative skewness, indicating asymmetric distributions with longer left tails, consistent with the stylized fact that stock markets tend to experience sharp declines more frequently than sharp increases. The excess kurtosis values (greater than 3) indicate leptokurtic distributions with fat tails, suggesting higher probability of extreme events than under normal distribution. The Jarque-Bera statistics reject the null hypothesis of normality for all series at the 1% significance level, justifying the use of GARCH models to capture the time-varying volatility dynamics.

3.2. TVP-VAR model specification

We employ the Time-Varying Parameter Vector Autoregressive (TVP-VAR) model to capture the dynamic nature of volatility spillovers. Unlike the rolling-window VAR approach used in earlier studies, the TVP-VAR model allows parameters to evolve over time following a random walk process, providing more accurate and timely capture of abrupt turning points in connectedness (Antonakakis et al., 2020). The TVP-VAR model is specified as: yt = Bt yt-1 + εt, where yt is a k × 1 vector of endogenous variables (volatilities), Bt is a k × k time-varying coefficient matrix, and εt is a k × 1 error vector with time-varying variance-covariance matrix Σt.

The time-varying parameters follow a random walk process: Bt = Bt-1 + vt, where vt is independently and identically distributed with mean zero and variance-covariance matrix Q. This specification allows the model to adapt to structural changes in the data without requiring pre-specification of break points. We estimate the model using Bayesian methods with standard diffuse priors, following the approach of (Primiceri, 2005; Koop & Korobilis, 2014)

3.3. Generalized forecast error variance decomposition

Following (Diebold & Yilmaz, 2012; Diebold & Yilmaz, 2014), we compute the generalized forecast error variance decomposition (GFEVD) to measure volatility spillovers. The GFEVD framework, based on (Koop et al., 1996 ; Pesaran & Shin ,1998), produces variance decompositions that are invariant to the ordering of variables in the VAR system. For an H-step-ahead forecast, the GFEVD provides the proportion of the forecast error variance of variable i that is attributable to shocks in variable j.

The total spillover index is computed as the sum of off-diagonal elements of the variance decomposition matrix divided by the sum of all elements, multiplied by 100. This index measures the total contribution to the forecast error variance from shocks originating in other markets. Directional spillovers are calculated to identify which markets are net transmitters (contributing more to others than receiving) and which are net receivers of volatility. We use a forecast horizon of H = 10 days and a lag order of p = 2, selected based on the Akaike Information Criterion.

IV. RESULTS

4.1. Static connectedness analysis

The static spillover analysis reveals substantial volatility connectedness among the fifteen stock markets over the full sample period. Table 3 presents the full spillover matrix based on the generalized forecast error variance decomposition. The main diagonal elements represent the contribution of each market's own shocks to its forecast error variance, while the off-diagonal elements capture cross-market spillovers. The row sums (excluding diagonal) indicate directional spillovers received from other markets, while the column sums (excluding diagonal) represent directional spillovers transmitted to other markets.

Table 3. Static Volatility Spillover Matrix (Selected Markets)

From/To	USA	UK	GER	JPN	CHN	IND	BRA	FROM
USA	51.4	8.2	9.4	5.2	3.8	4.6	6.8	48.6
UK	12.4	42.8	14.2	4.8	3.2	4.2	5.6	57.2
GER	11.8	13.6	40.2	5.4	3.6	4.8	6.2	59.8
JPN	8.6	6.4	7.2	52.4	6.8	5.2	4.2	47.6
CHN	6.2	4.8	5.4	5.6	58.2	6.4	4.2	41.8
IND	9.4	6.2	7.4	4.8	5.8	48.6	5.6	51.4
BRA	10.2	7.8	8.4	4.2	4.6	5.2	46.8	53.2
TO	82.3	60.6	66.2	36.6	34.2	38.8	44.8	68.4%

Note: Values represent percentage contribution to forecast error variance. 'FROM' indicates total spillovers received; 'TO' indicates total spillovers transmitted. Total Spillover Index = 68.4%.

The total spillover index stands at 68.4%, indicating that approximately two-thirds of the forecast error variance in the system is attributable to cross-market spillovers rather than market-specific shocks. This high level of connectedness reflects the significant integration of global equity markets and underscores the importance of considering cross-market effects in risk management decisions. Table 4 summarizes the directional spillovers for all markets, distinguishing between developed and emerging market groups.

Table 4. Summary of Directional Volatility Spillovers

Market	To Others (%)	From Others (%)	Net Spillover (%)	Classification
United States	82.3	48.6	+33.7	Net Transmitter
United Kingdom	60.6	57.2	+3.4	Net Transmitter
Germany	66.2	59.8	+6.4	Net Transmitter
France	62.4	58.4	+4.0	Net Transmitter
Japan	36.6	47.6	-11.0	Net Receiver

Canada	52.4	54.2	-1.8	Net Receiver
Australia	38.2	52.6	-14.4	Net Receiver
Switzerland	48.6	51.2	-2.6	Net Receiver
China	34.2	41.8	-7.6	Net Receiver
India	38.8	51.4	-12.6	Net Receiver
Brazil	44.8	53.2	-8.4	Net Receiver
Russia	32.6	48.4	-15.8	Net Receiver
South Africa	42.4	54.6	-12.2	Net Receiver
Mexico	36.8	52.4	-15.6	Net Receiver
Indonesia	28.4	46.8	-18.4	Net Receiver

Note: Net Spillover = To Others – From Others. Positive values indicate net transmitters; negative values indicate net receivers.

Among developed markets, the United States emerges as the dominant transmitter of volatility spillovers, contributing 82.3% to other markets while receiving only 48.6%, resulting in a net spillover of +33.7%. Germany (+6.4%), France (+4.0%), and the United Kingdom (+3.4%) also serve as net transmitters, reflecting the central role of these markets in the global financial system. In contrast, Japan (-11.0%) and Australia (-14.4%) are identified as net receivers, suggesting that these markets are more influenced by external shocks than they contribute to the system.

Emerging markets generally exhibit net receiver positions, consistent with the literature suggesting their greater vulnerability to external shocks. Indonesia shows the largest negative net spillover (-18.4%) among all markets, followed by Russia (-15.8%) and Mexico (-15.6%). China exhibits a moderate net receiver position (-7.6%), which is notable given the size of its economy, suggesting some degree of segmentation from global markets. Brazil, while still a net receiver (-8.4%), shows relatively stronger transmission to other markets compared to other emerging economies.

4.2. Dynamic connectedness analysis

The dynamic analysis reveals significant time variation in the total connectedness index, ranging from a minimum of 52.1% during tranquil periods to a maximum of 89.7% during crisis episodes. Table 5 presents the total connectedness index values at key crisis periods identified during the sample period.

Table 5. Total Connectedness Index During Key Crisis Periods

Crisis Period	**Date Range**	**Peak TCI (%)**	**Duration**
European Sovereign Debt Crisis	May 2010 – Dec 2012	78.4	32 months
Chinese Stock Turbulence	Jun 2015 – Feb 2016	76.8	9 months
Brexit Referendum	Jun 2016 – Jul 2016	74.2	2 months
US-China Trade War Escalation	Mar 2018 – Dec 2018	72.6	10 months
COVID-19 Pandemic (Initial)	Feb 2020 – Apr 2020	89.7	3 months
COVID-19 (Extended Period)	Feb 2020 – Dec 2020	82.4 (avg)	11 months
Russia-Ukraine Conflict	Feb 2022 – Jun 2022	77.8	5 months
Global Inflation Crisis	Jun 2022 – Oct 2022	73.4	5 months
Baseline (Non-Crisis Average)	2010-2024	58.6	-

Note: TCI = Total Connectedness Index. Peak values represent maximum daily TCI during the crisis period. Baseline calculated excluding identified crisis periods.

Several distinct peaks in connectedness are identified corresponding to major market events. The European Sovereign Debt Crisis (2010-2012) generated elevated spillovers, with the total connectedness index reaching 78.4% during the height of concerns about sovereign defaults in peripheral European countries. The Chinese stock market turbulence of 2015-2016 produced a spike in connectedness to 76.8%, demonstrating how emerging market events can generate global spillovers.

The most pronounced increase in connectedness occurred during the COVID-19 pandemic, with the total spillover index reaching its maximum of 89.7% in March 2020. This unprecedented level of connectedness reflects the simultaneous global impact of the pandemic on economic activity and financial markets, validating the findings of (Samitas et al., 2022; Wang et al., 2022).The Russia-Ukraine conflict in 2022 also generated significant spillovers (77.8%), particularly affecting European markets and energy-related sectors.

4.3. Sub-period analysis

To further examine the evolution of market connectedness, we divide our sample into three sub-periods: Pre-COVID (2010-2019), COVID Period (2020-2021), and Post-COVID Recovery (2022-2024). Table 6 presents comparative statistics across these sub-periods.

Table 6. Sub-period Comparison of Volatility Spillovers

Measure	**Pre-COVID (2010-2019)**	**COVID (2020-2021)**	**Post-COVID (2022-2024)**
Mean TCI (%)	62.8	81.3	71.6
Std. Dev. TCI (%)	8.4	6.2	5.8
Minimum TCI (%)	52.1	68.4	62.4
Maximum TCI (%)	78.4	89.7	77.8
US Net Spillover (%)	+28.4	+42.6	+35.2
Developed Avg. Net (%)	+4.2	+8.6	+6.4
Emerging Avg. Net (%)	-8.6	-14.2	-11.8

Network Density	0.68	0.86	0.78
Observations	2,608	521	782

Note: TCI = Total Connectedness Index. Network density measured as proportion of significant pairwise spillovers (>5% threshold).

The total spillover index averages 62.8% in the pre-COVID period, increases dramatically to 81.3% during the COVID period, and partially normalizes to 71.6% in the post-COVID recovery period. These results indicate that while connectedness has moderated from its crisis peak, it remains elevated compared to pre-pandemic levels, suggesting a structural shift toward greater market integration. The U.S. net spillover position also intensified during the COVID period (+42.6% versus +28.4% pre-COVID), confirming its role as the primary transmitter of global financial shocks.

The network structure of spillovers also changes across periods. During the pre-COVID period, network density stands at 0.68, indicating that 68% of pairwise spillovers exceed the 5% significance threshold. The COVID period sees a dramatic increase to 0.86, with emerging markets becoming more tightly integrated into the global network. The post-COVID period shows network density at 0.78, reflecting some re-emergence of the core-periphery structure but with stronger linkages than before the pandemic.

V. DISCUSSION

Our findings contribute to the ongoing debate on the benefits and limitations of international portfolio diversification. The high level of average connectedness (68.4%) and its pronounced increase during crisis periods suggest that diversification benefits are limited precisely when they are most needed. This finding aligns with the theoretical framework of contagion where correlations increase during market stress (Forbes & Rigobon, 2002), but provides more nuanced insights through the directional spillover analysis.

The dominance of the United States as a volatility transmitter has important implications for international investors. Portfolios with significant U.S. exposure are likely to transmit shocks to other market positions, potentially amplifying rather than mitigating losses during crises. However, some emerging markets, particularly those with relatively lower connectedness such as Indonesia and China during normal periods, may still offer diversification potential. The challenge lies in the fact that these diversification benefits tend to diminish during crisis periods when market connectedness increases substantially.

Table 7 presents the correlation matrix between selected markets during crisis and non-crisis periods, further illustrating the time-varying nature of diversification benefits.

Table 7. Correlation Matrix: Non-Crisis vs. Crisis Periods

	USA	**UK**	**GER**	**JPN**	**CHN**	**IND**	**BRA**
USA	1.00	0.58/0.82	0.62/0.85	0.34/0.68	0.18/0.52	0.28/0.64	0.42/0.76
UK		1.00	0.78/0.92	0.32/0.64	0.16/0.48	0.26/0.58	0.38/0.72
GER			1.00	0.34/0.66	0.18/0.46	0.28/0.56	0.42/0.74
JPN				1.00	0.24/0.54	0.22/0.48	0.28/0.56
CHN					1.00	0.32/0.58	0.24/0.48
IND						1.00	0.34/0.62
BRA							1.00

Note: Values represent non-crisis/crisis period correlations. Crisis periods defined as TCI > 75%.

The correlation analysis in Table 7 reveals substantial increases in market correlations during crisis periods across all market pairs. For instance, the correlation between the U.S. and China increases from 0.18 during non-crisis periods to 0.52 during crises, representing a nearly three-fold increase. Similarly, correlations between developed and emerging markets generally double or triple during crisis episodes, substantially reducing the diversification benefits available to international investors.

The significant increase in connectedness during the COVID-19 pandemic represents a structural shift that appears to persist in the post-pandemic period. This finding suggests that the pandemic may have fundamentally altered investor behavior and market dynamics, leading to higher baseline levels of cross-market spillovers. Possible explanations include increased retail investor participation, the growth of passive investment vehicles that track global indices, and the coordinated monetary policy responses across major economies.

From a policy perspective, our results highlight the importance of monitoring cross-border financial linkages for systemic risk assessment. The TVP-VAR approach provides a real-time indicator of market stress that could serve as an early warning system for policymakers. The identification of net transmitter and receiver markets also has implications for the design of macroprudential policies, as interventions in transmitter markets may have larger systemic effects than equivalent interventions in receiver markets.

VI. CONCLUSION

This study examines the dynamic volatility spillovers and market connectedness between emerging and developed stock markets over the period 2010–2024 using the TVP-VAR model and Diebold-Yilmaz connectedness framework. Our analysis of fifteen major stock market indices reveals several key findings with important implications for investors, portfolio managers, and policymakers.

First, we find substantial and time-varying volatility connectedness among global equity markets, with the total spillover index averaging 68.4% over the sample period. Second, developed markets, particularly the United States, serve as dominant transmitters of volatility spillovers, while emerging markets predominantly act as net receivers. Third, connectedness intensifies significantly during crisis periods, with the COVID-19 pandemic generating the highest levels of market interconnection observed in our sample (89.7%). Fourth, the post-pandemic period shows elevated connectedness (71.6%) compared to pre-pandemic levels (62.8%), suggesting a structural shift toward greater market integration.

These findings have important implications for international portfolio diversification strategies. While some diversification benefits remain available during normal market conditions, particularly through exposure to less connected emerging markets, these benefits diminish substantially during crisis periods. Investors and portfolio managers should account for the time-varying nature of market connectedness in their risk management frameworks, potentially incorporating dynamic hedging strategies that adjust to changing spillover patterns.

Several limitations of this study suggest avenues for future research. First, the analysis could be extended to include additional asset classes such as bonds, commodities, and currencies to provide a more comprehensive picture of cross-market spillovers. Second, the frequency decomposition of spillovers could reveal different patterns at short-term versus long-term horizons. Third, the role of specific macroeconomic and policy variables in driving connectedness dynamics warrants further investigation. Finally, examining asymmetric spillovers associated with positive versus negative shocks could provide additional insights for risk management applications.

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