Navigating APEC Countries: TVP-VAR Insights into Developed and Emerging Stock Markets

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Abstract

The interdependence of stock markets provides important discernment into the behavior of the larger international financial markets. This study investigates magnitude and directional volatility spillover patterns among developed and emerging countries within the APEC bloc, utilizing the TVP-VAR model. The findings indicate that Russia (15.06%), Vietnam11.64%), and Thailand (11.57%) are identified as major transmitters, and Malaysia (-28.95%), Philippines (-9.28%), China (-9.53%) are major receptor of the volatility spillovers in APEC emerging countries. In APEC-developed countries, the United States (56.85%) and Canada (42.6%) are major transmitters, and Japan (-34.02%) and Australia (-53.54%) are identified as a major receptor of the spillover. Moreover, COVID-19 was the most significant crisis, with the highest volatility spillover identified in the APEC bloc's developed and emerging economies. The discoveries have substantial ramifications, offering valuable insights into optimal investment strategies by identifying patterns, magnitudes, and directions of economic volatility shocks.

Keywords: *Asia Pacific Economic Cooperation; COVID-19; Financial Stock Market; Russia-Ukraine crises; Volatility spillover.*

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1. Introduction

The correlation and interconnectedness of the global financial market are growing along with the globalization of finance (Zhong & Liu et al., 2021). The interconnection of global financial markets leads to a delayed impact on other nations' financial markets when one country's asset values fluctuate. This phenomenon, known as the volatility spillover effect, highlights the interdependence of international financial markets. Spreads of volatility are a typical occurrence in many financial markets. This effect is confirmed by the growing level of global financial integration (Kaur & Singh, 2014), which emphasizes the significance of researching the volatility spillover effect across many financial markets. The stock market serves as a precise barometer of a nation's or region's economy, faithfully capturing fluctuations and changes in economic conditions. Moreover, geo-political instability, health crises, financial crises, fraud allegations as negative news, etc., significantly impact the stock markets (Kakran, 2024a, Sapra et al., 2024; Kakran et al., 2024b).

The interconnection of global financial markets often leads to delayed effects when changes in one country's financial market impact the volatility of other nations' financial needs, giving rise to the phenomenon of volatility spillover. Investors, financial institutions, and policymakers can benefit from a thorough understanding of the dynamics of market/asset interdependence, which can be gained through a look at the nature, strength, and time-variation in cross-market volatility transmission (Majdoub and Mansour, 2014; Liow, 2015). Through such studies, one can discern the specific asset class or market that significantly influences the transfer of volatilities to local and international markets in international investments. In recent years, there has been substantial academic attention on financial risk spillover inside the stock market as various studies findings have contributed to the ongoing advancement of pertinent reflections on the volatility issues associated with financial risks in the stock market (Mishra & Mishra, 2020; Seth & Sidhu, 2021; Bharti & Kumar, 2022; Kakran et al., 2023; Mensi et al., 2023). Regional integration indicates that there should be an increased connectivity between countries (Ahmed & Huo, 2019) in Asian Pacific countries over the last two decades. It is crucial to unveil the interconnectedness and volatility spillover in the world's most prominent economic bloc (Asia Pacific Economic Cooperation (APEC)). APEC[1] is a free trade area economic bloc that consists of 21 developed and emerging economies (i.e. Peru, Papua New Guinea, Vietnam, Australia, Canada, China, Chile, Chinese Taipei, Hong Kong, Indonesia, Malaysia, Mexico, Russian Federation, Singapore, USA, Japan, Philippines, South Korea, Thailand, New Zealand), that represents for 61% of global GDP, 47% of international commerce, and 38% of global population (apec.org). Contextually, this study investigated the volatility of stock markets in the APEC bloc. The study's key research questions are:

1. What variations exist in volatility spillovers between developed and emerging economies within APEC?
2. How do resilience factors in developed economies contrast with vulnerabilities in emerging economies concerning APEC's volatility spillovers?
3. What valuable insights can policymakers and investors derive from comparing volatility spillovers in developed versus emerging APEC economies, enhancing economic stability and risk management strategies?

The above research questions provide deeper insights to APEC countries than the existing study of Kakran et al., 2023. Secondly, this study contrasts as a comparative study among emerging v/s developed countries, an improvement of Kakran et al. (2023) discussion, which shows behavior integration in the full period among all countries. Thirdly, BK (2018) unveils the short-, medium- and long-term impact not covered by Kakran et al., 2023, which provides an in-depth relationship across the crises among APEC countries. Fourth, this study has a more advanced approach, i.e., TVP-VAR, than Diebold-Yilmaz (2012; 2014), which indicates in a short period, this study has more robust results than Kakran et al., 2023. As in the DY model, key observations are skipped due to window size, which may have crucial implications for the short-term investors. Studying spillover effects in APEC financial markets is crucial for diversified portfolios (Kakran et al., 2023; Kakran et al., 2024c), especially in nations with low or negative correlations offering investment opportunities (Vermeulen, 2013).

Furthermore, this study used three core theoretical lenses: stock market reaction (SMR) theory, financial integration theory, and information transmission theory, which both support risk transfer because of a financial connection. The SMR theory indicates the "unbiased reaction" to public information, which serves as the foundation for efficiency, has been identified as a consequence of rational, maximizing investor behavior in competitive securities markets (Fama, 1965). Information from many markets may impact one another, and investors may consider the circumstances of other markets while making judgments (Spence, 1978). The connection between news transmission and uncertainty, as illustrated by volatility spillovers

[1] The Asia-Pacific market is set for a promising decade, with a growth rate two to three times higher than the EU or US, reaching 0.2 percent annually by 2031. Streamlined regulations and increased intraregional investments are driving this growth. Japan's investments in China alone, totaling $397.07 billion, highlight the region's robust economic ties.

(Luk et al., 2020), extends to fluctuations in equity and commodity return volatility across markets (Zhang et al., 2020; Kumar, 2022). Studying spillover effects in APEC financial markets is crucial for diversified portfolios (Kakran et al., 2023; Kakran et al., 2024c), especially in nations with low or negative correlations offering investment opportunities (Vermeulen, 2013).

The findings reaffirm earlier observations regarding the influence of diverse announcements and crises on stock markets, leading to volatility spillover in APEC markets. The results also shed light on the factors contributing to APEC stock market drops. The string of crises from the GFC to the Russia-Ukraine conflicts have all been key contributors to the stock market's downfall.

Moreover, the study is organized into five sections: Section 2 provides a concise literature review outlining the study's hypothesis; Section 3 covers the data and methodology; Section 4 presents the findings and discusses the analysis; and finally, Section 5 concludes the research and explores its implications.

2. Literature review

In the ever-evolving landscape of international finance, the regional integration of APEC stock markets has been reshaped by progressive financial deregulation, collaborative economic and financial efforts, and amplified mutual investments (Kuroda & Kawai, 2004). As a result of the high return and potential for risk in the Asia-Pacific equity markets, international investors are increasingly turning to them as essential parts of their portfolios. (Wu, 2020; Anwer et al. 2022). APEC's persistent endeavors toward regional integration and free capital movement have led to notable strides in member cooperation on economic fronts. Despite the region's significance, a limited corpus of literature explores APEC's stock market dynamics. Lin and Rajan (1999) delved into the repercussions of the Thai baht crisis (1997), profoundly impacting ASEAN and APEC's global stature. Bende-Nabende et al. (2003) meticulously explored FDI, output, and an array of spillover variables, revealing both positive (from developed to less developed nations) and negative (from less developed to developed countries) dynamics within APEC. Li and Rose (2008) uncovered severe correlations, illuminating market integration, while Lee et al. (2012) demonstrated the influence of intra-regional commodities trade on APEC stock market unity. Valdes et al. (2016) scrutinized Agri-based firm stock indexes, providing unique insights in a contemporary context. Idrees and Sarwar (2022) probed the global implications of creative resource availability, forming "global convergence clubs" among nations sharing innovation, economic integration, and trade advantages. Sun et al. (2023) also highlighted how China's liberalization policies amplified risk links, bolstering its resilience against external market shocks.

However, for a thorough analysis of the literature, a systematic approach adopted for data is extracted from the Scopus database using the search string TITLE-ABS-KEY ("Pacific OR "Asia*" AND "Volatility Spillover" OR "Spillover" AND "Stock*" OR "Equi* Market*") from which 367 articles identified after that results refined based on articles (source type), language (English), subject area (economics, econometrics, and finance) and on the relevance of the study, after that 55 documents shortlisted for the literature review.

In the literature, three significant themes divided into three clusters identified based on sample countries and emphasizing results implication are as follows:

2.1 Cluster of literature related to the US - Asia - Japan

Li and Giles (2015) examined linkages among the US, Japan, and Asian economies (Thailand, Malaysia, Philippines, Indonesia, China, and India) for the period 1993-2012 using MGARCH model results stated that US and Asian counties found integrated and transmitted shocks during the Asian financial crisis (AFC). Choi (2022) investigated connectedness among the US, China, Japan, and South Korea using Diebold and Yilmaz's (2012) results, showing interconnectedness with time-varying magnitude among the countries; the US indicated as a transmitter of the spillover and interdependence during the GFC is more than COVID-19. A study examining financial market volatility and economic policy uncertainty (EPU) in the US and Japan found that financial market indices serve as net spillover transmitters to the EPU group (Thiem, 2020). Similarly, Mensi et al. (2017) provided evidence of spillover effects in global equity markets (USA, Japan, Europe, and Asia) as well as in precious metals (gold, silver, palladium, and platinum). However, except for the Japanese market, all were the source of spillover during GFC.

Additionally, precious metal markets act as net recipients of spillover effects. Valls and Chulia (2012) observed changes in volatility behavior after the crisis. There is a conditional association between Asian stock markets and the US, indicating a lower correlation for countries with lower development levels. Maderitsch (2015), using quantile regression, found negative spillover magnitudes across different return quantiles in the Asian and US equity markets, including contagion during the GFC of 2007-2008. Sharkasi et al. (2005) investigated price interdependence among global stock markets, uncovering co-movements between the US and Brazilian markets and intra-Asian correlations. Shu and Chang (2019) found that volatility indexes such as VSTOXX and VKOSPI are sensitive to global economic shocks and exhibit movements similar to VIX, impacting stock returns. Liu (2001) indicated that Japna has the profitability or loss of a momentum approach is determined by the relative strength of its two components. The initial component is a notable factor in the losses incurred by momentum strategies in the Japanese stock market. In contrast, in the US market, the primary source of gains from momentum strategies is the changes in mean returns across different sections. Cha and Cheung (1998) stated that the seasonal or monthly effect in stock markets in emerging Asian countries poses an important research question as emerging Asian countries' economic footprint has been growing significantly. Aggarwal and Jha (2023) validate the presence of ARCH and GARCH effects in the monthly return series. Furthermore, the asymmetric GARCH models indicate that the returns of the growing Asian stock market have an asymmetric (leverage) impact.

In their study spanning 2014-2020, Zeng and Ahmed (2023) explored the integration of the Bitcoin market with East Asian stock markets. Their findings highlighted a significant spillover effect from the Japanese and Hong Kong stock markets onto others within the region. However, the East Asian spillover increased on bitcoin, although there is no intuition between them. Shamiri and Isa (2009) used a bivariate GARCH-BEKK model to examine financial crises, which resulted in the US being the transmitter of the spillover (with different reversions across the region) to Southeast Asia. On investigation of interdependence on Pacific basin equity market using Diebold and Yilmaz (2009, 2012), Chevallier et al. (2018) results pointed out that US shocks have high exposure for impacting developed countries of East Asia, even cross linkages over Pacific basin have a stronger impact (due to regional risk diversification). Lee (2007) examined the contagion effect based on heteroscedasticity for powerful earthquakes (2004) in Southeast Asia, resulting in India, the Philippines, and Hong Kong suffering from the contagion effect; the rest of the countries did not suffer much. However, analyzing volatility transmission channels in future stock indices across developed and emerging Asian markets has revealed a strong interdependence among regional markets. This indicates that the recipient markets respond to positive and negative volatility shocks, which impact investors' attention (Lohan, 2023; Lohan, 2023a). Shi and Zhou (2022) used GFEVD based on VAR, indicating that North America transmitted spillover to North America, intensified spillover identified after the significant risk events.

Moreover, growth by unexpected monetary events in the US has less consistently impacted the Asian stock markets and Latin America. Chiang (2021) stated that incredible monetary policy uncertainty (MPU) greatly impacts the North American stock indices. Moreover, the Russia-Ukraine war also impacted global stock markets (Kakran, 2022; Kumari et al., 2023; Pandey et al., 2023; Chortane & Pandey, 2023); such events have significant impacts on the stock market (Kashyap, 2023).

2.2 Cluster of literature related to Asia-Pacific Studies

Choudhry (2000) investigated the 1987 stock market crash in four major Pacific-Basin economies (Australia, Hong Kong, Japan, and Singapore) using the nonlinear GARCH-t model to show interdependence among equity markets. Worthington (2003) indicated the presence of weaker causal linkages between established and developing stock markets. Tay (2000) focused on Pacific-Rim stock markets using GARCH and VAR models and pointed out the relevance of distinctive factors in the volatility return of stocks. Shamiri & Isa (2010) indicated that the US and Japan are the major spillover transmitters to the Asia-Pacific market (Korea, Singapore, and Hong Kong are high receivers). Liu (2014) proposed measuring forecast downside risks with extreme downside risks in the Japanese and US markets, focusing on the Asia-Pacific market, which is significantly affected by the S&P 500 and Nikkei 225. Abidin et al. (2014) focused on five Asia Pacific basin regions using the VAR model by emphasizing the results of the Australian and Chinese regions, which indicated significant spillover in the markets. On examining China's influence on Asia–Pacific stock markets, using Diebold and Yilmaz (2009, 2012, 2015), results indicated that Chinese markets have high integration and spillover effects on Asia-Pacific stocks (Ma et al. 2020). A study on the Chinese stock market crash of 2015-16 reveals substantial spillover effects on Asia-Pacific stocks, indicating the significant impact of this event (Ahmed & Huo, 2019). Fatima et al. (2022) found there is no significant spillover between hedge fund returns and stock returns in twelve Asia-Pacific countries. Al-Hajieh (2023) identified spillover among the US and Asia-Pacific equity markets (12 stocks) for the period 2000-2020 using generalized VAR, resulting in Hong Kong and Singapore having straightforward returns direction of stocks, while China was the net recipient. India, New Zealand, and Hong Kong have the best portfolio weights and hedging markets, but the US does not have as many efficient hedging ratios. Guru and Yadav (2023) investigated volatility spillover across 24 Asia-Pacific and 12 European Union (EU), and results indicated the highest volatility transmission on Asia-Pacific (EU) from Singapore and Denmark stock indices. However, gross volatility in the EU (Asia-Pacific) was identified during GFC at 80% (67%), EDC at 80% (65%), and COVID-19 at 67% (73%).

Bhardwaj et al. (2022) findings revealed co-integration among Asian markets over an extended period, with a significant portion of volatility attributed to internal shocks within each market at the intra-week scale. However, the magnitude of the spillover effect amplifies over time due to evolving market volatility dynamics. Yin et al. (2017) found that the European market is the hub for transmitting information to the global stock market during events like quantitative easing and bailouts. Fukuda and Tanaka (2017) observed that Shocks originating from the manufacturing sector pose a greater vulnerability to Asian financial markets. Sarwar et al. (2019) emphasized the significance of shock dependence and conditional volatility in the Chinese, Japanese, and Indian stock exchanges. Sugimoto and Matsuki (2019) noted the regional connectedness of Asian markets after the GFC. Panda et al. (2021) revealed the differential reactions of stock indices to negative news and identified significant cross-means spillover effects among various stock markets.

2.3 Cluster of literature related to the regional Studies and economic bloc related to Asia-Pacific

Haddad et al. (2020) found vulnerability to domestic stock in DJIM Canada, Japan, and Asia-Pacific, while DJIM US, UK, Europe, and GCC indices showed integration with domestic and foreign shocks. Yarovaya et al. (2016) observed inter-regional contagion in developed and emerging markets across continents. Qian and Diaz (2017) delved into the enduring volatility dynamics between Malaysia's stock market and European counterparts following a free trade agreement. Mensi (2021) revealed the heightened sensitivity of both oil and stocks to crises, with the most significant impacts observed during major events like the Global Financial Crisis (GFC), the mid-2014 oil price drop, and the COVID-19 pandemic. The oil market functions as a risk receiver, the Asia equity index functions as a net receiver, and the US and European stock markets function as transmitters.

The previous studies raised three core theoretical lenses: SRM theory, information transmission theory, and financial integration theory. The process of linking one economy's stock markets and financial institutions to those in other nations or across the globe is known as financial integration. Moreover, financial integration highlights three fundamental characteristics: 1) It is independent of regional financial structures; 2) It integrates via asymmetric or symmetric effects because of the percentage; and 3) It distinguishes between the supply and demand for investment possibilities, two components of the stock market (Stavarek et al., 2012). In information transmission theory, the transmission of information via various channels substantially influences stocks, which subsequently turns to the stock market reactions.

Table 1. Descriptive statistics of the Developed and emerging countries of the APEC bloc equity market volatility series.

Stock index	Mean	Median	Variance	St. Dev	Skewness	Kurtosis
			Developed Countries (07)			
AS51	0.008742	0.00784	0.000015	0.003831	4.887698	38.33818
SPTSX	0.007729	0.006603	0.000025	0.004989	6.865352	68.16897
HIS	0.011815	0.010907	0.000012	0.003503	1.871224	4.686078
NKY	0.012168	0.011248	0.000015	0.003925	2.594147	10.58684
STI	0.007673	0.006956	0.000008	0.002895	4.148226	28.73479
SPX	0.009619	0.008098	0.00003	0.005511	4.44447	34.59343
NZSE50	0.006893	0.00569	0.000132	0.011485	20.12205	465.9605
			Emerging Countries (12)			
IPSA	0.009802	0.008073	0.000031	0.005588	3.961651	26.57746
JCI	0.009579	0.008548	0.000014	0.003749	3.183075	14.67123
KOSPI	0.00937	0.008419	0.000014	0.003687	3.625218	21.73686
FBMKLCI	0.000042	0.000298	0.000022	0.0000478	8.16811	95.59322
MEXBOL	0.009144	0.008446	0.000008	0.002907	2.55406	10.16037
IGBVL	0.010893	0.009438	0.000025	0.004961	2.596855	10.41751
PCOMP	0.010825	0.009948	0.000016	0.003998	4.53068	34.72207
IMOEX	0.013128	0.010968	0.000066	0.008096	6.314319	62.61122
TWSE	0.00925	0.008498	0.000007	0.002722	2.234122	8.116055
SET	0.008967	0.007828	0.000021	0.004566	3.564546	20.38787
VNINDEX	0.011141	0.01004	0.000015	0.003915	1.597431	3.001043
SHCOMP	0.01174	0.010439	0.000024	0.004926	2.304877	7.429246

A thorough literature study has shown that economies change and are contingent upon the dynamics of economic policy, which are influenced by distinct economic fundamentals that exhibit time-varying characteristics. The Asia and Pacific economies had a response in their stock markets because of many indicators and information channels during big crises. This response has the potential to develop into financial contagion. It became essential to unveil the interconnectedness of the time and frequency domain among the emerging and developed countries of the APEC bloc. In the case of an economic bloc, the literature indicating the APEC bloc has not been taken by any study, showing a potential research gap being fulfilled by this study. Moreover, in the significant stream of literature, the TVP-VAR approach and Baruník and Křehlík (2018) model as these models have the potential to capture the objectives of this study.

3. Data and Methodology

3.1. Data

We compiled daily closing price data for APEC benchmark stock indices from 19 countries, including Australia (AS51), Canada (SPTSX), Chile (IPSA), Japan (NKY), Hong Kong (HSI), Indonesia (JCI), South Korea (KOSPI), Malaysia (FBMKLCI), Mexico (MEXBOL), Peru (IGBVL), Philippines (PCOMP), Russia (IMOEX), Singapore (STI), Taiwan (TWSE), Thailand (SET), US (SPX), and Vietnam (V). Table 1 provides a summary of the log return series data. Our empirical findings indicate that all series maintain stability at I (0).

3.2. Methodology

A financial asset's volatility is greatly influenced by its closing prices. In this work, we use the stocks' log returns to account for the data's heterogeneity and nonstationary. Equation (1) is used to determine the log returns for a specific date, *t*:

$$R_t = log\left(\frac{P_t}{P_{t-1}}\right) \tag{1}$$

To ensure the reliability of our results and minimize the risk of false findings, we adopt a meticulous approach to handle consecutive days with identical prices by substituting minute numerical variations. This cautious methodology prevents the introduction of null values into our prediction models, upholding the integrity of the study.

3.3. TVP-VAR Model

To evaluate the degree of interdependence among the target variables, we use the Time-Varying Parameter Vector Autoregressive (TVP-VAR) model, which draws inspiration from research conducted by Antonakakis and Gabauer (2017). Diebold and Yilmaz (2009, 2012, and 2014) have established the fundamental basis for examining dynamic connectivity. The TVP-VAR technique has a notable benefit in comparison to other methods due to its lack of reliance on a fixed window size. This characteristic mitigates the potential for inconsistent outcomes arising from selection bias. The use of rolling windows in data analysis mitigates the loss of data points, hence offering the added benefit of accommodating relatively smaller sample sizes. The TVP-VAR technique has a notable benefit in comparison to other methods due to its lack of reliance on a fixed window size. This characteristic mitigates the potential for inconsistent outcomes arising from selection bias. The use of rolling windows in data analysis mitigates the loss of data points, hence offering the added benefit of accommodating relatively smaller sample sizes. This facilitates a more comprehensive understanding of the underlying principles of return connectedness in the TVP-VAR model. A more comprehensive elucidation of the framework's operation is provided below to enhance comprehension of its functioning. Equations 2 and 3 delineate a Time-Varying Parameter Vector Autoregressive (TVP-VAR) model.

$$Z_t = B_t Z_{t-1} + \varepsilon_t \sim N(0, S_t) \tag{2}$$

$$B_t = B_{t-1} + v_t \sim N(0, R_t) \tag{3}$$

The conditional volatilities vector, denoted as Z_t, has a dimension of k * *1*. *Zt - 1* represents the lagged dependent vector with a dimension of *kp* * 1. B_t *r*epresents a dynamic coefficient matrix with dimensions $k * kp$, while R_t is an error disturbance vector with dimensions $k * 1$. These components are linked to a time-varying variance-covariance matrix, St, measuring $k * k$ in size.

The parameter *Bt* is contingent upon the lag values of B_{t-1} and a $k * kp$ dimensional error matrix with a variance-c *Bt c*ovariance matrix of $kp * kp$.

After reviewing the studies of Koop et al. (1996) and Pesaran and Shin (1998), the next step is to compute the scaled generalized forecast error variance decomposition (GFEVD) using an H-step forwards forecast. In contrast to Diebold and Yilmaz (2009) error decomposition variance technique, which is based on variable ordering, the GFEVD is unaffected by such issues.

The Generalised Forecast Error Variance Decomposition (GFEVD) is generated by applying the Wold theorem to the Time-Varying Parameter Vector Autoregressive (TVP-VAR) model's vector moving average representation (VMA), as described by Diebold and Yilmaz (2014). The metamorphosis is accomplished by means of the procedure outlined in Equation 4.

$$Z_t = B_{it} Z_{t-i} + \varepsilon_t = \sum_{j=0}^{\infty} A_{jt} \varepsilon_{t-j} \tag{4}$$

The unscaled GFEVD is represented as $\phi_{ij,t}^{g}(H)$ and the scaled version is obtained by normalizing this value. As shown in Equation 5, the total of the factors in each matrix row is made equal to one by this normalizing procedure. From this, we get the directionality between variables j and i, denoted by $\left(\widetilde{\phi_{ij,t}^{g}(H)}\right)$ in the Equation (6). This metric evaluates the significance of the variable j's influence on variable i by calculating its weight in the prediction error variance. Equations (5) and (6) detail the process that must be followed to calculate these terms:

$$\phi_{ij,t}^{g}(H) = \frac{S^{-1} \sum_{i=1, i \neq j}^{H-1} \left(l_i' A_t S_t l_j\right)^2}{\sum_{j=1}^{k} \sum_{i=1, i \neq j}^{H-1} \left(l_i' A_t S_t A_t' l_i\right)} \tag{5}$$

$$\left(\widetilde{\phi_{ij,t}^{g}(H)}\right) = \frac{\phi_{ij,t}^{g}(H)}{\sum_{j=1}^{k} \phi_{ij,t}^{g}(H)} \tag{6}$$

The index *i* is assigned a value of 1 in the selection vector, represented by 1*i*, whereas all other indices are assigned a value of 0. Then, the Diebold and Yilmaz (2012, 2014) paradigm is used to create connection measures, as shown in Equations (7–10).

$$TO_{jt} = \sum_{i=1, i \neq j}^{k} \widetilde{\phi_{ji,t}^{g}(H)} \tag{7}$$

$$From_{jt} = \sum_{i=1, i \neq j}^{k} \widetilde{\phi_{ji,t}^{g}(H)} \tag{8}$$

$$NET_{jt} = TO_{jt} - FROM_{jt} \tag{9}$$

$$TCI_t = k^{-1} \sum_{j=1}^{k} TO_{jt} \tag{10}$$

Equation (7) measures the total one-way connection from variable j to every other variable in the network. On the other hand, Equation (8) quantifies the sum of all directional connections in the network that point towards variable *j*. Subtracting Equations (7) and (8) yields Equation (9), indicating the overall net connectivity direction linked to variable j. This Equation allows us to infer the direction of net connectivity associated with variable j within the network. If *j* has a positive value in Equation (9), it means that it impacts other variables more than it gets from them. Conversely, a negative value for variable j signifies a substantial influence from other nodes in the network, indicating a net inward direction of connectivity. This means it affects the variable more significantly than it is affected by others.

Equation (9), when considered, sheds light on the predominant intensity and direction of the interconnectivity linked to variable j inside the link. For instance, if $NET_{jt} > 0$, this analysis may be used to determine the network variable *j* status as the network's primary shock transmitter. This implies that variable *j* plays a pivotal role in shaping the network's dynamics by propagating and modifying the transmission of shocks among the variables. Equation (10), which measures the total interdependence of all the network's variables, provides this information. This metric serves as a stand-in for measuring interconnectedness and associated market risk.

Investigating the Total Connectedness Index (TCI) derived from Equation (10) offers valuable insights into market dynamics. A higher TCI signifies elevated interconnectedness and market risk, indicating that a shock in one variable can swiftly propagate through the network, potentially causing significant market volatility. Conversely, a lower TCI reflects reduced interconnectivity and associated market risk. In this scenario, shocks are less likely to broadly impact the network, leading to a more stable market environment.

Assessing the TCI provides a nuanced understanding of market interconnectedness and risk, enabling effective risk assessment and management. A higher TCI underscores the importance of closely monitoring interactions between factors, signifying higher vulnerability to systemic risks. In contrast, a lower TCI indicates a resilient and diverse market where shocks are less prone to widespread propagation, fostering stability across the network.

3.4. Spillover Index

This approach builds upon the original Diebold and Yilmaz (2009) spillover measure, commonly known as the DY spillover index, established through variance decomposition within an N-variable vector autoregression (VAR). While the DY framework primarily focuses on capturing total spillovers within a basic VAR structure, potentially influenced by variable ordering via Cholesky factor orthogonalization, our method goes beyond that. It measures directional spillovers within an expanded VAR framework, eliminating the impact of different sequences on the results. This ensures more precise, order-independent conclusions, enhancing the accuracy and reliability of our findings.

In the context of a covariance stationary N-variable VAR(p) model, represented as $T_{yx_t} = \sum_{i=1}^{p} \phi_i X_{t-i} + \epsilon_t$, where $\epsilon \sim (0, \sum)$ denotes a vector of independently distributed disturbances, the moving average representation becomes $x_t = \sum_{i=1}^{\infty} A_i \epsilon_{t-i}$. Here, the $N*N$ coefficient matrices A_i follow the recursion $A_i = \phi_1 A_{i-1} + \phi_2 A_{i-2} + \cdots + \phi_p A_{i-p}$, with A_0 *b* as an $N*N$ identity matrix and with $A_i = 0$ for i<0. Understanding the system's dynamics relies on its moving average coefficients, essential for analyzing impulse response functions and variance decompositions. We employ variance decompositions to dissect the prediction error variance of each variable xi, attributing specific portions to distinct system shocks. This method enables us to calculate the H step-ahead error variance fraction in predicting xi resulting from shocks to x, enhancing our comprehension of the system's behavior.

The assumption of orthogonal innovations is frequently required when calculating variance decompositions. In this scenario, innovations in the VAR model are contemporaneously linked. Achieving orthogonality involves employing identification methods like Cholesky factorization, yet this approach imposes constraints on the variable order in variance decompositions. To tackle this issue, we employ the generalized VAR framework, also called KPPS, created by Pesaran and Shin (1998) and Koop et al. (1996). This method yields variance decompositions that remain independent of variable ordering. Unlike approaches attempting to orthogonalize shocks, the generalized VAR framework permits associated shocks, effectively capturing them using the known historical error distribution.

Consequently, the row total in the variance decomposition table, representing contributions to prediction error variance, may or may not equal one, as the shocks for each variable are not orthogonalized. The amount of the H-step, ahead error variances in forecasting x_i that can be attributable to shocks directly impacting x_i is what we refer to as the "own variance shares" for $i = 1, 2,..., N$. The percentage of the H-step-ahead error variances in forecasting x_i that can be attributed to shocks influencing other variables $x_{j,}$ for $i, j = 1, 2,..., N$ such that $i\ j$, are referred to as cross variance shares or spillovers. The KPPS H-step-ahead forecast error variance decompositions are represented as $\theta_{ij}^{g}(H)$ for $H = 1, 2,...,$ as shown in Equation (11).

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma_{e_j})^2}{\sum_{h=0}^{H-1} (e_i' A_{h_h}' \Sigma_{e_i})} \tag{11}$$

In this context, Σ represents the error vector's variance matrix, ϵ, σ_{ij} denotes the standard deviation of the error term for the jth Equation and e_i signifies the selection vector, with a value of one in the ith element and zeros elsewhere. It's crucial to note that the elements in the variance decomposition table, $\sum_{j=1}^{N} \theta_{ij}^{g}(H) \neq 1$ do not sum up to 1. To compute the spillover index, each element in the variance decomposition matrix is divided by the sum of its respective row, as demonstrated in Equation (12).

$$\left(\widetilde{\theta_{ij,t}^{g}(H)}\right) = \frac{\theta_{ij,t}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{12}$$

The total volatility spillover index is calculated using Equation (13) utilizing the volatility contributions obtained by the KPPS variance decomposition:

$$S^{g}(H) = \frac{\sum_{i=1, i\neq j}^{N} \widetilde{\theta_{ij}^{g}(H)}}{\sum_{i=1, i=j}^{N} \widetilde{\theta_{ij}^{g}(H)}} * 100 \tag{13}$$

The overall volatility spillover index offers insights into the magnitude of volatility shocks transmitted across various asset classes. However, we employ the generalized VAR technique for a nuanced comprehension of the spillover directions. Integrating generalized impulse responses with variance decompositions, this method resolves the variable ordering challenge. We utilize normalized components from the generalized variance decomposition matrix to calculate directional spillovers. Equation (14) is employed to quantify the directional volatility spillovers received by market i from all other markets j.

$$S_{i.}^{g}(H) = \frac{\sum_{i=1, i\neq j}^{N} \widetilde{\theta_{ij}^{g}(H)}}{\sum_{i=1, j=1}^{N} \widetilde{\theta_{ij}^{g}(H)}} * 100 \tag{14}$$

As illustrated in Equation (15), Similarly, the directional volatility spillovers from market i to all other markets j are quantified:

$$S_{.i}^{g}(H) = \frac{\sum_{i=1,i\neq j}^{N} \widetilde{\theta_{ji}^{g}(H)}}{\sum_{i=1,j=1}^{N} \widetilde{\theta_{ji}^{g}(H)}} * 100 \tag{15}$$

The directional spillovers can be seen as a subset of all spillovers, highlighting those originating from or going to a single source, as depicted in Equation (15). Utilizing Equation (16), we can calculate the net volatility spillovers from market *i* to all other markets *j*:

$$S_{i}^{g}(H) = S_{.i}^{g}(H) - S_{.i}^{g}(H) \tag{16}$$

The net volatility spillover is computed by subtracting the total volatility shocks transmitted to and received from all other markets. This metric offers a concise overview of each market's individual impact on the volatility observed in other markets. Furthermore, examining net pairwise volatility spillovers, as defined in Equation (17), provides valuable insights into specific market interactions.

$$S_{ij}^{g}(H) = \left(\frac{\widetilde{\theta_{ji}^{g}(H)} - \widetilde{\theta_{ij}^{g}(H)}}{N}\right) * 100 \tag{17}$$

The net pairwise volatility spillover between markets *i* and *j* is computed by deducting the total volatility shocks transmitted from market *i* to market *j* from those communicated from market *j* to market *i*. This calculation precisely illustrates the mutual impact between the two markets, quantifying the net directional flow of volatility between them.

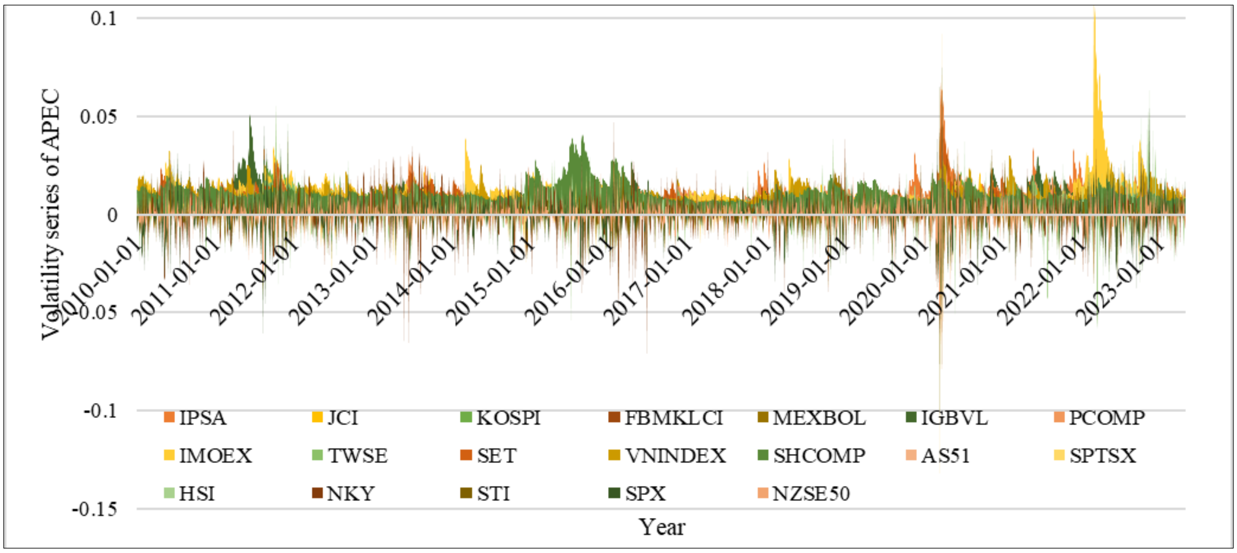

Figure 1. Volatilities among the developed and emerging economies of APEC Bloc.

4. Results and discussions

The combined volatility series (Figure 1) of the emerging and developed countries of the APEC Bloc indicated that IMOEX in March 2022 showed the highest volatility due to the Russia-Ukraine war, followed by the US (SPX). In the overall series, Japan (NKY) exhibited high negative volatility in March 2011 to its typical level of response during 5-10 days after an incident (Pacific Coast of Tohoku Earthquake), as among the 33 sectors, those that are directly and indirectly affected tend to have an adverse reaction (Tao et al. 2019) and double-dip recession of the GFC indicated slugging growth, followed by New Zealand (NZSE) in March 2020 due to COVID-19.

Figure 2 indicated volatility in individual series among developed countries, which exhibited Covid-19 as a major crisis that impacted all countries except Japan (NKY) due to the earthquake. In emerging economies of the APEC bloc (Figure 3), major countries affected by the COVID-19 crisis except IMOEX during the Russia-Ukraine crisis – 2022, Peru (IGBVL) in 2011 due to the European sovereign debt crisis and US debt limit dispute caused political instability (two presidents quitting in a few months), and China (SHCOMP) due to Chinese crash -2016.

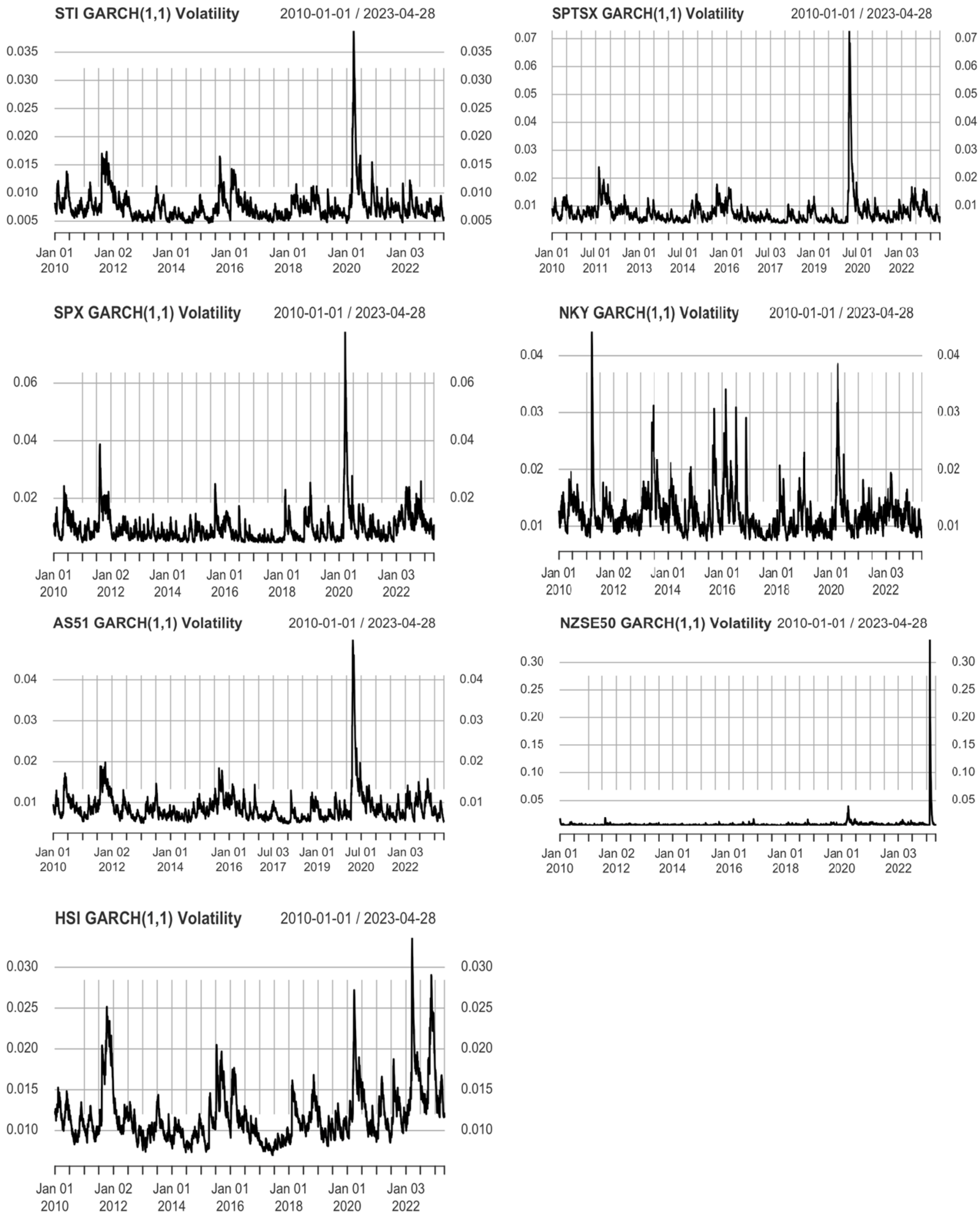

Figure 2. Volatility spillover in developed economies of the APEC bloc.

The results of the TVP-VAR connectedness analysis are in Table 2 (developed countries of the APEC bloc) and Table 3 (emerging nations of the APEC bloc). Table 2 shows the expected contribution to the variance of prediction errors for stocks *i* caused by interruptions in stocks *j*, as demonstrated by the *ij*th item. The off-diagonal components reflect spillover rates, whereas the diagonal details indicate self-induced return spillovers.

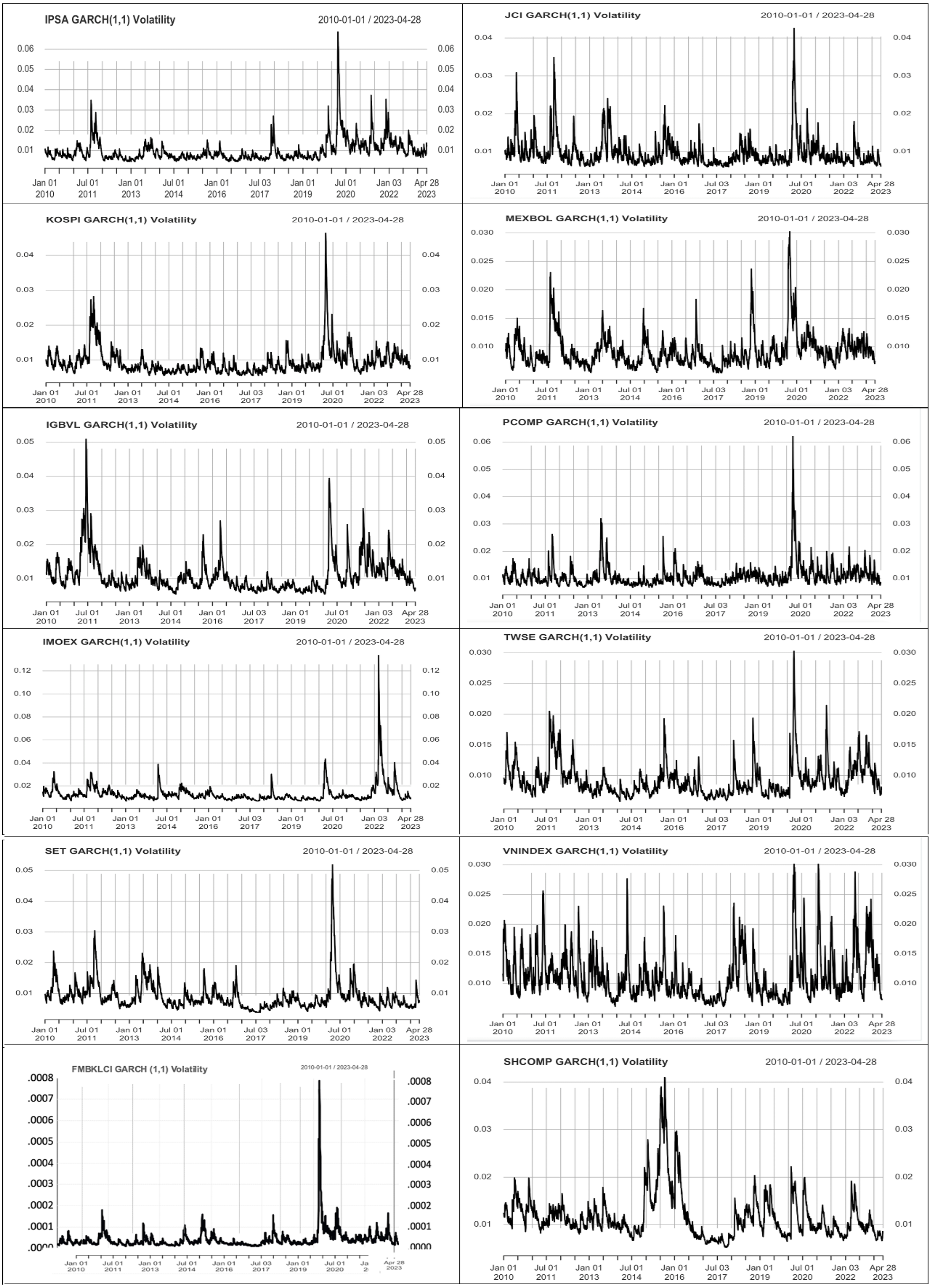

Figure 3. Volatility spillover in emerging economies of the APEC bloc.

As results (Table 2) indicated among developed countries, SPX (US) (56.85%) and SPTSX (Canada) (42.6%) were identified as the major transmitters as the reason could lie in inter-regional connectivity, say the spillover effects from North American free trade agreement (NAFTA) bloc to APEC countries.

On the other side, NKY (Japan) (34.02%) and AS51 (Australia) (23.54%) are identified as major recipient spillover; the reason could be that both countries are part of the quadrilateral security dialogue (Quad) economic bloc in which investors may have diverted some portfolio in any crises. This is understandable as Australia is among Japan's top trade partners. Large trading volume impacts the volatility among the countries (Ministry of Finance, 2019), as similar results indicated by Mensi et al. (2022). Among developed countries, HSI (Hong Kong) (11.78%) and STI (Singapore) (13.57%) were identified as the least recipients of the spillover as they can act as a hedge among the APEC bloc's Asia-Pacific region among developed countries.

Table 2. Volatility Spillover among the developed countries of the APEC bloc using TVP-VAR

	AS51	SPTSX	HSI	NKY	STI	SPX	NZSE50	FROM
AS51	**32.91**	19.65	7.35	5.57	7.51	20.32	6.68	67.09
SPTSX	6.72	**48.83**	4.91	2.47	6.32	26.47	4.28	51.17
HIS	8.01	10.59	**46.1**	3.74	11.86	14.3	5.4	53.9
NKY	8.25	14.24	5.19	**43.26**	6.25	16.78	6.01	56.74
STI	7.97	11.37	13.96	3.99	**42.88**	14.13	5.7	57.12
SPX	5.23	26.87	4.36	2.93	5.41	**50.86**	4.34	49.14
NZSE50	7.37	11.05	6.34	4.02	6.2	13.98	**51.05**	48.95
TO	43.55	93.78	42.12	22.72	43.55	105.99	32.4	384.1
Inc. Own	76.46	142.6	88.22	65.98	86.43	156.85	83.45	
Net	-23.54	42.6	-11.78	-34.02	-13.57	56.85	-16.55	54.87

As results (Table 3) indicated that in emerging countries, IMOEX (Russia) (15.06%), VNINDEX (Vietnam) (11.64%), and SET (Thailand) (11.57%) are identified as the major transmitters, which may be due to Southeast Asian countries are strengthening their economic relations with Russia to reduce inflation and accelerate their recovery post-GFC. Russia-Vietnam comprehensive partnership (2012) also opened a two-way relationship that flourished gradually before accelerating in tandem with Russia's economic resurgence. It makes sagacity for relationships to advance to the status of all-encompassing strategic partners. On the other side, FBMLCI (Malaysia) (28.95%) and PCOMP (Philippines) (9.82%) were identified as major recipients of the spillover. Although post-crisis statistics indicate a lower spillover impact of greater variance across foreign stock markets, market connections remain stronger than before the crisis. Southeast Asian nations, such as Malaysia and the Philippines, are expanding their commercial and financial ties with one another and with bigger economies. Because of their interdependence, a big economic event in one of the larger economies may have spillover effects in these markets (Dai et al., 2022; Nguyen et al., 2022). Other studies by Kogid et al. (2022) and Guru and Yadav (2023) also indicated similar results based on different selections of the countries.

In the overall period, KOSPI (South Korea) was identified as the safest stock market indices, which can be used as a hedge as it identified the least recipient of spillover, i.e., 0.52% among the emerging countries of the Asia-Pacific region in the APEC bloc. In the frequency domain of the developed economies (Table 4) and emerging economies (Table 5), this study finds that during any crises, there is significant spillover among the countries that act as less volatility spillover during the non-crises period. Moreover, in the period of the global financial crisis (GFC) in 2008, there was still some impact in the series due to the double dip of the recession, and many economies impacted the stock market with slugging growth.

Table 3. Volatility Spillover among the emerging countries of the APEC bloc using TVP-VAR

	IPSA	JCI	KOSPI	FBMKLCI	MEXBOL	IGBVL	PCOMP	IMOEX	TWSE	SET	VNINDEX	SHCOMP	FROM
IPSA	**51.97**	3.49	5.29	1.48	6.81	7.45	3.39	5.53	3.5	5.16	3.31	2.62	48.03
JCI	4.91	**46.88**	4.84	2.64	5.54	3.11	4.87	4.93	7.04	8.3	4.06	2.87	53.12
KOSPI	6.16	4.39	**38.53**	3.73	5.07	3.34	4.12	6.25	12.03	6.7	5.77	3.92	61.47
FBMKLCI	5.07	4.7	5.32	**38.69**	6.67	5.27	5.26	5.66	5.86	7.12	5.95	4.43	61.31
MEXBOL	7.28	2.94	6.12	3.04	**43.95**	5.64	3.85	7.14	4.98	7.84	3.78	3.45	56.05
IGBVL	6.39	3.56	3.06	2.01	6.66	**55.31**	4.31	4.73	2.89	3.88	4.44	2.75	44.69
PCOMP	5.33	7.87	5.67	3.81	4.91	3.54	**44.1**	4.13	4.61	7.48	5.32	3.23	55.9
IMOEX	4.66	3.89	3.76	2.03	6.92	5.5	2.91	**54.8**	3.94	5.07	4.07	2.46	45.2
TWSE	4.77	3.65	13.08	3.23	4.41	3.77	4.27	6.66	**39.96**	5.42	6.54	4.24	60.04
SET	4.41	8.07	4.01	3.72	4.73	4.78	5.09	5.19	4.61	**47.1**	4.57	3.71	52.9
VNINDEX	2.09	3.4	4.63	4.12	3.33	2.9	4.94	4.3	5.9	3.76	**57.74**	2.9	42.26
SHCOMP	1.98	2.54	5.16	2.54	3.86	3.02	3.07	5.74	8.37	3.73	6.09	**53.89**	46.11
TO	53.06	48.49	60.95	32.36	58.9	48.32	46.08	60.26	63.74	64.46	53.9	36.58	627.08
Inc. Own	105.02	95.37	99.48	71.05	102.85	103.63	90.18	115.06	103.69	111.57	111.64	90.47	57.01
Net	5.02	-4.63	-0.52	-28.95	2.85	3.63	-9.82	15.06	3.69	11.57	11.64	-9.53	52.26

On the other side, in the selected period in the second sub-period of 5-22 days, volatility spillover increased, which also gave retrospective results in the third sub-period 22-inf with more high volatility spillover in the longer period due to clinch of different crises over the period. These findings align with the SMR theory with information transmission theory and financial integration theory a theoretical lens suggesting that market prices indicate integration during the different crises over the period of the APEC bloc to depict price sequences, where future changes are perceived as random shifts from historical values (Malkiel, 2003). In the APEC bloc, both developed and emerging countries are significantly affected by volatility spillovers during crises.

Table 4. Volatility spillover in the frequency domain using BK (2018) among the developed APEC countries

				1-5 days- short term				
	AS51	SPTSX	HSI	NKY	STI	SPX	NZSE50	FROM
AS51	3.28	0.24	0.3	0.65	0.43	0.26	0.35	2.22
SPTSX	0.18	2.9	0.17	0.18	0.18	1.01	0.08	1.8
HIS	0.25	0.21	1.55	0.34	0.34	0.33	0.07	1.55
NKY	0.87	0.17	0.38	5.73	0.41	0.28	0.27	2.39
STI	0.36	0.15	0.53	0.31	3.1	0.15	0.18	1.67
SPX	0.22	1.28	0.16	0.35	0.15	3.85	0.1	2.26
NZSE50	0.92	0.28	0.45	0.78	0.64	0.31	7.68	3.38
TO	2.79	2.34	1.99	2.62	2.14	2.34	1.06	15.27
Inc. Own	6.07	5.24	3.54	8.34	5.25	6.18	8.73	
Net	0.56	0.54	0.44	0.23	0.47	0.08	-2.33	2.18
				5-22 days (medium term)				
	AS51	SPTSX	HSI	NKY	STI	SPX	NZSE50	FROM
AS51	7.11	1.18	0.74	1.54	1.16	1.77	0.76	7.15
SPTSX	0.5	6.76	0.39	0.43	0.57	2.4	0.27	4.56
HIS	0.55	0.64	3.82	0.55	0.89	0.89	0.24	3.76
NKY	1.65	1.09	0.89	12.66	1.1	2.07	0.71	7.52
STI	0.85	0.7	1.31	0.8	8.28	0.94	0.58	5.18
SPX	0.65	3.3	0.41	0.65	0.55	9.12	0.4	5.96
NZSE50	1.75	1.4	0.99	1.65	1.52	2.11	15.48	9.42
TO	5.95	8.32	4.73	5.61	5.79	10.17	2.97	43.54
Inc. Own	13.06	15.08	8.55	18.27	14.06	19.29	18.44	
Net	-1.2	3.76	0.97	-1.9	0.61	4.22	-6.45	6.22
				Above 22 days (long term)				
	AS51	SPTSX	HSI	NKY	STI	SPX	NZSE50	FROM
AS51	22.52	18.24	6.32	3.38	5.93	18.3	5.56	57.72
SPTSX	6.05	39.17	4.36	1.86	5.57	23.07	3.92	44.82
HIS	7.21	9.73	40.73	2.84	10.63	13.09	5.08	48.58
NKY	5.74	12.98	3.92	24.88	4.74	14.43	5.03	46.83
STI	6.76	10.52	12.12	2.88	31.5	13.05	4.94	50.27
SPX	4.36	22.29	3.79	1.93	4.71	37.9	3.84	40.93
NZSE50	4.7	9.36	4.9	1.59	4.04	11.56	27.9	36.14
TO	34.81	83.12	35.4	14.49	35.62	93.48	28.38	325.29
Inc. Own	57.34	122.29	76.13	39.37	67.12	131.38	56.28	
Net	-22.91	38.3	-13.19	-32.34	-14.65	52.55	-7.77	46.47

The behavior of the different countries in different frequencies indicated in Figure4 indicated volatility among the developed individual countries, and in Figure 5, all developed countries in the full period; in these figures, different frequencies are taken (1-5 days (Red colour), 5-22 (Green colour), 22-Inf (Blue colour) to identify the impact on the series over the period due to different events. Similarly, emerging countries result in other frequency domains indicated by Figure 6 and Figure 7.

Moreover, in Figure 8, the results indicated that post-GFC in the normal period during the short frequency period (1-5 days) among developed countries, New Zealand (NZSE50) is the only spillover receptor, but in the second sub-frequency period (6-21 days) New Zealand (NZE50), Australia (AS51), Japan (NKY) identified as spillover receptor. In the rest of the period (22 above days), HIS and STI also emerged as receptors of the spillover, which is similar to the full period, and the remaining countries acted as spillover transmitters.

Among emerging countries of the APEC bloc, in Figure 9, FBMLCI, JCI, IGBVL, and PCOMP found receivers in short frequency period (1-5 days), but in medium term (6-21 days) VNINDEX, but in longer frequency period (22 days) SHCOMP acted as receptor and IGBVL, VNINDEX as transmitter which is like the full data period. The results indicate that investors can decide about the investment based on their selection of the frequency as different countries' actions as transmitter or receptor changes with the period. This study finds KOSPI and HSI as hedging indices as these are fewer receivers of the volatility spillover in the APEC bloc among developed and emerging countries.

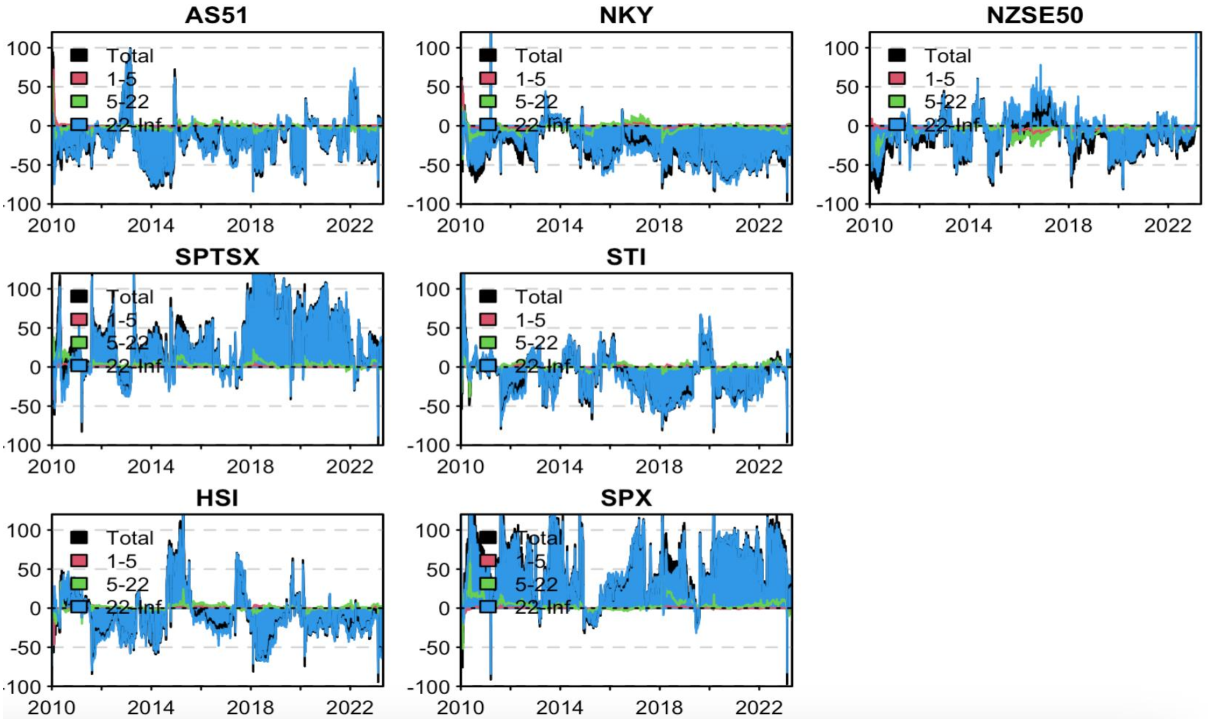

Figure 4. Volatility spillover in the frequency domain (BK, 2018) in developed economies of the APEC bloc.

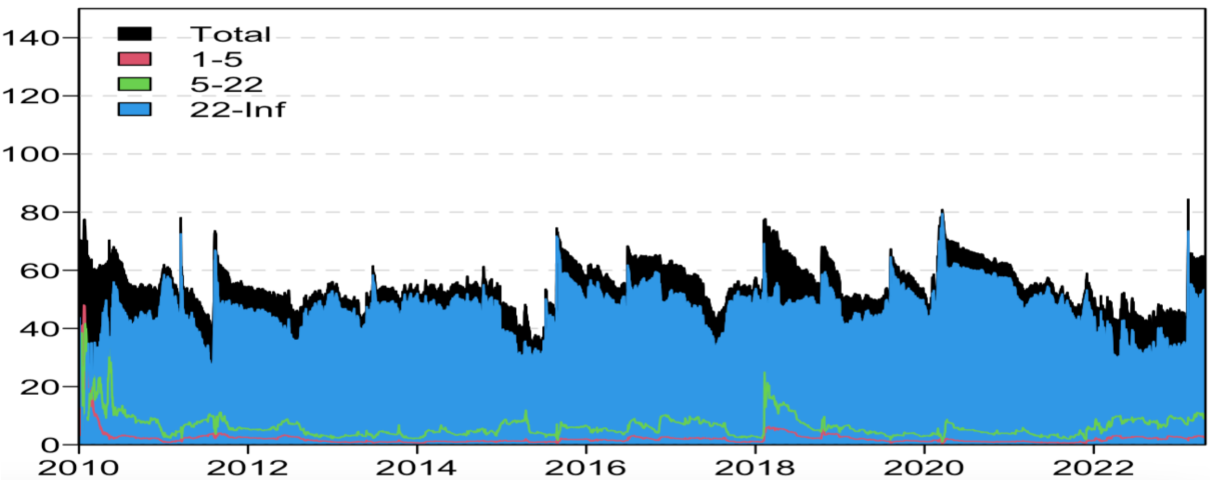

Figure 5. Volatility spillover in the frequency domain (BK, 2018) in total countries of the developed economies in the APEC bloc.

Table 5. Volatility spillover in the frequency domain using BK (2018) among the emerging APEC countries

	IPSA	JCI	KOSPI	FBMKLCI	MEXBOL	IGBVL	PCOMP	IMOEX	TWSE	SET	VNINDEX	SHCOMP	FROM
1-5 days (Short Term)													
IPSA	3.27	0.17	0.07	0.08	0.24	0.14	0.09	0.17	0.08	0.12	0.12	0.11	1.38
JCI	0.24	6.04	0.26	0.26	0.29	0.07	0.4	0.17	0.31	0.41	0.24	0.16	2.82
KOSPI	0.09	0.15	3.3	0.13	0.11	0.09	0.19	0.06	0.62	0.13	0.14	0.3	2.04
FBMKLCI	0.25	0.65	0.47	14.39	0.76	0.24	1.25	0.35	0.7	0.74	1.27	0.5	7.18
MEXBOL	0.22	0.15	0.1	0.14	4.08	0.21	0.16	0.13	0.11	0.13	0.14	0.17	1.65
IGBVL	0.15	0.1	0.12	0.14	0.23	2.59	0.17	0.11	0.1	0.11	0.18	0.17	1.58
PCOMP	0.18	0.45	0.31	0.54	0.36	0.21	6.65	0.16	0.43	0.42	0.56	0.31	3.94
IMOEX	0.13	0.13	0.05	0.07	0.13	0.1	0.08	3.13	0.08	0.12	0.08	0.09	1.06
TWSE	0.11	0.23	0.58	0.26	0.17	0.09	0.29	0.08	2.96	0.16	0.23	0.38	2.58
SET	0.12	0.22	0.17	0.26	0.24	0.12	0.31	0.12	0.22	2.57	0.26	0.19	2.25
VNINDEX	0.12	0.24	0.23	0.52	0.35	0.18	0.55	0.15	0.34	0.36	4.19	0.24	3.31
SHCOMP	0.12	0.11	0.22	0.13	0.19	0.13	0.14	0.12	0.25	0.11	0.17	2.58	1.68
TO	1.73	2.6	2.59	2.54	3.09	1.58	3.64	1.62	3.25	2.81	3.38	2.62	31.47
Inc.Own	5	8.65	5.89	16.92	7.18	4.17	10.3	4.75	6.21	5.38	7.58	5.19	
Net	0.35	-0.22	0.56	-4.64	1.44	0	-0.29	0.56	0.67	0.57	0.08	0.94	2.62
5-22 days (Medium Term)													
	IPSA	JCI	KOSPI	FBMKLCI	MEXBOL	IGBVL	PCOMP	IMOEX	TWSE	SET	VNINDEX	SHCOMP	FROM
IPSA	8.86	0.48	0.35	0.17	0.7	0.52	0.28	0.67	0.33	0.44	0.33	0.36	4.63
JCI	0.65	14.07	0.73	0.51	0.8	0.3	0.83	0.73	1	1.11	0.54	0.39	7.6
KOSPI	0.33	0.54	7.64	0.32	0.52	0.26	0.49	0.48	1.63	0.51	0.46	0.66	6.19
FBMKLCI	0.31	0.61	0.5	7.63	0.56	0.37	0.76	0.65	0.6	0.55	0.5	0.35	5.76
MEXBOL	0.6	0.46	0.54	0.37	10.46	0.67	0.51	0.77	0.56	0.6	0.33	0.5	5.92
IGBVL	0.54	0.38	0.36	0.32	0.98	7.33	0.47	0.71	0.33	0.41	0.38	0.55	5.43
PCOMP	0.59	1.55	0.88	0.75	0.72	0.52	14.65	0.74	0.9	0.94	0.79	0.59	8.98
IMOEX	0.48	0.57	0.33	0.25	0.68	0.43	0.36	8.93	0.33	0.52	0.29	0.35	4.58
TWSE	0.32	0.45	1.19	0.34	0.4	0.27	0.5	0.42	7.47	0.39	0.45	0.7	5.42
SET	0.34	0.67	0.5	0.52	0.52	0.41	0.73	0.66	0.61	6.87	0.51	0.46	5.93
VNINDEX	0.34	0.56	0.52	0.74	0.51	0.44	0.93	0.66	0.8	0.72	11.04	0.43	6.63
SHCOMP	0.34	0.33	0.37	0.24	0.49	0.37	0.32	0.73	0.62	0.38	0.4	6.62	4.58
TO	4.84	6.61	6.25	4.52	6.9	4.56	6.16	7.22	7.7	6.57	4.97	5.36	71.65
Inc.Own	13.7	20.68	13.89	12.16	17.36	11.89	20.81	16.16	15.17	13.44	16.01	11.97	
Net	0.2	-0.99	0.07	-1.24	0.97	-0.86	-2.82	2.65	2.28	0.64	-1.67	0.77	5.97

Table 5. Volatility spillover in the frequency domain using BK (2018) among the emerging APEC countries **(Continued)**

Above 22 Days (Long term)													
	IPSA	JCI	KOSPI	FBMKLCI	MEXBOL	IGBVL	PCOMP	IMOEX	TWSE	SET	VNINDEX	SHCOMP	FROM
IPSA	39.84	2.84	4.87	1.23	5.87	6.79	3.02	4.68	3.1	4.59	2.87	2.15	42.02
JCI	4.03	26.77	3.85	1.87	4.44	2.74	3.64	4.03	5.73	6.78	3.27	2.32	42.69
KOSPI	5.73	3.69	27.59	3.29	4.43	3	3.44	5.71	9.78	6.06	5.17	2.95	53.25
FBMKLCI	4.51	3.44	4.36	16.67	5.34	4.67	3.25	4.67	4.55	5.83	4.18	3.57	48.37
MEXBOL	6.46	2.33	5.48	2.53	29.41	4.76	3.18	6.23	4.31	7.11	3.31	2.77	48.48
IGBVL	5.7	3.08	2.59	1.54	5.44	45.39	3.67	3.91	2.46	3.36	3.89	2.03	37.68
PCOMP	4.55	5.86	4.47	2.52	3.83	2.81	22.8	3.23	3.28	6.12	3.98	2.33	42.98
IMOEX	4.06	3.19	3.38	1.72	6.1	4.96	2.47	42.74	3.53	4.44	3.7	2.01	39.56
TWSE	4.34	2.97	11.32	2.64	3.84	3.41	3.48	6.16	29.52	4.88	5.85	3.16	52.05
SET	3.94	7.19	3.33	2.93	3.96	4.24	4.05	4.41	3.78	37.67	3.8	3.07	44.72
VNINDEX	1.63	2.59	3.88	2.85	2.47	2.28	3.46	3.49	4.76	2.67	42.5	2.23	32.32
SHCOMP	1.53	2.09	4.57	2.18	3.18	2.53	2.6	4.89	7.51	3.23	5.53	44.7	39.85
TO	46.49	39.27	52.1	25.3	48.91	42.17	36.28	51.41	52.79	55.08	45.55	28.61	523.96
Inc.Own	86.33	66.04	79.7	41.97	78.32	87.57	59.08	94.15	82.31	92.75	88.05	73.3	
Net	4.47	-3.42	-1.15	-23.07	0.44	4.49	-6.7	11.85	0.74	10.36	13.23	-11.24	43.66

5. Robustness results

Robustness checks were conducted on the final findings of spillover, utilizing varying rolling widths (W). As indicated by the first findings of the preceding analysis, the rolling width of 200, 250, and 300 days was employed (Figure 10). The robustness analysis of the dynamic spillover index for APEC countries, conducted across varying rolling window lengths, reveals a noteworthy trend. Specifically, extending the rolling window size from 200 to 250 days results in a more stable and consistent spillover plot for APEC nations. Despite this adjustment, the observed pattern remains unchanged, underscoring the resilience of our initial findings to the alternative rolling window technique.

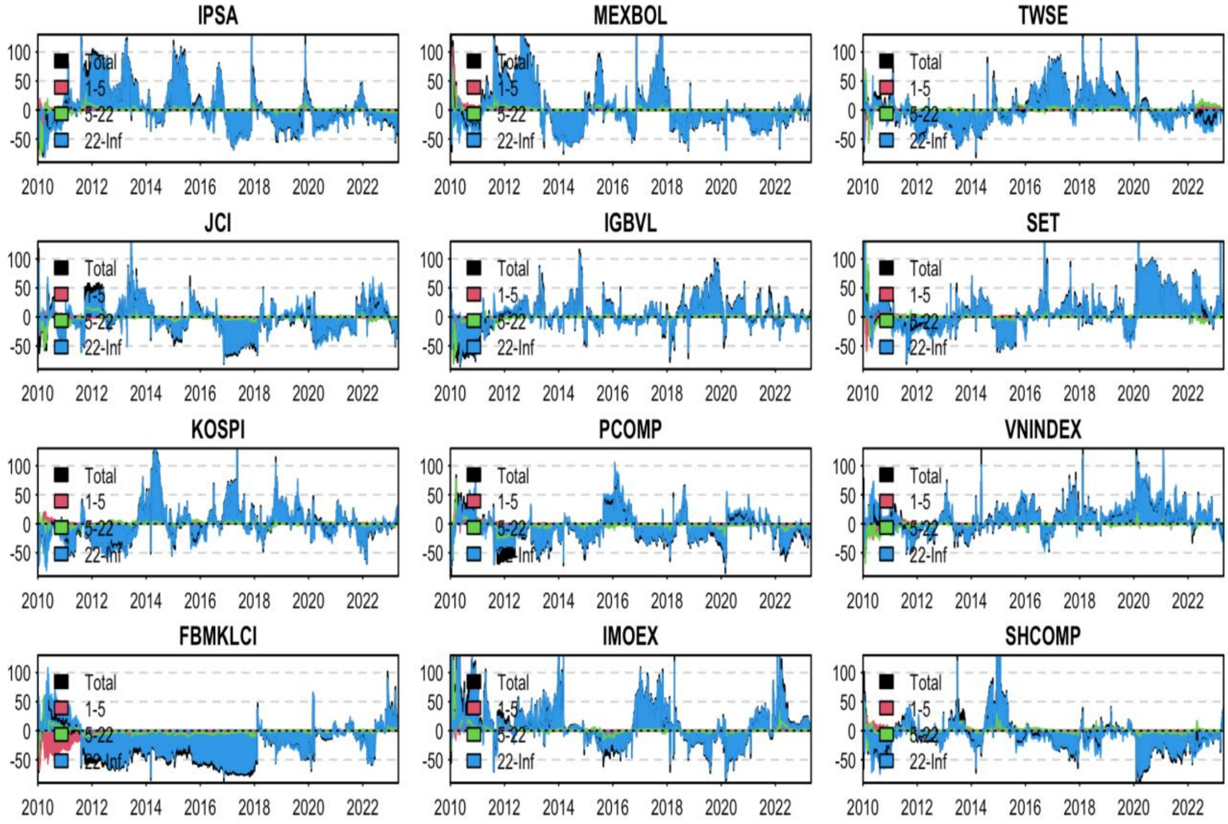

Figure 6. Volatility spillover in the frequency domain (BK, 2018) in emerging economies of the APEC bloc.

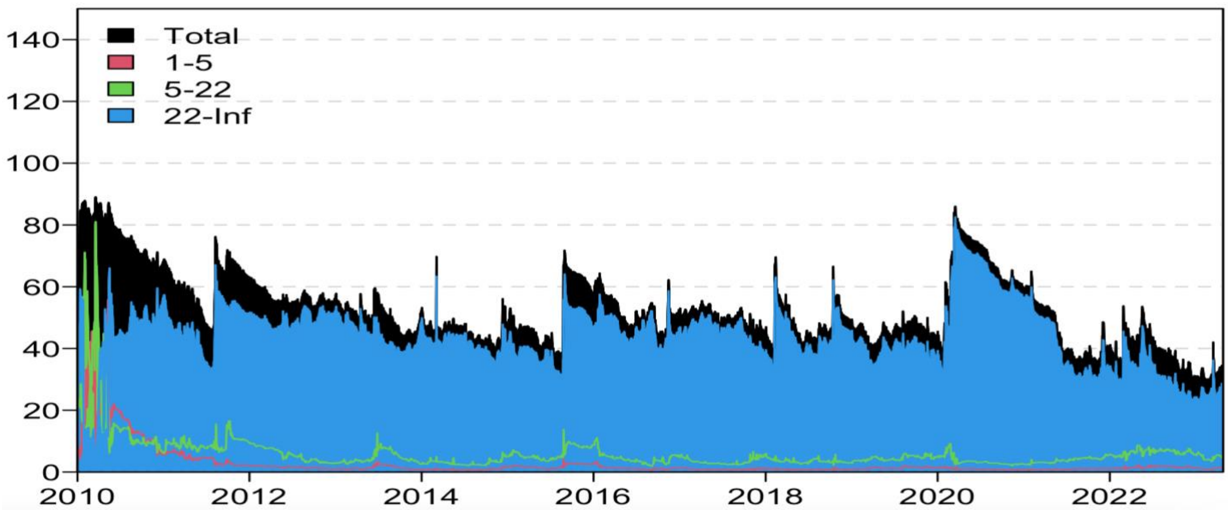

Figure 7. Volatility spillover in the frequency domain (BK, 2018) in total countries of the emerging economies in the APEC bloc.

6. Conclusion

This study was conducted to identify the magnitude and directional volatility spillover among the developed and emerging countries of the APEC bloc by implementing the TVP-VAR model for volatility spillover in the time domain and Barunik and Krehlik (2018) Model for understanding spillover in the frequency domain. The findings of the study indicated that Russia (IMOEX) (15.06%), Vietnam (VINDEX) (11.64%), and Thailand (SET) (11.57%) stock markets are significant transmitters of volatility spillovers in APEC developing nations, while Malaysia (FBMKLCI) (28.95%), Philippines (PCOM) (9.28%), and China (SHCOMP) (9.53%) are identified as key receptors of these spillovers. In the APEC developed countries, the SPX index exhibits a significant positive spillover effect of 56.85%. The Canada (SPTSX) index also plays a big role as a transmitter, with a spillover effect of 42.6%. On the other hand, the NKY index shows a notable negative spillover effect of 34.02%, and the Australia (AS51) index demonstrates an even larger negative spillover effect of 53.54%. Therefore, the Japan (NKY) and Australia (AS51) indices may be characterized as prominent receptors of the spillover in this context.

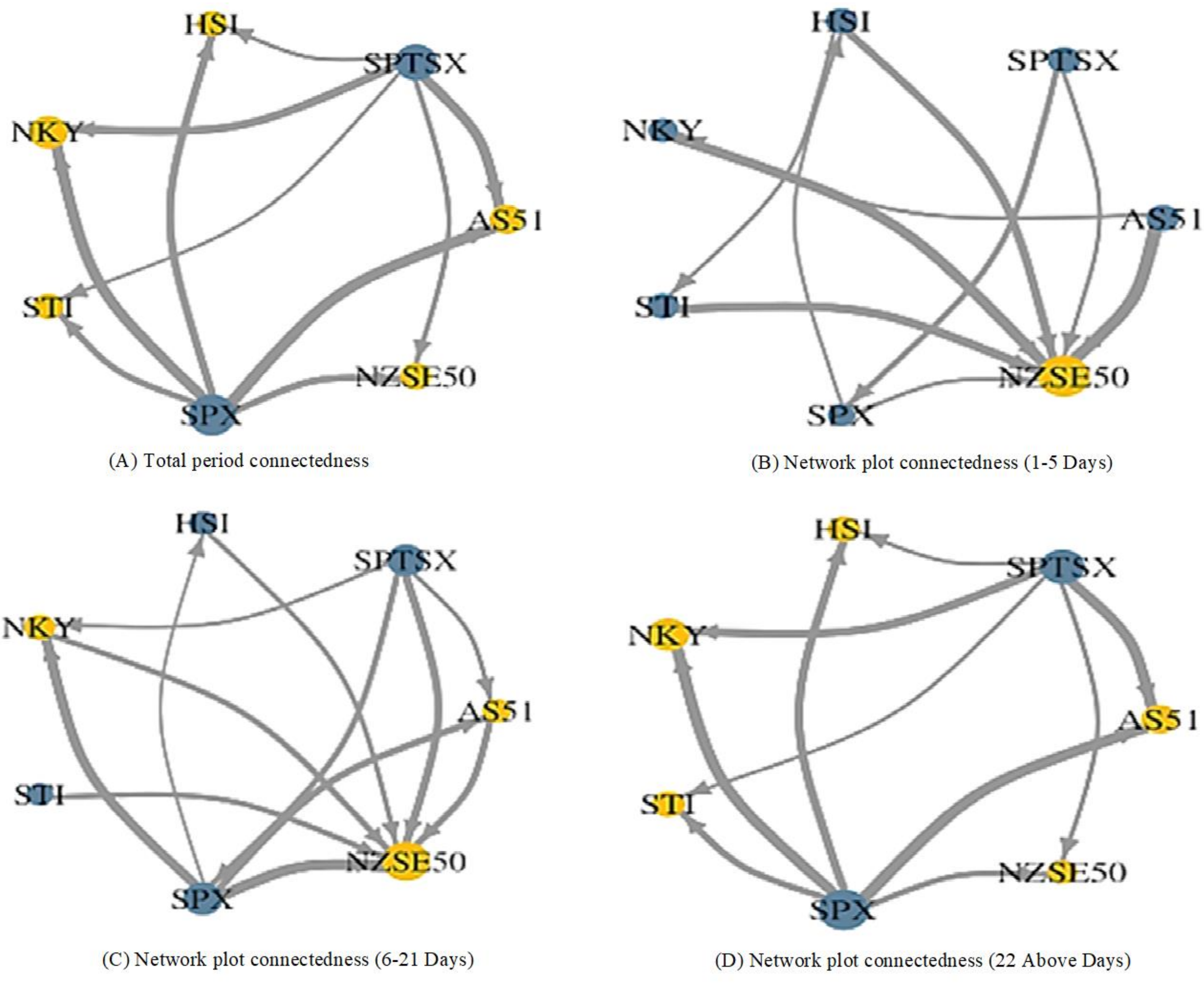

Figure 8. Net connectedness during the full sample period in the developed economies of the APEC nations

Furthermore, the COVID-19 pandemic has been recognized as a major crisis, with the highest volatility spillover observed in the economies of developed and emerging countries within the Asia-Pacific Economic Cooperation (APEC) bloc. The degree of economic integration between these nations and the rest of the area is a crucial determinant. The inception of the North American Free Trade Agreement (NAFTA) established a tightly interconnected trading system and economic bloc, fostering substantial trade and investment exchanges among Mexico, Canada, and the United States. Consequently, changes in financial circumstances or policy choices in one of these nations may greatly impact the economies of the other APEC members. Among developed nations, HSI (Hong Kong) (11.78%) and STI (Singapore) (13.57%) were recognized as the least likely recipients of spillover as a hedge in the APEC bloc's Asia-Pacific area. Our research offers invaluable insights for domestic investors, equipping them with a deeper understanding of the risks and opportunities within the APEC financial stock market. With this enhanced expertise, investors can adopt more effective and specialized investment approaches, enabling them to manage risks, optimize portfolios, and implement hedging strategies. We unveil crucial dynamics driving stock market interactions by identifying net volatility spillover effects and return connectedness. These insights serve as a foundation for developing strategies to control and minimize market risks, proving invaluable for policymakers dedicated to upholding market stability and implementing robust risk management practices.

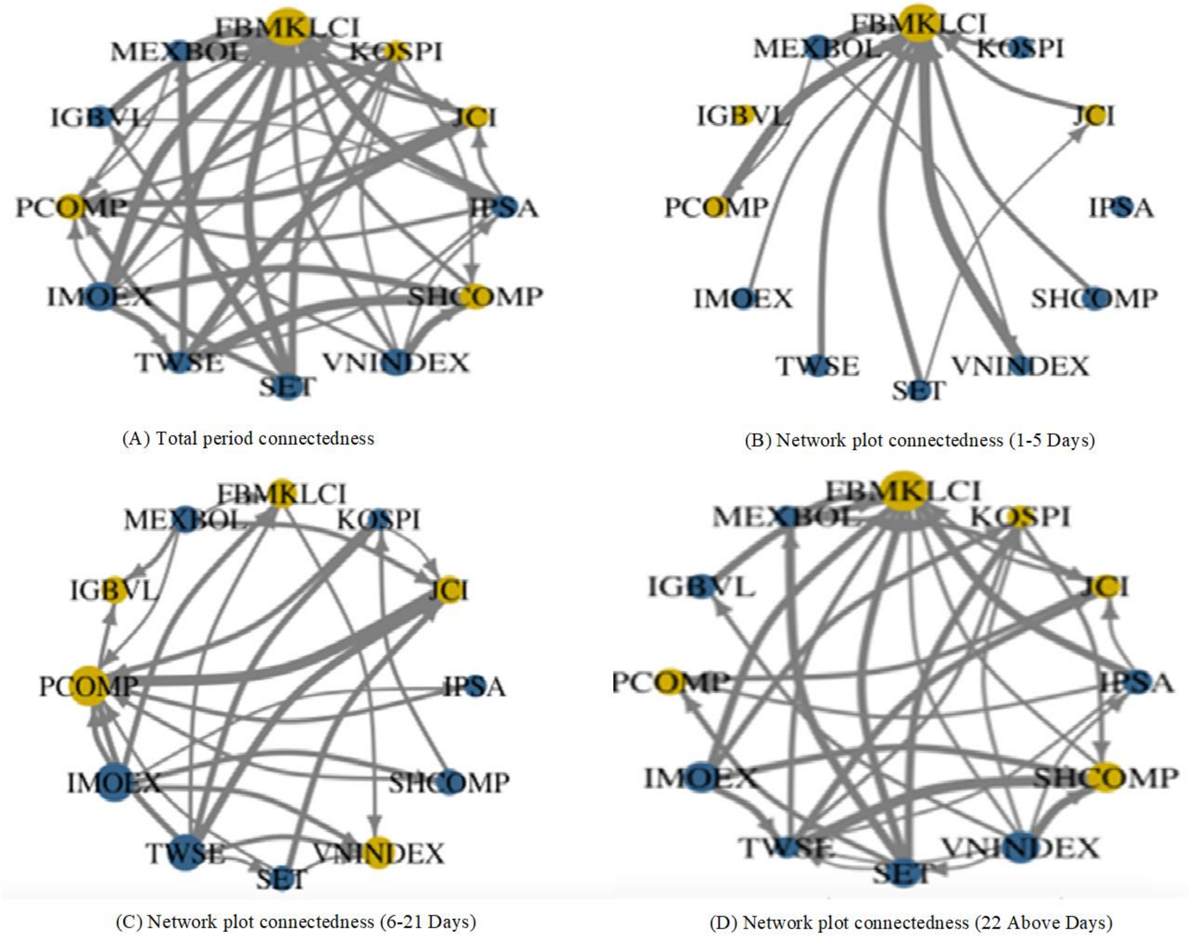

Figure 9. Net connectedness during the full sample period in the emerging economies of the APEC nations.

Additionally, our study sheds light on the intricate interactions among emerging commodity markets, illuminating their evolving landscape. Stock markets, pivotal for forecasting global and local macroeconomic conditions, offer a unique lens into broader economic trends. Analyzing the dynamics and interconnections within these markets yields profound insights, empowering researchers and policymakers to anticipate and navigate economic shifts effectively. Employing our technique to scrutinize interconnectivity and volatility dynamics can significantly inform decision-making processes, providing crucial foresight into potential economic trends.

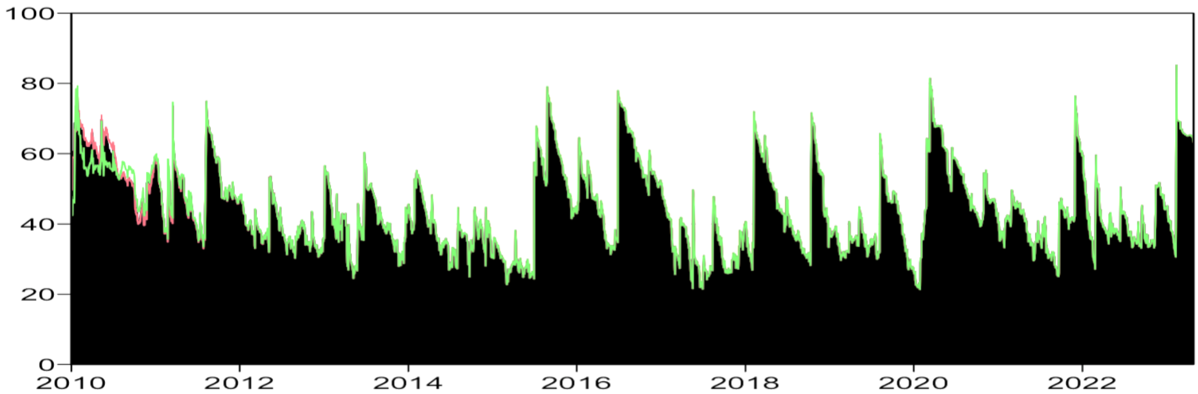

Figure 10. Robustness of the results for the different window sizes (Black-200, Red-250, and Green -300 trading days) in the entire period of the APEC bloc.

This study is limited to the volatility spillover in the stock markets of APEC countries. Further study could be conducted on APEC currency exchange rates by studying the impacts of the COVID-19 crisis and the Russia-Ukraine crisis.

Declaration of Conflicting Interests

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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