economies

Article

Should South Asian Stock Market Investors Think Globally? Investigating Safe Haven Properties and Hedging Effectiveness

Md. Abu Issa Gazi [1,2,*], Md. Nahiduzzaman [3,*], Sanjoy Kumar Sarker [4], Mohammad Bin Amin [5,*], Md. Ahsan Kabir [6], Fadoua Kouki [7], Abdul Rahman bin S Senathirajah [1] and László Erdey [8]

1 Faculty of Business and Communications, INTI International University, Persiaran Perdana BBN Putra Nilai, Nilai 71800, Negeri Sembilan, Malaysia; arahman.senathirajah@newinti.edu.my
2 School of Management, Jiujiang University, Jiujiang 332005, China
3 Department of Finance and Banking, Bangabandhu Sheikh Mujibur Rahman Science and Technology University, Gopalganj 8100, Bangladesh
4 Department of Finance and Banking, Islamic University, Kushtia 7003, Bangladesh; sanjayru06@gmail.com
5 Doctoral School of Management and Business, Faculty of Economics and Business, University of Debrecen, 4032 Debrecen, Hungary
6 Department of Statistics and Mathematics, Zhejiang Gongshang University, Hangzhou 310018, China; ahsancbat@gmail.com
7 Applied Management Program, Applied College at Muhyle, King Khalid University, Abha 61421, Saudi Arabia; falkoki@kku.edu.sa
8 Faculty of Economics and Business, University of Debrecen, 4032 Debrecen, Hungary; erdey.laszlo@econ.unideb.hu
* Correspondence: maigazi@yahoo.com or dr.issa@jju.edu.cn (M.A.I.G.); info.nahiduzzaman.bd@gmail.com (M.N.); binamindu@gmail.com (M.B.A.)

Abstract: In this study, we examine the critical question of whether global equity and bond assets (both green and non-green) offer effective hedging and safe haven properties against stock market risks in South Asia, with a focus on Bangladesh, India, Pakistan, and Sri Lanka. The increasing integration of global financial markets and the volatility experienced during recent economic crises raise important questions regarding the resilience of South Asian markets and the potential protective role of global assets. Drawing on methods like VaR and CVaR tail risk estimators, the DCC-GJR-GARCH time-varying connectedness approach, and cost-effectiveness tools for hedging, we analyze data spanning from 2014 to 2022 to assess these relationships comprehensively. Our findings demonstrate that stock markets in Bangladesh experience lower levels of downside risk in each quantile; however, safe haven properties from the global financial markets are effective for Bangladeshi, Indian, and Pakistani stock markets during the crisis period. Meanwhile, the Sri Lankan stock market neither receives hedging usefulness nor safe haven benefits from the same marketplaces. Additionally, global green assets, specifically green bond assets, are more reliable sources to ensure the safest investment for South Asian investors. Finally, the portfolio implications suggest that while traditional global equity assets offer ideal portfolio weights for South Asian investors, global equity and bond assets (both green and non-green) are the cheapest hedgers for equity investors, particularly in the Bangladeshi, Pakistani, and Sri Lankan stock markets. Moreover, these results hold significant implications for investors seeking to optimize portfolios and manage risk, as well as for policymakers aiming to strengthen regional market resilience. By clarifying the protective capacities of global assets, particularly green ones, our study contributes to a nuanced understanding of portfolio diversification and financial stability strategies within emerging markets in South Asia.

Keywords: South Asia; financial market; DCC-GARCH; safe haven; hedging effectiveness; sustainable growth

JEL Classification: C32; C58; G11; G12; G15; J11

check for updates

Citation: Gazi, Md. Abu Issa, Md. Nahiduzzaman, Sanjoy Kumar Sarker, Mohammad Bin Amin, Md. Ahsan Kabir, Fadoua Kouki, Abdul Rahman bin S Senathirajah, and László Erdey. 2024. Should South Asian Stock Market Investors Think Globally? Investigating Safe Haven Properties and Hedging Effectiveness. *Economies* 12: 309. https://doi.org/10.3390/economies12110309

Received: 6 October 2024
Revised: 9 November 2024
Accepted: 12 November 2024
Published: 15 November 2024

1. Introduction

The integration of global financial markets with financial markets from different regions or continents is regarded as a magnificent system for investors to diversify their investments. Since asset values in many markets are simultaneously affected by unexpected shocks, the coordination of financial markets across nations may protect investors' portfolios against these shocks (Ahmed et al. 2024; Shi 2022). According to Markowitz's portfolio theory, investors diversify their portfolios based on risk–return interconnectedness (Markowitz 1952; Kabir et al. 2023). Therefore, as a result of global financial integration, financial markets have expanded despite the severe negative effects of major domestic and global crises (Aloui et al. 2011).

Kim and McKenzie (2007) state that equity markets in the Asia–Pacific region are regionally integrated because of improvements in financial deregulation and expansions in inter-regional investment via financial markets. Over the past 15 years, economic transformations have taken place in Bangladesh, India, Pakistan, and Sri Lanka, and trade obstacles have reduced (World Bank 2012). A total of USD 135 billion in net foreign equity investment inflows was documented between 2001 and 2012 for the four nations (Khan et al. 2015). Another recent report by the World Bank conveyed that South Asia is expected to expand at an average rate of 6.7 percent per fiscal year from 2024 to 2026, positioning it as the fastest-growing region globally (World Bank 2024). However, due to the increased susceptibility to volatile overseas investment flows, the stock markets of emerging Asian countries are currently thought to become more financially fragile due to global events (Derbali and Lamouchi 2020). Furthermore, owing to the scarcity of inter-regional trade, three major economies in the region—India, Pakistan, and Bangladesh—are the least integrated in South Asia, despite growing levels of trade quantities on an individual basis (Gandhi and Ahmed 2020). Consequently, in 2021, South Asia was the only subcontinent to experience a 26% decrease in FDI (UNCTAD 2022). In such situations, domestic investors in this area may face tremendous trouble in safeguarding their funds because any kind of economic turmoil caused by internal or external events incurs huge losses for investors due to the spillover effect.

In addition, multiple global events such as global financial crises caused by US market turmoil, the subprime crisis (Longstaff 2010; Ackermann 2008), the Eurozone debt crisis (Samitas and Tsakalos 2013), geopolitical issues (Dimic et al. 2015; Kapar and Buigut 2020), the COVID-19 pandemic (Mazur et al. 2021; Akhtaruzzaman et al. 2021; Gazi et al. 2022a; Gazi et al. 2024), and the Russia–Ukraine invasion (Ahmed et al. 2022; Umar et al. 2022) have significantly impacted stock markets around the world. When the US real estate bubble broke in August 2007, the subprime mortgage crisis of 2007–2009 was underway and then rapidly spread to emerging and developed countries (Claessens et al. 2010). Furthermore, Lehman Brothers' bankruptcy in September 2008 triggered the outbreak of the global financial crisis, which extended quickly to financial markets in developed and developing countries (Dungey and Gajurel 2014). Hence, to overcome these situations, investors always search for alternative investment sources that can provide hedging effectiveness or safe haven benefits during the crisis period against their securities. In financial market integration, hedging effectiveness measures the ability of an asset to offset risk exposure in volatile or declining markets, typically assessed through metrics like the long-term negative correlation, hedge ratio, hedging cost, and reduction in portfolio volatility (Kharbanda and Singh 2018; Liu et al. 2023; Olstad et al. 2021). Assets with high hedging effectiveness stabilize returns, while safe haven benefits refer to the capability of an asset to retain or increase value during market stress, often showing a low or negative correlation with other assets (Niveditha 2024; Janani Sri et al. 2022). Together, these properties help diversify portfolios, minimizing systemic risk impacts by counteracting negative spillovers from global financial markets. However, the relationship between safe haven properties and stock markets is complex and influenced by various factors including market conditions and asset characteristics. Safe haven assets, such as gold and the US dollar, typically exhibit negative correlations with stock market performance during periods of financial distress, providing investors with a hedge against volatility (Sokhanvar and Hammoudeh 2024). In contrast, assets like Bitcoin demonstrate weaker safe haven properties, often behaving more like risky investments (Feder-Sempach et al. 2024). For instance, investments migrated from risky to safe assets during the 1987 stock market collapse (Caballero and Krishnamurthy 2008), and this has continued up until now, emphasizing new identifiers.

In these instances, assets from foreign financial markets can be considered sources that may reduce the risk of investors' portfolios through capital diversification. Numerous types of assets playing the characteristics of hedging benefits and safe haven properties for the equity holders are well documented; particularly, gold (Baur and Lucey 2010), treasury bonds (Flavin et al. 2014), commodities and currencies (Grisse and Nitschka 2015), Bitcoin (Aysan et al. 2019; Bouri et al. 2017), and green bond and clean energy assets (Kuang 2021) play roles as safe haven assets for the equity investors. Particularly, global assets consistently demonstrate safe haven properties during economic downturns, such as the COVID-19 pandemic, and geopolitical crises like the Russia–Ukraine war (Azimli 2024; Feder-Sempach et al. 2024). However, its effectiveness can diminish during extreme market declines, indicating that while it serves as a refuge, it is not infallible (Rusmita et al. 2024). In addition, global risks continue to lean toward the downside, although some positive surprises may still emerge. Rising geopolitical tensions could trigger fluctuations in commodity prices, and increasing trade fragmentation threatens further disturbances in trade networks.

In these regards, by incorporating a mix of domestic and international assets, investors can enhance portfolio performance while reducing exposure to market volatility. Data from the past 15 years indicate that portfolios including international securities not only reduce risk but also offer higher growth potential, outperforming domestic investments (Kundurthy and Nozari 2024). As a result, Forbes articulated that it is possible to increase returns and reduce risk by investing in a diversified portfolio[1]. Hence, on the one hand, the global financial markets safeguard investments in various situations, and on the other hand, these platforms protect the ecological environment by reducing carbon emissions. Specifically, green bonds and stocks are now regarded as the two most important environmentally friendly financial assets that significantly contribute to the mobilization of the resources needed to support the development of a sustainable economy (Ferrer et al. 2021) because global climate change is a serious issue for the present time and has reached a worrying point everywhere (Gazi et al. 2022b). Recent studies (e.g., Broadstock et al. 2020; Kuang 2021; Arif et al. 2022) have shown that global green bonds are viewed as lower-risk assets in portfolios that promote investor diversity. Therefore, it is necessary to interlink global green and conventional financial assets with the assets of South Asian stock markets to determine the possible benefits for South Asian investors.

In the context of South Asia, the current literature shows that several studies (e.g., Habiba et al. 2020; Ameer 2006; Shahzad et al. 2016; Mukherjee and Bose 2008) have interconnected the various global stock markets to the South Asian stock markets, while some other studies (e.g., Rahman and Uddin 2009; Mohsin and Rivers 2011; Perera and Wickramanayake 2012; Singhania and Prakash 2014; Gulzar et al. 2019; Khan et al. 2015) have revealed the regional interconnection among the South Asian countries' stock markets. Kumar and Dhankar (2017) and Arya and Singh (2022) explored the impact of global financial vulnerability on emerging South Asian stock markets. The majority of the studies focused on equity markets from both global and South Asian perspectives, although global bond markets could play a significant role in investment diversification for South Asian investors. Furthermore, many researchers (e.g., Tiwari et al. 2022; Banga 2019; Naeem and Karim 2021) have emphasized investments in green assets.

Existing research indicates that while South Asian markets exhibit significant interlinkages, their integration with global markets remains nuanced, with varying degrees of correlation and responsiveness to external shocks. Moreover, in the current literature, from the viewpoint of South Asian stock markets, there is no evidence of the interconnectedness between the global green (green equity and green bond) markets and South

Asian stock markets. Thus, it is important to explore the dynamic linkage between global green markets and South Asian stock markets in order to search for safe haven roles and hedging effectiveness for South Asian investors. Habiba et al. (2020) demonstrated that volatility spillovers are pronounced during financial crises, with significant effects observed from the US market to South Asian markets. To the best of our knowledge, this is the first attempt to exhibit the dynamic time-varying interconnectedness between diverse global asset classes and multiple asset classes from the Bangladeshi, Indian, Pakistan, and Sri Lankan stock markets. In addition, we determine the potential downside risk and cost of hedging effectiveness for the studied asset classes.

To bridge the gap, we endeavor to search for the following five research questions that perfectly reflect current limitations in the literature and provide insights into how these questions accommodate these shortcomings: First, do the South Asian stock markets and global financial markets have the same downside risk potential? Second, is there any volatility of return between the assets of global financial markets and those of South Asian stock markets? Third, do global financial markets provide safe haven benefits or hedging strategies against the assets of South Asian stock markets, and if yes, then which asset classes (green or non-green; bonds or equities) are the more effective sources for providing portfolio diversification facilities? Fourth, what are the ideal portfolio weights if a cost is associated with effective hedging?

However, to answer these questions, we use sophisticated methodologies including VaR, CVaR, DCC-GJR-GARCH, and hedging implication tools. Specifically, Value at Risk (VaR) and Conditional Value at Risk (CVaR) are well-regarded tools for quantifying potential losses under adverse market conditions, with VaR offering a threshold-based metric of maximum expected losses and CVaR providing a more nuanced assessment by accounting for the expected tail losses beyond the VaR limit. Furthermore, for analyzing the evolving dynamics of volatility and co-movements, we utilize the dynamic conditional correlation–generalized autoregressive conditional heteroskedasticity (DCC-GJR-GARCH) model, which is advantageous for its ability to capture time-varying correlations and asymmetric volatility responses to positive and negative shocks. This model is particularly effective in financial markets, where assets exhibit varying responses under different market conditions, and provides a more accurate representation of volatility clustering and shock spillovers (Siddique et al. 2024). In addition, after establishing the baseline risk assessment through VaR and CVaR, attention can shift to modeling the volatility and correlation dynamics among assets, especially during market stress or volatility clustering, where the DCC-GJR-GARCH model becomes essential. Finally, to assess hedging efficacy, the study incorporates tools such as hedge ratio calculations, hedging cost assessments, and hedging effectiveness metrics.

According to the findings, we reveal that while the Indian and Pakistani stock markets experience higher downside risk, Bangladeshi stock markets witness relatively lower downside risk in South Asia. This study also finds that global financial markets offer safe haven functions and hedging benefits against the assets of the Bangladeshi stock market, but these markets only help Pakistani stock market investors during crises by acting as safe havens for their investments. Finally, our portfolio implication techniques reveal that South Asian stock investors should invest most of their funds in global equity assets to achieve optimal hedge effectiveness.

The scheduling of the remaining sections of the paper is as follows: Section 2 features the prior research that is pertinent to our topic. The data sources and methodology are presented in Section 3. Section 4 presents and discusses the empirical results. Finally, Section 5 presents our conclusions.

2. Literature Review

The subject of financial market integration and volatility spillover shocks from one market to another has attracted the attention of academics, investors, investment managers, and policymakers in contemporary finance (Habiba et al. 2020). Studies show that South

Asian stock markets have recently surpassed developed financial markets (Kumar and Dhankar 2017). However, global financial markets and countless international events significantly affect South Asian stock markets. Consequently, investors are constantly looking for a sector that can protect their investments under both favorable and tough economic circumstances in this area. Moreover, despite the keen interest of researchers, there is a scarcity of investigations that may inspire exploration of the roles of global markets in South Asian stock markets. We carefully reviewed the existing literature that shows what is needed for further research, such as:

Habiba et al. (2020) investigated the dynamic association between South Asian and US stock markets using the bivariate EGARCH method along with cointegration and causality tests. They consider the stock markets of India, Pakistan, and Sri Lanka as samples of South Asian stock markets. Their findings reveal a noticeable volatility spillover from the US stock markets to all chosen South Asian markets during and after the crisis; however, relative to the non-financial crisis period, returns and volatility spillover shocks are larger during the financial crisis period. Kumar and Dhankar (2017) also revealed that global financial vulnerability impacts South Asian stock markets significantly over long- and short-run periods. Using the VECM-based Granger causality and ARDL approach, Shahzad et al. (2016) evaluated South Asian stock markets' strength for diversification in comparison with Western and European financial markets. They found that the US financial market has an effect on not only the European but also the South Asian stock markets, and the interconnectedness between the global and South Asian stock markets increased after the 2007–2008 global financial crisis. However, since 2005, the US and other Asian stock markets have had a considerable impact on the Indian stock market (Mukherjee and Bose 2008), while the Sri Lankan stock market is weakly linked to the stock markets of China, India, Malaysia, Pakistan, Singapore, and the USA (Sriananthakumar and Narayan 2015).

Furthermore, using the ARDL multivariate cointegration methodology, Narayan et al. (2004) explore the dynamic connections between the stock markets of Bangladesh, India, Pakistan, and Sri Lanka. Surprisingly, many studies (e.g., Rahman and Uddin 2009; Mohsin and Rivers 2011; Perera and Wickramanayake 2012; Singhania and Prakash 2014; Gulzar et al. 2019) have investigated the regional connectedness among the South Asian stock markets, and most of them (e.g., Narayan et al. 2004; Rahman and Uddin 2009; Perera and Wickramanayake 2012; Gulzar et al. 2019) used cointegration and VECM approaches to explore the inter-relationship. They used the ARDL, VECM, and Granger causality tests. In general, these models are fundamentally linear, which means they assume a constant relationship between variables over time. Financial markets, however, often exhibit non-linear relationships due to factors like abrupt policy changes, structural breaks, or speculative bubbles. The adoption of a time-varying connectedness approach in analyzing financial market dynamics is significant as it captures the evolving interdependencies among markets over time, particularly during periods of economic stress or geopolitical events.

Apart from the South Asian financial markets, Derbali and Lamouchi (2020) witnessed that, on average, volatility clustering has a considerable impact on all Southeast Asian nations' stock market return volatilities. Specifically, Hung (2019) computes the interlinkage between Chinese stock markets and four Southeast Asian stock markets. The results show that China's stock market has a significant influence on the stock markets in Southeast Asia. The integration of the Chinese stock market with the Southeast Asian stock market is linked not only in the crisis period but also in the post-crisis period.

In addition, Lee and Lee (2020) examined how equity, bonds, and foreign exchange markets in Northeast Asia, namely, China, Korea, and Japan, are connected to US financial markets. The main conclusion of their study is that US markets are a significant contributor to network effects on the Northeast Asian financial markets, while the connectivity among Northeast Asian nations appears to be quite modest. Gopalaswamy et al. (2010) document a price spillover between the Asian and US stock markets; however, the Chinese stock markets receive the least spillover from the US stock market. Further, Corbet et al. (2021)

examine the volatility spillovers from Chinese financial markets to the prices of gold, oil, soybeans, spot FX rate of the US dollar against RMB, and Bitcoin.

Academics are curious about developing and emerging markets in Asia, and they conclude that there may be some potential benefits to exploring these markets for diversification; nonetheless, a variety of contradictory outcomes are created (Mohti et al. 2019). In Asian financial markets, Goh et al. (2005) and Khan and Park (2009) demonstrated that the stock markets of Indonesia, Malaysia, the Philippines, Singapore, Korea, and Thailand interact dynamically with each other. Their studies are foundational in establishing the interconnectedness of these markets. Nonetheless, they lack a broader temporal context that might provide insights into how these relationships have evolved over time. To bridge the gap, Yarovaya et al. (2016) concentrated on six emerging and developed Asian stock markets and found the same strong associations across time. However, Dhanaraj et al. (2013) find that Asian stock markets are dominated by US stock markets due to the US's role as a leading economy and key supplier of funds to Asian countries. In addition, the majority of investigations (e.g., Tiwari et al. 2013; Yang et al. 2003) documented that, more often than not, developed stock markets, such as the US, have a considerable impact on emerging Asian stock markets. Furthermore, several other studies (e.g., Park and Lee 2011; Liu 2013; Boubakri and Guillaumin 2015) have revealed the interconnectedness and effects between the developed and emerging Asian financial markets. Shu et al. (2018) emphasize the comparison between spillover shocks from the financial markets of China and the US in Asian financial markets.

In Asian and global financial markets, the US and Chinese financial markets are the main transmitters of uncertainty (Foglia and Dai 2022; Kido 2018). These studies shed light on significant bilateral relationships that influence market behavior. However, it overlooked interactions with other key markets in the region, limiting the broader applicability of its findings. In this regard, Yousaf et al. (2022) interconnected the stock markets of GCC countries, namely Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the UAE with five global variables, such as bonds, Islamic equities, gold, oil, and real estate, employing the VAR-asymmetric-BEKK-GARCH approach. Therefore, various types of market integration and their dependence on each other in Asian financial markets in comparison with global marketplaces are important. However, the current literature does not sufficiently explore the implications of this uncertainty for emerging markets, particularly in terms of risk management strategies.

Researchers worldwide have become more circumspect about the incorporation and co-movement of financial markets due to their spillover shocks after the crisis period (Gulzar et al. 2019). Many scholars (e.g., Beirne et al. 2010; Liang et al. 2015; Lucey and Zhang 2010; Tissaoui and Zaghdoudi 2021) have acknowledged this convergence and its impact on international stock markets. For instance, recent studies indicate that during crises, green energy instruments exhibit unique characteristics in their connectivity and volatility, often acting as transmitters of shocks, while traditional brown assets tend to be receivers (Banerjee et al. 2024). This dynamic suggests that green assets can enhance portfolio resilience, particularly during economic downturns, as they have been shown to outperform gray assets in terms of risk-adjusted returns (Argentiero et al. 2023). However, their studies do not fully explore the implications of these findings for portfolio management strategies such as the determination of optimal portfolio weights and associated costs and hedging effectiveness. Furthermore, events like the COVID-19 pandemic and geopolitical tensions have underscored the importance of green investments in maintaining energy security while transitioning to sustainable practices (Belaïd et al. 2023).

In addition, Uddin et al. (2022) investigated the impact of COVID-19 on the interconnectedness between global and Asian stock markets using the (DCC) Student-t copula method. They found that the structure of dependence between different market classes varied from weakly negative to strongly positive, and the inter-relationship increased across markets in terms of the announcement of COVID-19 as a pandemic. Employing the DCC-MGARCH method, Kim et al. (2015) inspected spillover shocks due to the implications of the recent US financial crisis on five rising Asian nations' financial markets: Indonesia, Korea, the Philippines, Thailand, and Taiwan. Their findings demonstrate that developing Asian nations are particularly susceptible to external shocks, and changes in the capital and foreign exchange markets could cause a significant increase in systemic risk. Furthermore, Yiu et al. (2010) examine the dynamic spillover volatility connectedness between the US and Asian financial markets during the global turmoil situation. Gulzar et al. (2019) conducted the same kind of study, but they considered the pre-crisis, crisis, and post-crisis periods, from 1 July 2005 to 30 June 2015. Throughout Asia, the US financial market, and to some extent, the Japanese financial market, is the major dominator nation (Wang and Liu 2016). Moreover, the global financial crisis that originated in the United States has impacted both developed and developing nations' financial and real sectors (Edey 2009; Johansson 2011; Kim et al. 2015).

Singhania and Anchalia (2013) examine the volatility of returns in Asian stock markets due to two major crises: the subprime crisis and the Eurozone debt crisis. They find that during the subprime crisis, the stock markets of China, Japan, and India experienced a positive impact, while the Hong Kong stock market did not face any trouble due to this crisis in the case of the volatility of returns. However, the same case is negatively influenced by the Eurozone debt crisis in China and India's stock markets. Hence, Asian stock markets cannot ignore the hostile effects of the unfavorable conditions of the US financial market and, at the same time, the global crises caused by geopolitical issues, epidemic periods, and international conflict. However, during times of financial crisis, there is an increase in connectivity across Asian equity markets inside the global financial network, but this connectivity declines after the crisis period (Chowdhury et al. 2019).

Furthermore, the interconnectedness between cryptocurrency markets and South Asian financial markets has gained significant attention, particularly in the context of recent global events such as the COVID-19 pandemic. Research indicates that cryptocurrencies, especially Bitcoin and Ethereum, notably impact stock market performance in South Asia, with increased volatility and spillover effects observed during the pandemic. For instance, Zeng et al. (2023) revealed a net return spillover from Bitcoin to South Asian stock markets, particularly in Pakistan. The pandemic heightened the influence of cryptocurrencies on South Asian stock markets, with a reported increase in impact from 1.3% to 1.5% for cryptocurrencies (Syed and Kamal 2024). During the post-COVID-19 period, volatility connectedness among cryptocurrencies and emerging markets intensified, indicating a shift in market dynamics (Balcilar et al. 2022).

After a proper assessment of the current literature, we may draw some conclusions that emphasize the need to conduct our study from the South Asian stock market perspective. First, the existing literature explores regional interconnectedness among South Asian stock markets. However, to some extent, some studies interlink South Asian stock markets with US financial markets. Second, multiple studies have been conducted to explore the association between the US financial market, the Chinese financial market, and various stock markets on the Asian continent, where there is insufficient information specifically for domestic investors in South Asian stock markets. Third, while several studies explore the interconnectedness and spillover effects between South Asian and global financial markets, limited attention has been given to analyzing and comparing the downside risk potential of these markets specifically. Fourth, the distinct roles of global green assets, such as green bonds and equities, and global conventional assets, such as conventional bonds and equities, on Asian stock markets are absent, despite the fact that researchers consider a variety of asset types when examining the relationships between different financial markets. Fifth, the cost of hedging effectiveness tools such as the hedge ratio and optimal portfolio weight are considered crucial factors that can help investors formulate ideal portfolios; however, in the current literature, we do not find such findings that not only South Asian equity investors but also Asian equity investors could consider global financial assets at the time of allocating their funds in diverse asset classes to obtain optimal investment benefits. Sixth, previous studies have examined the effects of a number of crises, including the COVID-19 pandemic crisis, the subprime mortgage crisis, the Eurozone debt crisis, the US financial crisis, and other global financial crises, on the co-movement of global financial markets; however, the Russian–Ukrainian invasion, which has an impact on financial markets worldwide, has yet to be proven, particularly on the interconnection between global financial and South Asian stock markets. Therefore, in this study, we attempt to fill this gap in the existing literature and provide noteworthy investment decision-making strategies to investors who invest their funds in South Asian stock markets.

3. Data and Methodology

3.1. Data

The major goal of this study is to determine how well global financial markets function as safe havens and hedging instruments when compared to equity assets traded on the stock exchanges of Bangladesh, India, Pakistan, and Sri Lanka in South Asia. In doing so, on the one hand, we select the Dow Jones Sustainability World Index (DJSW) and S&P Global 1200 Index (S&PG1200) as proxies for global green and traditional equity assets, and on the other hand, the S&P Green Bond Index (S&PGB) and S&P International Corporate Bond Index (S&PICB) are selected as proxies for global green and traditional bond assets. Furthermore, the DSE Broad Index (DSEB) and DSEX Shariah Index (DSEXS) from the stock market of Bangladesh, the BSE Sensex 30 Index (BSES30) and the Nifty 50 Index (NFTY50) from the stock market of India, the Karachi 100 Index (KRH100) and Karachi 30 Index (KRH30) from the stock market of Pakistan, and the CSE All-Share Index (CSEAS) and S&P Sri Lanka 20 Index (S&PS20) from the stock market of Sri Lanka are chosen as proxies for South Asian equity assets throughout the study to serve the objectives. Data cover the period from 22 January 2014 to 8 August 2022. The selection of this period reflects the availability of daily data, balancing comprehensiveness with consistency across indices. The date 8 August 2022 serves as the cut-off due to restrictions in data availability, aligning with key global and regional economic trends for robust and relevant insights. Daily data frequency is chosen because it provides higher granularity, capturing short-term fluctuations and spillovers between markets more effectively than weekly or monthly data. Several researchers (e.g., Siddique et al. 2024; Hasan et al. 2021; Yoon et al. 2018) used daily data in their investigations. This granularity is critical to assessing safe haven and hedging properties, particularly during periods of market volatility. Global indices were collected from www.spglobal.com (accessed on 10 August 2022) and country-based indices were collected from www.investing.com (accessed on 12 August 2022). Finally, we calculate the returns and transform them into a logarithmic form $\{R_t = \ln(\frac{p_t}{p_{t-1}}) \times 100\}$.

Figure 1 shows graphs of the dynamic price movements of each asset. We see that from the study period to the first quarter of 2016, each global asset followed an almost downward trend; however, the price trends of DJSW and S&PG1200 increased from 2016 to 2018. Specifically, S&PGB and S&PICB gradually increased with upward and downward trends and reached a peak stage after the collapse caused by the COVID-19 pandemic in 2020. We also notice that the price of each asset, both from global financial markets and South Asian stock markets, significantly decreased during the COVID-19 pandemic period. Mazur et al. (2021) demonstrated that due to the COVID-19 pandemic, global financial markets around the world are negatively and significantly affected. However, it is surprising to observe that after the COVID-19 period, the price of each asset increased, although the same collapse was seen during the time of market turbulence instigated by the Russia–Ukraine invasion. Umar et al. (2022) state that global financial markets are also negatively impacted by the conflict between Russia and Ukraine.

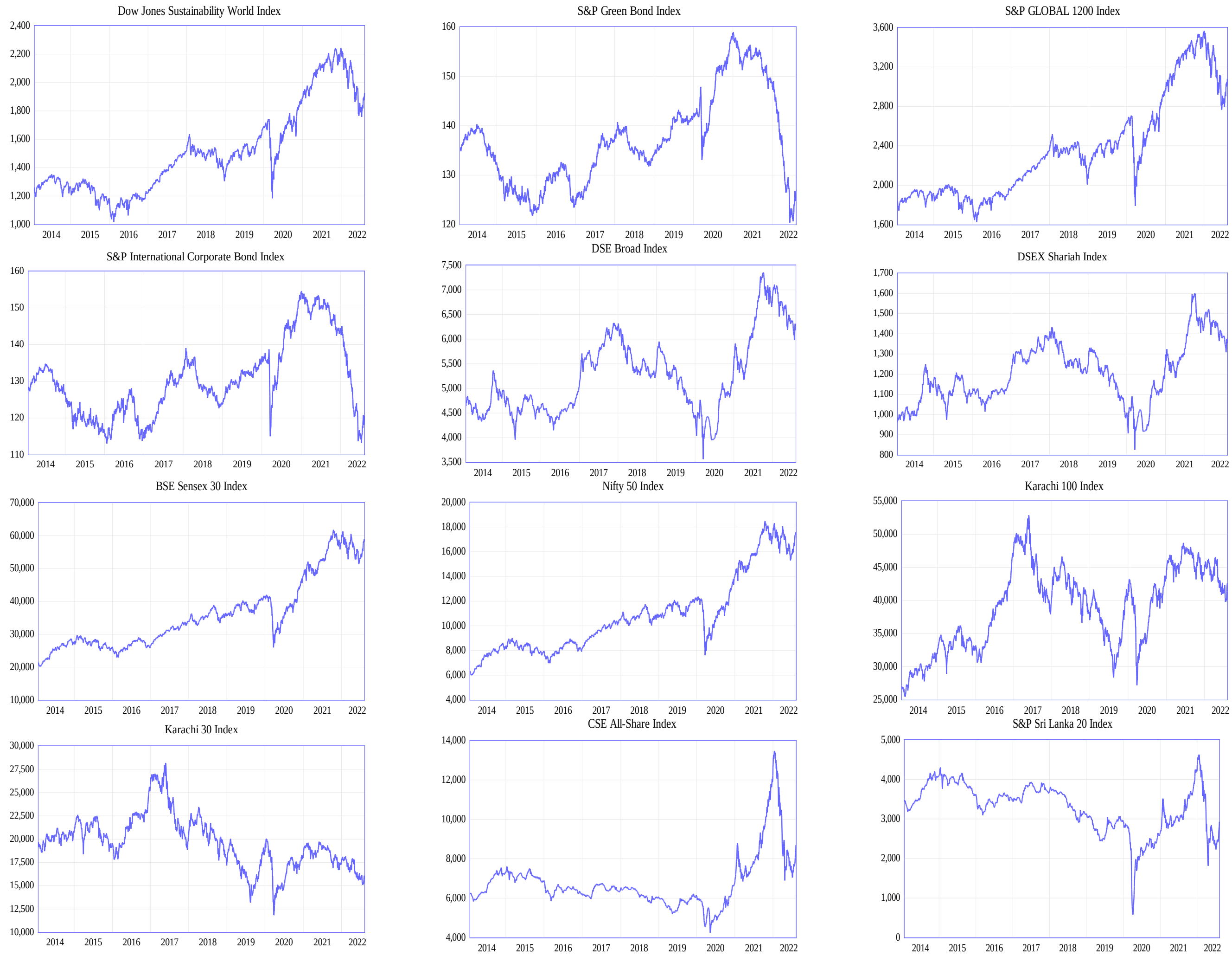

Figure 1. Price dynamic graph of each index [Notes: The vertical axis of the graph represents price, while the horizontal axis denotes the time period].

Figure 2 depicts the dynamic return series of the asset classes studied. We notice that the return of each asset was between −2 and 2; however, in recession periods such as the geopolitical issue in 2017, the COVID-19 pandemic in 2020, and the Russia–Ukraine invasion in 2022, the profit of most of the assets is hugely and negatively affected.

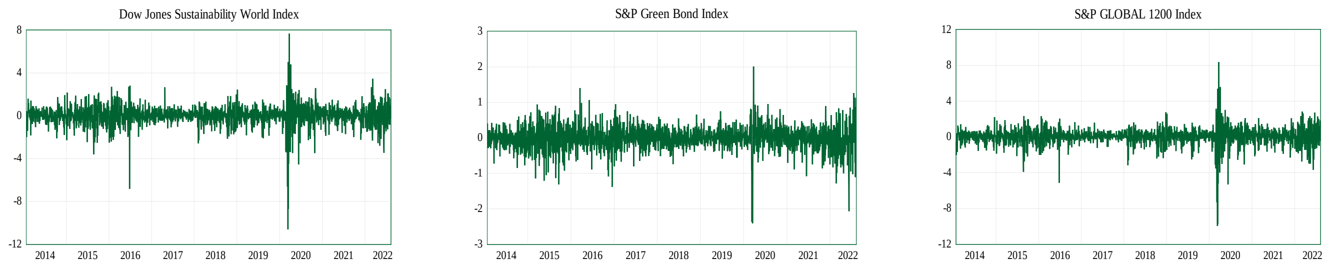

Figure 2. *Cont.*

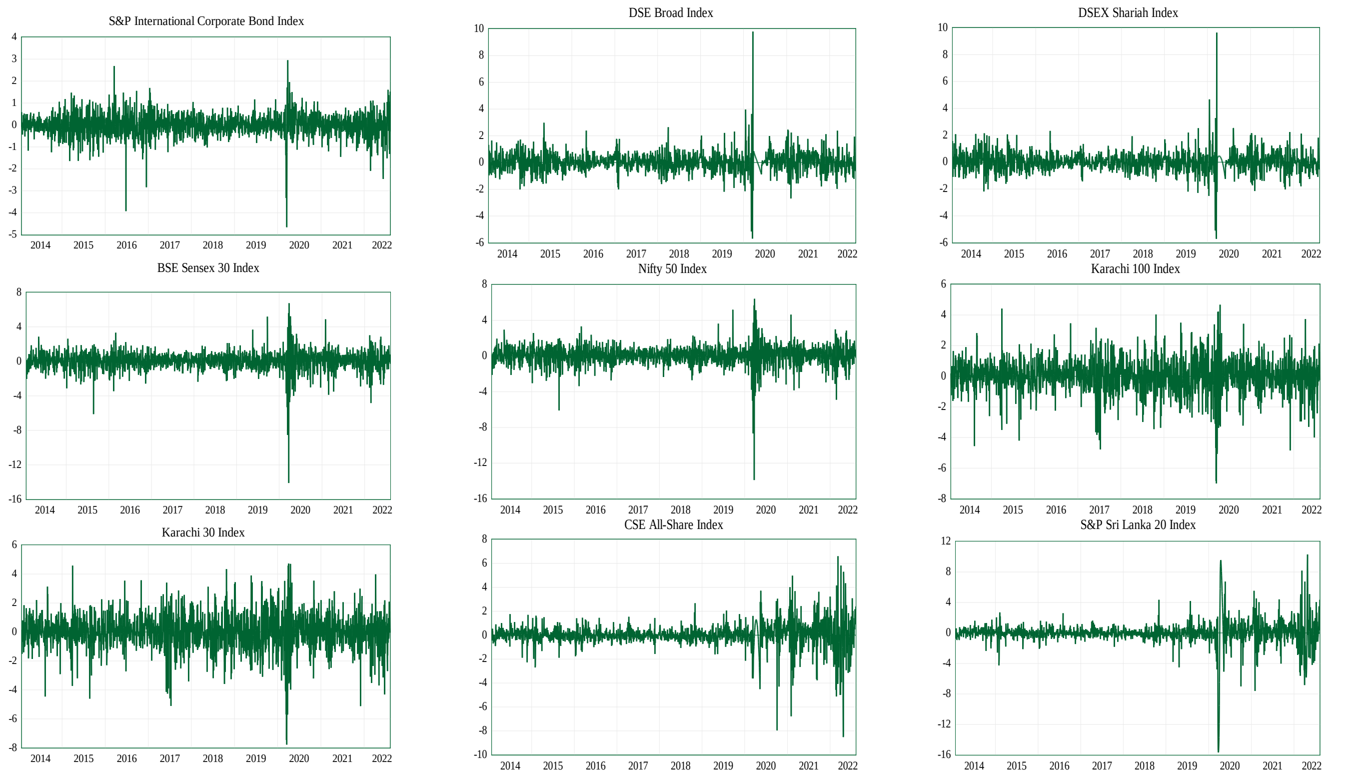

Figure 2. Return dynamic graph of each index [Notes: The vertical axis of the graph represents return as percentage, while the horizontal axis denotes the time period].

3.2. Descriptive Statistics and Correlation Matrix

The descriptive summary (Panel A) and correlation matrix (Panel B) are demonstrated in Table 1. Focusing on the mean returns, we observe that the logarithmic returns of DSEB, DSEXS, BSES30, and NFTY50 are positive, implying that investors in the Bangladeshi and Indian stock markets generate positive average returns. However, global financial assets—S&PGB and S&PICB, Pakistani equity assets (KRH30), and Sri Lankan equity assets (S&PS20)—experience negative average returns. The results of the volatility measurement tool show that S&PS20 has higher volatile returns with a value of 1.591, followed by KRH (1.157), BSES30 (1.053), and NFTY50 (1.048), as these are seen as achieving higher standard deviation; in contrast, S&PGB and S&PICB depict lower volatility with values of 0.324 and 0.495, respectively, followed by DSEXS (0.717) and DSEB (0.724). Moving into tail dependence, the results indicate that most variables, except for DSEB and DSEXS, are negatively skewed, meaning they have a higher likelihood of extreme losses, and exhibit high positive kurtosis, suggesting a greater probability of outlier returns or extreme market movements. This skewness and leptokurtic nature reflect the asymmetric risk profile of global assets, where adverse economic events or market shocks tend to drive large negative returns. Economically, this aligns with systemic risks in interconnected markets, where external shocks, like economic downturns or policy changes, amplify tail risks. These non-normal, asymmetric, and leptokurtic circulations are further supported by the Jarque–Bera (JB) statistic, as they are rejected at the 1% significance level.

Furthermore, testing the stationarity of the time series variables, the ERS (Elliott et al. 1996), ADF (Dickey and Fuller 1981), and PP (Phillips and Perron 1988) tests reveal that all implied return volatility series are stationary or free from the unit root. Finally, it is clear that our series data are susceptible to autocorrelation and display ARCH effects according to Q(10) and Q(20) test statistics.

Table 1. Descriptive statistics and correlation matrix.

Panel A: Descriptive Statistics												
	Δln(DJSW)	Δln(S&PGB)	Δln(S&PG1200)	Δln(S&PICB)	Δln(DSEB)	Δln(DSEXS)	Δln(BSES30)	Δln(NFTY50)	Δln(KRH100)	Δln(KRH30)	Δln(CSEAS)	Δln(S&PS20)
Mean	0.019	−0.003	0.023	−0.003	0.013	0.015	0.045	0.046	0.020	−0.009	0.015	−0.007
Maximum	7.694	2.013	8.370	2.948	9.798	9.660	6.747	6.415	4.684	4.728	6.590	10.304
Minimum	−10.605	−2.410	−9.976	−4.655	−5.689	−5.696	−14.102	−13.904	−6.986	−7.780	−8.521	−15.677
Std. Dev.	0.921	0.324	0.934	0.495	0.724	0.717	1.053	1.048	1.040	1.157	0.962	1.591
Skewness	−1.279	−0.595	−1.223	−0.897	0.743	0.732	−1.602	−1.609	−0.545	−0.466	−1.160	−1.985
Kurtosis	21.043	8.305	21.816	11.930	23.358	23.669	24.696	23.785	7.241	7.056	18.033	34.465
Jarque–Bera	30,856 *	2746 *	33,451 *	7708 *	38,716 *	39,892 *	44,691 *	41,104 *	1781 *	1609 *	21,499 *	93,456 *
ERS	−11.848 *	−6.919 *	−11.424 *	−7.351 *	−4.914 *	−4.157 *	−18.655 *	−19.083 *	−18.894 *	−19.382 *	17.245 *	−12.964 *
Q(10)	56.986 *	33.337 *	64.761 *	34.118 *	367.331 *	365.584 *	38.535 *	37.535 *	62.356 *	59.377 *	255.258 *	2086.858 *
Q(20)	1060.45 *	436.620 *	1448.225 *	447.198 *	647.760 *	651.676 *	852.054 *	788.699 *	555.345 *	669.145 *	1110.790 *	4746.549 *
ADF	−14.901 *	−42.625 *	−14.489 *	−42.560 *	−17.744 *	−18.095 *	−17.633 *	−17.505 *	−40.069 *	−40.218 *	−23.128 *	−14.225 *
PP	−46.182 *	−42.815 *	−47.260 *	−42.736 *	−31.202 *	−31.068 *	−45.503 *	−45.529 *	−40.207 *	−40.203 *	−33.212 *	−22.015 *
Panel B: Correlation Matrix												
Δln(DJSW)	1											
Δln(S&PGB)	0.224 *	1										
Δln(S&PG1200)	0.951 *	0.141 *	1									
Δln(S&PICB)	0.315 *	0.918 *	0.223 *	1								
Δln(DSEB)	0.058 *	−0.019	0.056 *	0.030	1							
Δln(DSEXS)	0.058 *	−0.016	0.055 *	0.030	0.931 *	1						
Δln(BSES30)	0.486 *	0.121 *	0.454 *	0.193 *	0.131 *	0.117 *	1					
Δln(NFTY50)	0.484 *	0.119 *	0.449 *	0.191 *	0.127 *	0.113 *	0.995 *	1				
Δln(KRH100)	0.134 *	0.070 *	0.121 *	0.113 *	0.100 *	0.109 *	0.172 *	0.174 *	1			
Δln(KRH30)	0.143 *	0.072 *	0.128 *	0.119 *	0.109 *	0.118 *	0.176 *	0.177 *	0.987 *	1		
Δln(CSEAS)	0.085 *	0.045 **	0.088 *	0.066 *	0.089 *	0.092 *	0.077 *	0.080 *	0.092 *	0.087 *	1	
Δln(S&PS20)	0.004	0.004	0.000	−0.012	0.040 ***	0.058 *	0.062 *	0.063 *	0.064 *	0.055 *	0.541 *	1

Notes: Std. Dev. indicates the standard deviation; ADF and PP denote the Augmented Dickey–Fuller and Phillips–Perron unit root tests, respectively. *, **, and *** indicate significance at the 1%, 5%, and 10% levels, respectively.

The outcomes of the correlation matrix between the assets show that all the pairs (except S&PGB-DSEB, S&PGB-DSEXS, and S&PICB-S&PS20 pairs) are positively correlated to each other; however, the relationship between S&PS20 and DJSW, S&PGB, and S&PG1200 is not significant, suggesting that S&PS20 is somewhat not significantly influenced by global financial markets.

3.3. Methodology

DCC GARCH-Based Multivariate Connectedness Model

We employ Engle's dynamic conditional correlation (DCC) technique to capture the time-varying conditional correlation between the assets of global financial markets and South Asian stock markets. Despite its complexity, which makes estimation sensitive to parameter choices and potentially introduces instability in highly volatile or non-stationary environments (Silvennoinen and Teräsvirta 2009), and its assumption of constant parameters over time, this model combines an updated version of the DCC methodology with the generalized autoregressive conditional heteroskedasticity (GARCH) model based on the Glosten, Jagannathan, and Runkle (GJR) framework (Glosten et al. 1993), as extended by Al Mamun et al. (2020). The DCC-GJR-GARCH model is particularly effective in contexts where the volatility asymmetry is pronounced, as recent studies demonstrate that GJR models often outperform traditional GARCH specifications in tracking volatility dynamics and the leverage effect (Brownlees et al. 2011; Laurent et al. 2012). Furthermore, the ICAPM (intertemporal capital asset pricing model), an extended version of the capital asset pricing model developed by Sharpe (1964), Lintner (1965), and Mossin (1966), suggests that optimal hedging strategies may vary over time as economic conditions change. The use of DCC-GARCH models aligns with the ICAPM framework, allowing for the examination of time-varying correlations and how they influence hedging strategies (Younis et al. 2023). In addition, the efficient market hypothesis (EMH) theory evidences that the presence of safe haven assets proposes temporary deviations from market efficiency, where certain assets remain undervalued or overvalued during periods of high volatility, thus protecting investors (Niveditha 2024). Hence, this model is thus well suited for analyzing assets with distinct asymmetric volatility responses, which enhances our understanding of risk in interconnected markets.

However, for assessment purposes, return series with zero mean are considered to be normally distributed, and the mean equation is articulated by the form below:

$$R_t = \varphi + \psi R_{t-1} + \varepsilon_t, \varepsilon_t = z_t h_t, z_t \sim N(0,1), \tag{1}$$

where $R_t = [R_{i,t}, \ldots, R_{n,t}]$ is the return on four global financial assets and eight South Asian financial assets in the $(n \times 1)$ vector. φ denotes a constant vector of length n. The coefficient vector is consistent with autoregressive terms and the vector of residuals is indicated by Ψ, and $\varepsilon_t = [\varepsilon_{i,t}, \ldots, \varepsilon_{n,t}]$, respectively. Subsequently, conditional volatility $h_{i,t}^2$ is determined from the GJR-GARCH (1,1) approach for weighted negative returns. Hence, the dynamics of volatility variance $h_{i,t}^2$ can be expressed as follows:

$$h_{i,t}^2 = Ӿ + \alpha\varepsilon_{t-1}^2 + \beta\alpha_{t-1}^2 + \gamma\varepsilon_{t-1}^2(I_{t-1}) \tag{2}$$

where $I_{t-1} = 1$ if $\varepsilon_{t-1} < 0$; otherwise, $I_{t-1} = 0$. γ denotes a leverage term that accounts for the asymmetric effects of positive and negative shocks. When the parameters Ӿ, α, β satisfy the conditions Ӿ $> 0, \alpha, \beta, \gamma \geq 0$, and $\gamma + (\alpha + \beta)/2 < 1$, the volatility mechanism in Equation (2) is guaranteed.

It is assumed that $\epsilon_{t-1}[\varepsilon_t] = 0$ and $\epsilon_{t-1}[\varepsilon_t, \acute{\varepsilon}_t] = H_t$, where the conditional expectation at time t is represented by $\epsilon[\cdot]$ using the available information. Thus, H_t can be defined as

$$H_t = D_t^{1/2} R_t D_t^{1/2} \tag{3}$$

where $D_t = \mathrm{diag}(h_{i,t}, \ldots, h_{n,t})$ denotes the diagonal matrix of the conditional variances and R_t denotes $(n \times n)$ times the time-varying conditional correlation matrix. Engle (2002) suggested the following dynamic correlation structure to simulate the right-hand side of Equation (4) rather than H_t directly:

$$R_t = \mathrm{diag}(K_t)^{-1/2} K_t \mathrm{diag}(K_t)^{-1/2} \tag{4}$$

Thus,

$$K_t = (1 - p - s)Q + a\mathrm{diag}(K_{t-1})^{1/2} \hat{\varepsilon}_{i,t-1} \mathrm{diag}(K_{t-1})^{1/2} + nK_{t-1}, \tag{5}$$

where Q represents the $n \times n$ unrestricted covariance matrix of standardized residuals $\hat{\varepsilon}_{i,t-1}$, and $p + s < 1$ is fulfilled by the non-negative scalars p and s.

4. Results and Discussion

4.1. VaR and CVaR Estimations

Table 2 shows the outcomes of the VaR and CVaR calculations, which show the likelihood of downside risk of global financial assets and assets in South Asian stock markets. However, by integrating coherent risk computation and considering the shortcomings of VaR, the CVaR method is superior to the VaR method (Artzner et al. 1999). The results reveal that the level of risk increases with quantile levels (higher than the 10% to 1% quantile level) for each asset. The downside risk of global bond assets (both green and non-green) is lower than that of global equity and South Asian asset classes. The OECD report[2] demonstrates that green and water bonds, which encourage investors to invest in green bond markets, are currently being issued by large institutional investors and issuers with the goal of resolving climate-related issues. Hence, risk volatility in bond markets is comparatively safer for investors. Meanwhile, the stock market of Bangladesh experiences a marginally lower downside risk than any other stock market on the South Asian continent, except in CSEAS. Mensi et al. (2017) state that during the crisis period, the Bangladeshi stock market emerged at a relatively lower risk. In addition, the downside risk in the Indian and Pakistani stock markets is substantially higher, indicating that the volatility of risk in these regions' stock markets is extreme.

Table 2. VaR and CVaR estimations.

Variables	VaR			CVaR		
	10%	5%	1%	10%	5%	1%
Historical VaR and CVaR[3]:						
Δln(DJSW)	−0.909	−1.353	−2.524	−1.7007	−2.2787	−4.0952
Δln(S&PGB)	−0.3691	−0.5194	−0.9460	−0.6114	−0.7933	−1.2922
Δln(S&PG1200)	−0.8973	−1.4116	−2.7526	−1.7300	−2.3582	−4.2269
Δln(S&PICB)	−0.5417	−0.7641	−1.3764	−0.9158	−1.1988	−2.0676
Δln(DSEB)	−0.7556	−1.0091	−1.6465	−1.2020	−1.5425	−2.5801
Δln(DSEXS)	−0.7534	−1.0226	−1.6053	−1.1978	−1.5234	−2.5813
Δln(BSES30)	−1.0064	−1.4020	−2.9129	−1.8414	−2.5107	−4.7490
Δln(NFTY50)	−1.0161	−1.4507	−2.9502	−1.8493	−2.5153	−4.6913
Δln(KRH100)	−1.0834	−1.6053	−3.2044	−1.9503	−2.5863	−4.1502
Δln(KRH30)	−1.2236	−1.7776	−3.5496	−2.1558	−2.8502	−4.6249
Δln(CSEAS)	−0.6754	−1.3085	−3.5953	−1.7505	−2.6048	−4.8346
Δln(S&PS20)	−0.8834	−1.6651	−4.8853	−2.6315	−4.0698	−8.9987

4.2. DCC-GRACH Estimations

4.2.1. Interconnectedness Between Stock Market of Bangladesh and Global Financial Markets

To depict the asymmetric time-varying dependence between global financial assets and stock market assets in Bangladesh, Table 3 provides the dynamic conditional correlation (DCC) of Engle (2002) between these diverse asset classes. In doing so, we combine the DCC approach with GJR-GARCH (1,1) developed by Glosten et al. (1993). The outcomes in Panel A show that the ARCH (α) parameters are statistically significant and positive in all premises at the 1% to 10% significance levels; however, GRACH (β) parameters are statistically significant and positive in all premises at the 1% significance level. The sum of ($\alpha + \beta$) is less than one; symbolically, $\alpha + \beta < 1$. Furthermore, GJR Gamma (γ) is statistically significant and positive in most cases, except for DSEB-S&PGB and DSEXS-S&PICB pairs, inferring that the volatility of return between global non-green assets and assets of the Bangladeshi stock market is more adverse in bad vibrancy than in good effervescence situations; in contrast, such volatility is inversely applicable to global green assets and Bangladeshi equity asset pairs.

Panel B of Table 3 shows the dynamic conditional correlation (DCC) results, where we notice that the average correlation between global financial assets and Bangladeshi equity assets is statistically not significant and negative for all pairs except for the DSEB-S&PGB and DSEXS-S&PG1200 pairs. Furthermore, it is surprising to see that there is no long-run or short-run relationship between these asset classes (excluding the long-run relationship between DSEB and S&PGB), indicating that the high volatility spillover effect between the global financial markets and Bangladeshi stock market is not significant over the long run and short run. However, a significantly high volatility spillover is seen only between the DSEB and S&PGB for a prolonged period.

From Panel C of Table 3, Ljung–Box Qs (20) (Ljung and Box 1978), multivariate Hosking (20) (Hosking 1980), and Li–McLeod (20) (Li and McLeod 1981) test statistics demonstrate no serial correlation in the asset pairs (except for DSEB-S&PGB and DSEXS-S&PGB), as these reject the null hypothesis at the 5% significance level.

Figure 3 shows the DCC-GJR-GARCH time-varying correlation charts between global financial assets and Bangladeshi stock market assets. Surprisingly, the magnitude of the nexus between the changes in the return of global financial assets and Bangladeshi equity assets is negative in every pair, suggesting that the role of hedging stratagem is efficacious. When economic turmoil or geopolitical tensions arise, local assets might react negatively due to domestic factors, while global assets might remain stable or perform positively. This differential response can lead to negative correlations, especially during crises when investors flock to safe haven assets (Baur and Lucey 2010). In addition, Lakdawala (2021) demonstrated that lower interest rates in developed markets can lead to increased capital flows into global assets, while domestic markets may react negatively to tightening monetary policy or economic slowdowns, resulting in negative correlations. Thus, stock market investors in Bangladesh can safeguard their investments by diversifying their investments in global markets. More specifically, global green and non-green equity and global green and non-green bond assets not only hedge their investments but also play roles as safe havens during market turbulence.

Table 3. Estimations of the DCC-GJR-GARCH model for the Bangladeshi stock market and global financial markets.

	Δln(DSEB)	**Δln(DJSW)**	**Δln(DSEXS)**	**Δln(DJSW)**	**Δln(DSEB)**	**Δln(S&PGB)**	**Δln(DSEXS)**	**Δln(S&PGB)**	**Δln(DSEB)**	**Δln(S&PG1200)**	**Δln(DSEXS)**	**Δln(S&PG1200)**	**Δln(DSEB)**	**Δln(S&PICB)**	**Δln(DSEXS)**	**Δln(S&PICB)**
Panel A: AR (1)-GARCH (1, 1) estimation																
Const. (M)	0.026 ***	0.001	0.026 ***	−0.000	0.004	0.001	0.003	−0.001	0.035 **	0.001	0.035 **	−0.000	0.002	0.001	0.003	−0.000
	(0.090)	(0.941)	(0.090)	(0.993)	(0.566)	(0.941)	(0.566)	(0.993)	(0.013)	(0.941)	(0.013)	(0.993)	(0.764)	(0.941)	(0.764)	(0.993)
AR (1)	0.254 **	−0.041	0.254 **	−0.003	0.283 ***	−0.041	0.283 ***	−0.003	0.293 ***	−0.041	0.293 ***	−0.003	0.217	−0.041	0.217	−0.003
	(0.048)	(0.378)	(0.045)	(0.941)	(0.073)	(0.378)	(0.073)	(0.941)	(0.087)	(0.378)	(0.087)	(0.941)	(0.360)	(0.378)	(0.360)	(0.941)
MA (1)	−0.153	0.582 *	−0.153	0.561 *	−0.229	0.582 *	−0.229	0.561 *	−0.216	0.582 *	−0.216	0.561 *	−0.183	0.582 *	−0.183	0.561 *
	(0.229)	(0.000)	(0.228)	(0.000)	(0.135)	(0.000)	(0.135)	(0.000)	(0.207)	(0.000)	(0.207)	(0.000)	(0.420)	(0.000)	(0.420)	(0.000)
Const. (V)	0.021 *	0.022 *	0.021 *	0.032 *	0.001 ***	0.022 *	0.001 ***	0.032 *	0.023 *	0.022 *	0.023 *	0.032 *	0.003 ***	0.022 *	0.003 ***	0.032 *
	(0.001)	(0.000)	(0.001)	(0.000)	(0.062)	(0.000)	(0.062)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.069)	(0.000)	(0.070)	(0.000)
α (1)	0.060 ***	0.176 *	0.060 ***	0.193 *	0.059 **	0.176 *	0.059 **	0.194 *	0.083 **	0.176 *	0.083 **	0.193 *	0.083 **	0.175 *	0.083 **	0.194 *
	(0.095)	(0.000)	(0.095)	(0.000)	(0.013)	(0.000)	(0.013)	(0.000)	(0.048)	(0.000)	(0.048)	(0.000)	(0.019)	(0.000)	(0.019)	(0.000)
β (1)	0.832 *	0.697 *	0.832 *	0.621 *	0.931 *	0.697 *	0.931 *	0.621 *	0.788 *	0.697 *	0.789 *	0.621 *	0.913 *	0.697 *	0.913 *	0.621 *
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
α + β	0.892	0.873	0.892	0.814	0.990	0.873	0.990	0.815	0.871	0.873	0.872	0.814	0.996	0.872	0.996	0.815
γ	0.163 *	0.189 *	0.163 *	.251 *	0.001	0.189 *	(0.001)	0.251 *	0.212 *	0.187 *	0.212 *	0.251 *	−0.009	0.189 *	−0.009	0.251 *
	(0.000)	(0.000)	(0.001)	(0.000)	(0.948)	(0.000)	(0.948)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.755)	(0.000)	(0.755)	(0.000)
Panel B: DCC estimates																
Average Correlation	−0.006		−0.004		0.024		−0.019		−0.000		0.004		−0.008		−0.001	
	(0.780)		(0.863)		(0.252)		(0.371)		(0.996)		(865)		(0.719)		(0.966)	
DCC1 (a)	0.000		0.000		0.000		0.010		0.005		0.000		0.000		0.000	
	(1.00)		(0.950)		(1.00)		(0.554)		(0.811)		(1.000)		(0.717)		(0.999)	
DCC2 (b)	0.264		0.379		0.988 *		0.446		0.000		0.420		0.362		0.004	
	(0.657)		(0.520)		(0.000)		(0.384)		(1.000)		(0.603)		(0.797)		(0.996)	
Panel C: Diagnostic tests																
Qs (20)	9.152	24.698	9.132	42.105	19.949	24.634	20.179	41.844	11.968	24.694	11.985	42.069	15.697	24.673	15.753	42.083
	(0.981)	(0.213)	(0.981)	(0.003)	(0.461)	(0.216)	(0.447)	(0.003)	(0.917)	(0.213)	(0.917)	(0.003)	(0.735)	(0.213)	(0.732)	(0.003)
Hosking (20)	75.561		87.494		106.390		127.454		68.622		79.955		82.312		101.536	
	(0.557)		(0.217)		(0.018)		(0.000)		(0.767)		(0.417)		(0.347)		(0.058)	
Li–McLeod (20)	75.595		87.473		106.322		127.247		68.689		79.963		82.324		101.435	
	(0.556)		(0.217)		(0.018)		(0.001)		(0.765)		(0.417)		(0.347)		(0.056)	

Notes: α, β, and γ indicate the ARCH, GARCH, and GJR (Gamma) terms, respectively. Squared standardized residuals and 20 lags were considered when applying the Ljung–Box test statistics Qs (20). Multivariate portmanteau statistics Hosking (20) and Li–McLeod (20) test the serial correlation problem. *, **, and *** indicate significance at the 1%, 5%, and 10% levels, respectively.

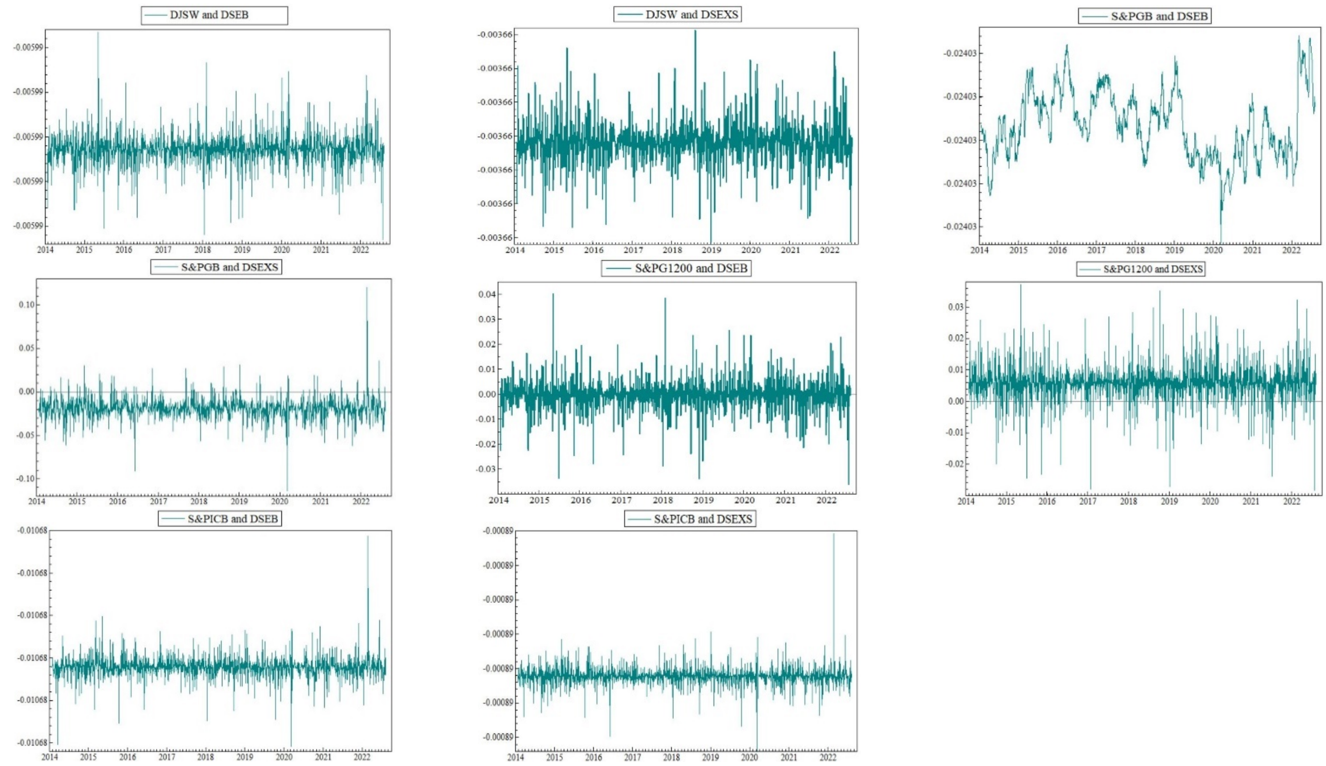

Figure 3. Dynamic conditional correlation plots between global financial markets and the stock market of Bangladesh.

4.2.2. Interconnectedness Between Stock Market of India and Global Financial Markets

Table 4 presents the dynamic conditional correlation (DCC) between the assets of the global financial market and the assets of the Indian stock market. Panel A of Table 4 shows that the GRACH (β) parameter is statistically significant and positive in all cases; however, mixed outcomes are found for the ARCH (α) parameter. The sum of ARCH (α) and GRACH (β) parameters (α + β) is < 1. Furthermore, GJR Gamma (γ) is statistically significant and positive in most cases except for NFTY50-S&PGB, BSES30-S&PICB, and NFTY50-S&PICB pairs, indicating that return volatility between global financial equity assets and Indian equity assets is more adverse in the bad news than in the good news.

The outcomes in Panel B of Table 4 demonstrate that there is a significant and positive association between the BSES30-DJSW, NFTY50-DJSW, BSES30-S&PG1200, and NFTY50-S&PG1200 pairs, while the BSES30-S&PGB, NFTY50-S&PGB, BSES30-S&PICB, and NFTY50-S&PICB pairs experience a non-significant and positive relationship, implying that asset returns of the Indian stock market increase when the returns of global equity assets increase. Rehman et al. (2022) also find a positive interconnection between Indian and international stock markets. Furthermore, we notice that the time-varying dependency between equity assets (both green and non-green) and assets of the Indian stock market is significant over the long and short run; however, the dependency between the same Indian asset classes and global bond assets (both green and non-green) is significant only over the long run. Hence, these outcomes suggest that there is a high volatility spillover between the global equity and Indian asset classes over the long and short run, whereas the same effect is diaphanous between the global bond asset and Indian equity asset pairs for a prolonged period. Our findings are consistent with the earlier study of Habiba et al. (2020), who observed a high volatility spillover between the US and Indian stock markets.

Table 4. Estimations of the DCC-GJR-GARCH model for the Indian stock market and global financial markets.

	Δln(BSES30)	Δln(DJSW)	Δln(NFTY50)	Δln(DJSW)	Δln(BSES30)	Δln(S&PGB)	Δln(NFTY50)	Δln(S&PGB)	Δln(BSES30)	Δln(S&PG1200)	Δln(NFTY50)	Δln(S&PG1200)	Δln(BSES30)	Δln(S&PICB)	Δln(NFTY50)	Δln(S&PICB)
Panel A: AR (1)-GARCH (1, 1) estimation																
Const. (M)	0.026 ***	0.047 **	0.026 ***	0.043 **	0.004	0.047 **	0.004	0.043 **	0.035 **	0.047 **	0.035 **	0.043 **	0.003	0.047 **	0.002	0.043 **
	(0.090)	(0.012)	(0.090)	(0.022)	(0.566)	(0.012)	(0.566)	(0.021)	(0.013)	(0.012)	(0.013)	(0.022)	(0.763)	(0.012)	(0.764)	(0.022)
AR (1)	0.253 **	−0.313 ***	0.253**	−0.313 ***	0.283 ***	−0.313 ***	0.283 ***	−0.313 ***	0.292 ***	−0.313 ***	0.293 ***	−0.313 ***	0.217	−0.313 ***	0.217	−0.313 ***
	(0.048)	(0.068)	(0.048)	(0.086)	(0.073)	(0.068)	(0.073)	(0.086)	(0.087)	(0.068)	(0.087)	(0.086)	(0.359)	(0.068)	(0.359)	(0.086)
MA (1)	−0.153	0.449 *	−0.153	0.456 *	−0.229	0.449 *	−0.229	0.456 *	−0.217	0.449 *	−0.216	0.456 *	−0.183	0.449 *	−0.183	0.456 *
	(0.228)	(0.005)	(0.228)	(0.007)	(0.135)	(0.005)	(0.135)	(0.007)	(0.207)	(0.005)	(0.207)	(0.007)	(0.420)	(0.005)	(0.420)	(0.007)
Const. (V)	0.021 *	0.031 *	0.021 *	0.034 *	0.001 ***	0.031 *	0.001 ***	0.034 *	0.023 *	0.031 *	0.023 *	0.034 *	0.004 ***	0.031 *	0.003 ***	0.034 *
	(0.001)	(0.000)	(0.001)	(0.000)	(0.062)	(0.000)	(0.062)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.069)	(0.000)	(0.069)	(0.000)
α	0.060 ***	−0.010	0.060 ***	−0.011	0.059 **	−0.010	0.059 **	−0.011	0.083 **	−0.010	0.083 **	−0.011	0.083 **	−0.010	0.083 **	−0.011
	(0.095)	(0.177)	(0.095)	(0.112)	(0.013)	(0.177)	(0.013)	(0.112)	(0.046)	(0.177)	(0.048)	(0.112)	(0.019)	(0.177)	(0.019)	(0.112)
β	0.832 *	0.877 *	0.832 *	0.869 *	0.931 *	0.877 *	0.931 *	0.869 *	0.788 *	0.877 *	0.789 *	0.869 *	0.913 ***	0.877 *	0.913 *	0.869 *
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\alpha + \beta$	0.155	0.867	0.892	0.858	0.990	0.867	0.990	0.858	0.871	0.867	0.837	0.858	0.996	0.867	0.996	0.858
γ	0.163 *	0.19 3 *	0.163 *	0.207 *	0.001	0.193 *	0.001	0.206 *	0.211 *	0.193 *	0.212 *	0.207 *	−0.009	193 *	−0.009	0.207 *
	(0.001)	(0.000)	(0.001)	(0.000)	(0.948)	(0.000)	(0.948)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.755)	(0.000)	(0.755)	(0.000)
Panel B: DCC estimates																
Average Correlation	0.364 ***		0.370 ***		0.020		0.017		0.333 *		0.338 *		0.070		0.067	
	(0.000)		(0.000)		(0.724)		(0.762)		(0.000)		(0.000)		(0.204)		(0.240)	
DCC1 (a)	0.023 **		0.023 **		0.012		0.012		0.010		0.011		0.013 **		0.014 **	
	(0.016)		(0.015)		(0.155)		(0.106)		(0.428)		(0.688)		(0.049)		(0.035)	
DCC2 (b)	0.936 *		0.932 *		0.981 *		0.980 *		0.962 *		0.949 *		0.978 *		0.978 *	
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Panel C: Diagnostic tests																
Qs (20)	11.587	19.412	11.452	22.142	21.087	18.905	21.310	21.884	17.223	18.553	17.332	21.415	16.365	19.804	16.334	22.918
	(0.930)	(0.495)	(0.934)	(0.333)	(0.392)	(0.528)	(0.379)	(0.347)	(0.638)	(0.551)	(0.631)	(0.373)	(0.694)	(0.470)	(0.696)	(0.293)
Hosking (20)	76.860		78.614		64.836		66.148		89.923		93.141		82.897		84.061	
	(0.515)		(0.459)		(0.857)		(0.828)		(0.168)		(0.116)		(0.331)		(0.299)	
Li–McLeod (20)	76.968		78.704		64.931		66.236		89.981		93.178		82.825		83.973	
	(0.512)		(0.456)		(0.855)		(0.826)		(0.167)		(0.116)		(0.333)		(0.302)	

Notes: *, **, and *** indicate significance at the 1%, 5%, and 10% levels, respectively. The rest of the notes is same as Table 3.

The diagnostic results in Panel C of Table 4 exhibit no serial correlation between the variables according to the Ljung–Box Qs (20) (Ljung and Box 1978), multivariate Hosking (20) (Hosking 1980), and Li–McLeod (20) (Li and McLeod 1981) test statistics because we reject the null hypothesis at the 5% significance level.

The DCC plots in Figure 4 display the time-varying conditional association between global financial assets and assets of the Indian stock market. The results show that the Indian stock market is positively influenced by the global financial market during most of the sample period; however, it is noticed that the global bond assets are negatively correlated with the assets of the Indian stock market during the Indian stock market crash in 2015, 2016, and 2018 caused by the value of BSE Sensex and Nifty indices dropping significantly due to fears over a slowdown in Chinese currency in 2015[4],[5] a high amount of non-performing assets (NPSs) of Indian banks in 2016[6], and finance ministers' comments regarding imposing a 10% tax on long-term capital gains in 2018[7]. This outcome implies that global bond assets play safe haven roles against the assets of the Indian stock market, suggesting that investors in this region can protect their investments during economic turmoil by including global bond assets in their portfolios. In addition, we observe that, during the COVID-19 pandemic period in 2020, the global green bond provides safe haven roles against BSES30 and NFTY50, as there is a negative linkage between these asset classes. Surprisingly, global bonds not only provide safe haven roles during a market crash caused by geopolitical or internal issues but also provide safe haven roles during the epidemic period against the assets of the Indian stock market. However, only global green-bond assets provide safe haven benefits during the Russia–Ukraine invasion of investors in the Indian stock market.

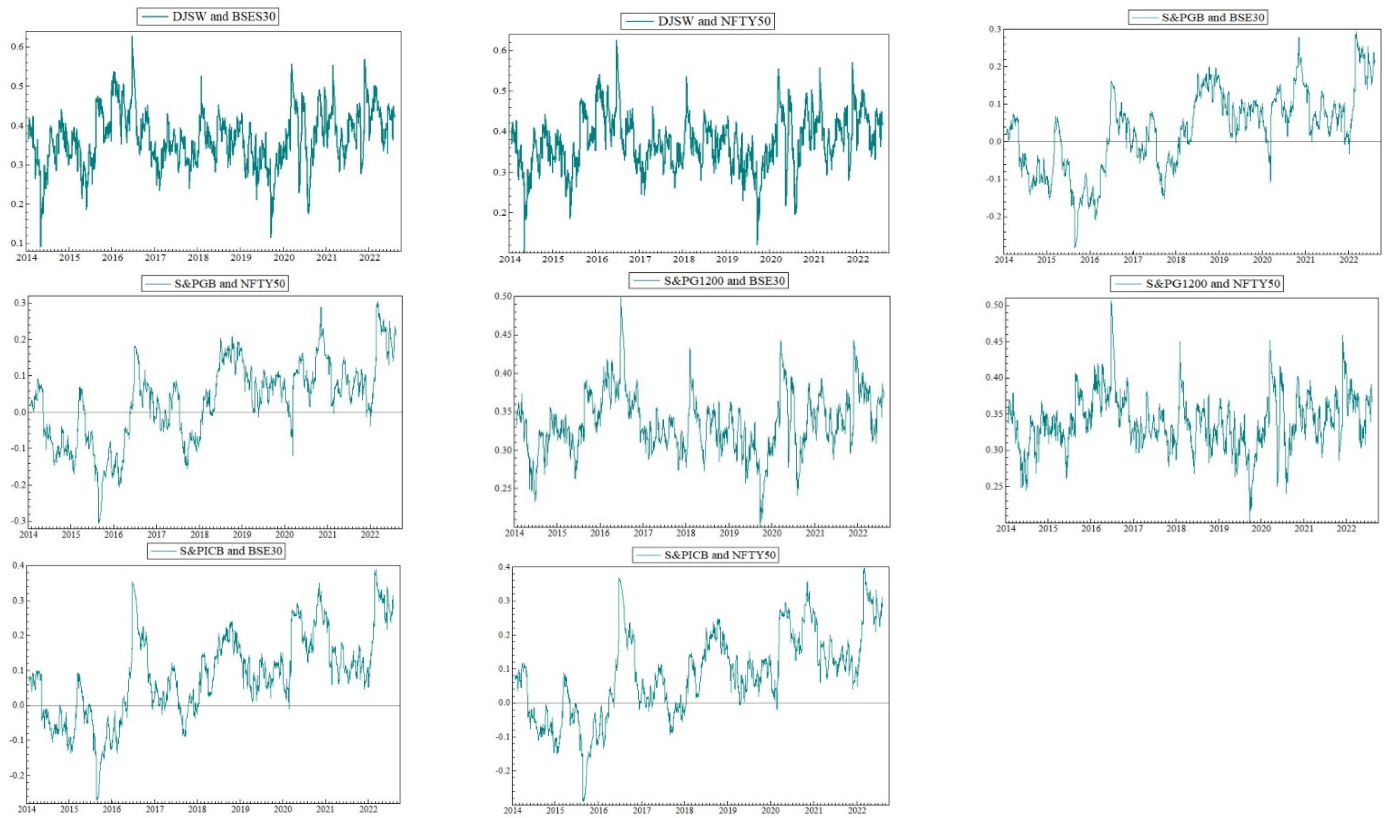

Figure 4. Dynamic conditional correlation plots between global financial markets and the stock market of India.

4.2.3. Interconnectedness Between Stock Market of Pakistan and Global Financial Markets

The dynamic conditional correlation (DCC) between the assets in the global financial market and those in the Pakistani stock market is shown in Table 5. The results in Panel A of Table 5 reveal that the ARCH (α) and GRACH (β) parameters are positive in every case; however, among them, KRH100 paired with DJSW, S&PG1200, and S&PICB, and KRH30 paired with DJSW, S&PGB, S&PG1200, and S&PICB, are statistically significant. The summation of ($\alpha + \beta$) is less than one; symbolically, $\alpha + \beta < 1$. Furthermore, GJR Gamma (γ) is statistically significant and positive in every pair (excluding KRH100-S&PGB and KRH30-S&PICB pairs), indicating that the volatility of return between non-green global assets and assets of the Pakistani stock market is more adverse in negative shudders than in positive shudders, while the same effect is inversely appropriate between the green asset classes and assets of the Pakistani stock market.

Panel B of Table 5 shows that the assets of the Pakistani stock market are significantly and positively connected with global equity assets in both the green and non-green markets, indicating that the Pakistani stock market is positively sensitive to global equity markets; alternatively, when the returns of global equity assets increase, the returns of Pakistani equity assets also increase. Our finding aligns with that of Rehman et al. (2022), who observed a positive association between the Pakistani stock market and the global equity market. Furthermore, it is surprising to note that the dependency between KRH100-DJSW and KRH100-S&PICB is significant over the long- and short-run periods; however, the remaining pairs experience significant values only in the long run. Thus, the magnitude of the outcomes indicates that the Pakistani stock market has a high volatility spillover in terms of global financial markets over the long run rather than in the short run.

In addition, the values of the Ljung–Box Qs (20) (Ljung and Box 1978), multivariate Hosking (20) (Hosking 1980), and Li–McLeod (20) (Li and McLeod 1981) test statistics in Panel C of Table 5 clearly show the absence of serial autocorrelation problems in each pair.

The DCC plots in Figure 5 show the time-varying conditional association between global financial assets and Pakistani stock market assets. The degree of connection between the changes in the return of each asset pair exhibits a positive correlation over the study period; however, there is a negative correlation between the same asset pair at different points of time, such as DJSW-KRH100 and DJSW-KRH30 pairs experiencing negative associations in 2016, 2019, the end quarter of 2021, and the first quarter of 2022; S&PCB-KRH100, S&PGB-KRH30, S&PICB-KRH100, and S&PICB-KRH30 pairs experiencing negative associations in the first quarter of 2016, and from the last quarter of 2017 to the third quarter of 2020; and S&PG1200-KRH100 and S&PG1200-KRH30 experiencing negative connections in mid-2015, 2019, and 2021–2022. These findings demonstrate that investors in the Pakistani stock market can shield their investments during economic turbulence by diversifying their portfolios to the global sector. In addition, investors in the Pakistani stock market can consider both green and non-green bond assets in their carts to hedge their funds from risks or unconditional financial situations because these assets provide safe haven benefits as well as hedging effectiveness. Furthermore, in the recent period, the association between global financial markets and the stock market of Pakistan has been positive during the COVID-19 pandemic period. According to the Indo-Asian News Service (IANS)[8], the Pakistani stock market was named the best-performing stock market in Asia in 2020; however, this market is now the worst-performing stock market in Asia after Sri Lanka. In recent years, there have been numerous debates surrounding Pakistan's stock markets, such as devaluation of currency, miscommunication between individuals and institutions, money laundering, corruption, and clashing speeches by officials[9]. Therefore, global financial assets such as DJSW, S&PG1200, and S&PICB can safeguard investors in the Pakistani stock market because these asset classes are negatively correlated with the assets of their domestic stock market.

Table 5. Estimations of the DCC-GJR-GARCH model for the Pakistani stock market and global financial markets.

	Δln(KRH100)	Δln(DJSW)	Δln(KRH30)	Δln(DJSW)	Δln(KRH100)	Δln(S&PGB)	Δln(KRH30)	Δln(S&PGB)	Δln(KRH100)	Δln(S&PG1200)	Δln(KRH30)	Δln(S&PG1200)	Δln(KRH100)	Δln(S&PICB)	Δln(KRH30)	Δln(S&PICB)
Panel A: AR (1)-GARCH (1, 1) estimation																
Const. (M)	0.026 ***	0.029	0.026 ***	−0.012	0.004	0.029	0.003	−0.012	0.035 **	0.029	0.035 **	−0.012	0.003	0.029	0.003	−0.012
	(0.090)	(0.173)	(0.090)	(0.615)	(0.566)	(0.173)	(0.566)	(0.615)	(0.013)	(0.173)	(0.013)	(0.615)	(0.764)	(0.173)	(0.764)	(0.615)
AR (1)	0.253 **	0.058	0.253 **	−0.010	0.283 ***	0.058	0.283 ***	−0.010	0.293 ***	0.058	0.293 ***	−0.010	0.217	0.058	0.217	−0.010
	(0.048)	(0.583)	(0.048)	(0.926)	(0.073)	(0.583)	(0.073)	(0.926)	(0.087)	(0.583)	(0.087)	(0.926)	(0.359)	(0.583)	(0.359)	(0.926)
MA (1)	−0.153	0.172 ***	−0.153	0.218 **	−0.229 ***	0.172 ***	−0.229	0.218 **	−0.216	0.172 ***	−0.216	0.218 **	−0.183	0.172 ***	−0.183	0.218 **
	(0.228)	(0.095)	(0.228)	(0.025)	(0.073)	(0.095)	(0.135)	(0.025)	(0.207)	(0.095)	(0.207)	(0.025)	(0.420)	(0.095)	(0.420)	(0.025)
Const. (V)	0.021 *	0.046 *	0.021 *	0.052 *	0.001 ***	0.046 *	0.001 ***	0.052 *	0.023 *	0.046 *	0.023 *	0.052 *	0.003 ***	0.046 *	0.003 ***	0.052 *
	(0.001)	(0.000)	(0.001)	(0.000)	(0.062)	(0.000)	(0.062)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.069)	(0.000)	(0.069)	(0.000)
α	0.060 ***	0.006	0.060 ***	0.005	0.059 **	0.006	0.059 **	0.005	0.083 **	0.006	0.083 **	0.005	0.083 **	0.006	0.083 **	0.005
	(0.095)	(0.692)	(0.095)	(0.741)	(0.013)	(0.692)	(0.013)	(0.741)	(0.048)	(0.692)	(0.048)	(0.741)	(0.019)	(0.692)	(0.019)	(0.741)
β	0.832 *	0.837 *	0.832 *	0.855 *	0.931 *	0.837 *	0.930 *	0.855 *	0.788 *	0.837 *	0.788 *	0.855 *	0.913 *	0.837 *	0.913 *	0.855 *
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\alpha + \beta$	0.892	0.843	0.892	0.860	0.990	0.843	0.989	0.860	0.871	0.843	0.871	0.860	0.996	0.843	0.996	0.860
γ	0.163 *	0.232 *	0.163 *	0.207 *	0.001	0.232 *	0.001	0.207 *	0.212 *	0.232 *	212 *	0.207 *	−0.009	0.232 *	−0.009	0.207 *
	(0.001)	(0.000)	(0.001)	(0.000)	(0.948)	(0.000)	(0.948)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.755)	(0.000)	(0.755)	(0.000)
Panel B: DCC estimates																
Average Correlation	0.080 *		0.092 *		0.008		0.011		0.083 *		0.094 *		0.028		0.034	
	(0.002)		(0.000)		(0.827)		(0.785)		(0.001)		(0.000)		(0.444)		(0.387)	
DCC1 (a)	0.016 ***		0.017		0.007		0.006		0.013		0.013		0.014 ***		0.011	
	(0.080)		(0.113)		(0.169)		(0.121)		(0.185)		(0.166)		(0.078)		(0.154)	
DCC2 (b)	0.905 *		0.906 *		0.983 *		0.987 *		0.893 *		0.905 *		0.969 *		0.978 *	
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Panel C: Diagnostic tests																
Qs (20)	9.806	22.175	9.854	15.634	21.214	22.770	21.352	15.925	12.719	22.163	12.693	15.598	16.143	22.822	15.860	16.109
	(0.972)	(0.331)	(0.971)	(0.739)	(0.385)	(0.300)	(0.377)	(0.721)	(0.889)	(0.332)	(0.890)	(0.741)	(0.708)	(0.298)	(0.725)	(0.710)
Hosking (20)	67.072		65.984		87.709		81.480		70.248		69.572		74.604		73.218	
	(0.807)		(0.832)		(0.212)		(0.372)		(0.722)		(0.741)		(0.588)		(0.632)	
Li–McLeod (20)	67.176		66.108		87.654		81.473		70.336		69.680		74.579		73.220	
	(804)		(0.829)		(0.213)		(0.372)		(0.719)		(0.738)		(0.589)		(0.632)	

Notes: *, **, and *** indicate significance at the 1%, 5%, and 10% levels, respectively. The rest of the notes is same as Table 3.

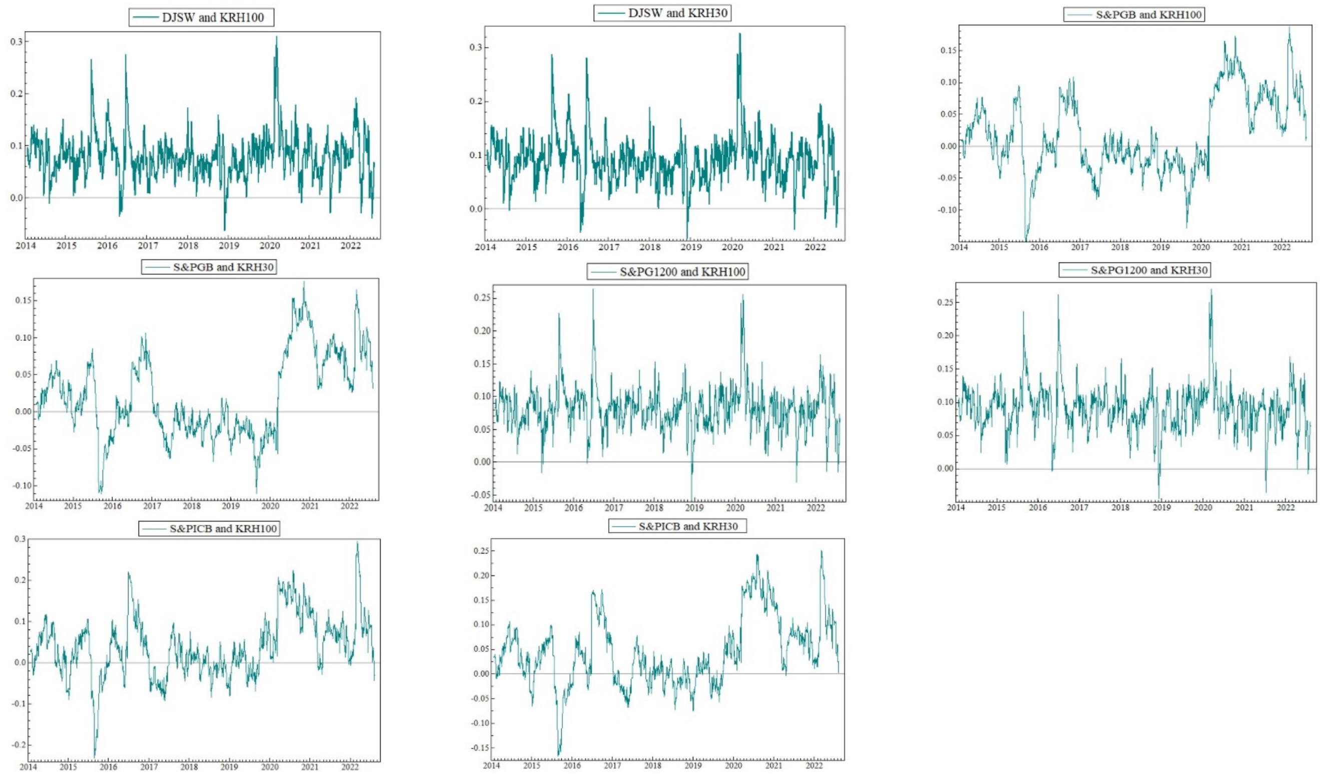

Figure 5. Dynamic conditional correlation plots between global financial markets and the stock market of Pakistan.

4.2.4. Interconnectedness Between Stock Market of Sri Lankan and Global Financial Markets

Table 6 displays the dynamic conditional correlation (DCC) between the financial assets traded in the global financial market and the financial assets traded in the Sri Lankan stock market. The findings from Panel A of Table 6 reveal that ARCH (α) and GARCH (β) are statistically significant and positive in every case; accordingly, the sum of the ARCH (α) and GARCH (β) parameters is <1. Furthermore, GJR Gamma (γ) is also positively significant for all the variables (except for S&PS20-S&PGB and S&PS20-S&PICB pairs) suggesting that between the global financial markets and the Sri Lankan stock market, the hostile shocks cause more volatility return than the positive shocks.

The results in Panel B of Table 6 show that there is a significant and positive dynamic conditional linkage between the assets of global financial markets and assets of the Sri Lankan stock market in most of the asset pairs; however, only global green bond and equity markets make statistically significant positive connections with CSEAS. Furthermore, the long-run and short-run findings demonstrate a non-significant dependency between global financial markets and the Sri Lankan stock market over the long- and short-run periods, except for the relationship between pairs S&PS20-S&PGB, S&PS20-S&PG1200, S&PS20-S&PICB, and CSEAS-S&PG1200 over a prolonged period. Hence, this outcome implies that the high volatility spillover between global financial markets and the Sri Lankan stock market is more diaphanous in the long run than in the short run. Habiba et al. (2020) find significant volatility spillovers between the US and Sri Lankan stock markets, similar to the result of volatility between the Indian and US financial stock markets.

Additionally, in Panel C of Table 6, the diagnostic statistics, namely Ljung–Box Qs (20) (Ljung and Box 1978), multivariate Hosking (20) (Hosking 1980), and Li–McLeod (20) (Li and McLeod 1981), are rejected at the 5% significance level, indicating the absence of serial autocorrelation between the asset pairs.

Table 6. Estimations of the DCC-GJR-GARCH model for the Sri Lankan stock market and global financial markets.

	Δln(CSEAS)	**Δln(DJSW)**	**Δln(S&PS20)**	**Δln(DJSW)**	**Δln(CSEAS))**	**Δln(S&PGB)**	**Δln(S&PS20)**	**Δln(S&PGB)**	**Δln(CSEAS)**	**Δln(S&PG1200)**	**Δln(S&PS20)**	**Δln(S&PG1200)**	**Δln(CSEAS)**	**Δln(S&PICB)**	**Δln(S&PS20)**	**Δln(S&PICB)**
Panel A: AR (1)-GARCH (1, 1) estimation																
Const. (M)	0.026 ***	−0.013	0.026 ***	−0.018	0.004	−0.013	0.004	−0.018	0.035 **	−0.013	0.035 **	−0.018	0.003	−0.013	0.003	−0.018
	(0.090)	(0.427)	(0.090)	(0.317)	(0.566)	(0.427)	(0.566)	(0.317)	(0.013)	(0.427)	(0.013)	(0.317)	(0.764)	(0.427)	(0.764)	(0.317)
AR (1)	0.254 **	0.555 *	0.254 **	0.317 ***	0.283 ***	0.555 *	0.283 ***	0.317 ***	0.293***	0.555 *	0.293 ***	0.317 ***	0.217	0.555 *	0.217	0.317 ***
	(0.048)	(0.001)	(0.048)	(0.059)	(0.073)	(0.007)	(0.073)	(0.059)	(0.087)	(0.007)	(0.087)	(0.059)	(0.360)	(0.007)	(0.359)	(0.059)
MA (1)	−0.153	−0.258	−0.153	0.043	−0.229	−0.258	−0.229	0.043	−0.217	−0.258	−0.217	0.043	−0.183	−0.258	−0.183	0.043
	(0.228)	(0.270)	(0.228)	(0.810)	(0.135)	(0.270)	(0.135)	(0.810)	(0.207)	(0.270)	(0.207)	(0.810)	(0.420)	(0.270)	(0.420)	(0.810)
Const. (V)	0.021 *	0.014 *	0.021 *	0.020 *	0.001 ***	0.014 *	0.001 ***	0.020 *	0.023 *	0.014 *	0.023 *	0.020 *	0.003 ***	0.014 *	0.003 ***	0.020 *
	(0.001)	(0.000)	(0.001)	(0.000)	(0.062)	(0.000)	(0.062)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.069)	(0.000)	(0.069)	(0.000)
α	0.060 ***	0.202 *	0.060 ***	0.222 *	0.059 **	0.202 *	0.059 **	0.222 *	0.083 **	0.202 *	0.083 **	0.222 *	0.083 **	0.202 *	0.083 **	0.222 *
	(0.095)	(0.000)	(0.095)	(0.000)	(0.013)	(0.000)	(0.013)	(0.000)	(0.048)	(0.000)	(0.048)	(0.000)	(0.019)	(0.000)	(0.019)	(0.000)
β	0.832 *	0.745 *	0.832 *	0.761 *	0.931 *	0.745 *	0.931 *	0.761 *	0.788 *	0.745 *	0.788 *	0.761 *	0.913 *	0.745 *	0.913 *	0.761 *
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\alpha + \beta$	0.892	0.947	0.892	0.983	0.990	0.947	0.990	0.983	0.871	0.947	0.871	0.983	0.996	0.947	0.982	0.983
γ	0.163 *	0.117 **	0.163 *	0.059 *	0.001 *	0.117 **	0.001	0.059	0.212 *	0.117 **	0.212 *	0.059 *	−0.009	0.117 **	−0.009	0.059
	(0.001)	(0.046)	(0.001)	(0.272)	(0.948)	(0.046)	(0.948)	(0.272)	(0.000)	(0.046)	(0.000)	(0.272)	(0.755)	(0.046)	(0.755)	(0.272)
Panel B: DCC estimates																
Average Correlation	0.041 **		0.019		0.007		0.013		0.038 ***		0.013		0.011		.0007	
	(0.049)		(0.367)		(0.733)		(0.539)		(0.072)		(0.551)		(0.602)		(0.739)	
DCC1 (a)	0.000		0.000		0.000		0.000		0.000		0.000		0.000		0.000	
	(1.000)		(1.000)		(1.000)		(1.000)		(0.997)		(0.982)		(1.000)		(0.996)	
DCC2 (b)	0.835		0.849		0.666		0.836 *		0.836 ***		0.827 *		0.732		0.819 *	
	(0.511)		(0.351)		(0.237)		(0.000)		(0.081)		(0.001)		(0.224)		(0.000)	
Panel C: Diagnostic tests																
Qs (20)	9.232	27.933	9.909	19.161	19.977	27.903	19.767	19.170	12.070	27.982	11.956	19.156	15.677	28.030	15.700	19.175
	(0.980)	(0.111)	(0.981)	(0.511)	(0.459)	(0.112)	(0.473)	(0.511)	(0.914)	(0.110)	(0.918)	(0.512)	(0.737)	(0.109)	(0.735)	(0.511)
Hosking (20)	69.900		73.357		87.904		67.778		76.659		77.517		83.054		55.220	
	(0.732)		(0.628)		(0.208)		(0.789)		(0.522)		(0.494)		(0.327)		(0.976)	
Li–McLeod (20)	69.991		73.364		87.910		67.843		76.712		77.506		83.046		55.336	
	(0.729)		(0.628)		(0.208)		(0.787)		(0.520)		(0.495)		(0.327)		(0.976)	

Notes: *, **, and *** indicate significance at the 1%, 5%, and 10% levels, respectively. The rest of the notes is same as Table 3.

According to the DCC charts in Figure 6, the connection between assets in global financial markets and assets in the Sri Lankan stock market is perfectly positive in every pair throughout the study period, meaning that the global financial markets neither provide safe haven roles nor offer effective hedging strategies. This phenomenon can be attributed to high levels of market integration, where both local and global markets respond similarly to macroeconomic factors, leading to shared vulnerabilities during volatility (Kose et al. 2003; Haddad 2023; Karanasos et al. 2021). Furthermore, structural characteristics of the Sri Lankan market, including sector concentration, can also reinforce this relationship, making local equities closely tied to global economic conditions (Cappiello et al. 2006). Consequently, during periods of crisis, the tendency for both markets to react similarly undermines the ability of global assets to serve as effective hedges, leaving Sri Lankan investors without adequate protection for their domestic investments.

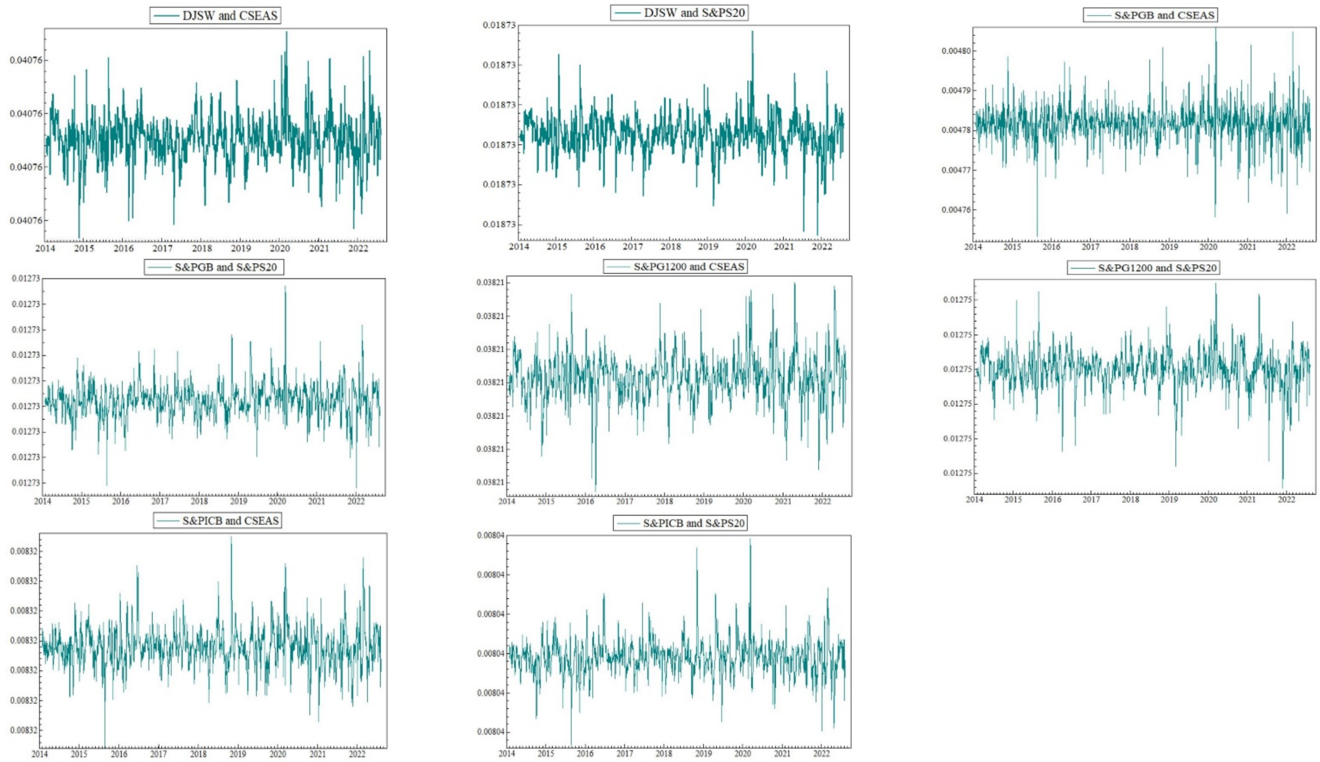

Figure 6. Dynamic conditional correlation plots between global financial markets and the stock market of Sri Lanka.

Therefore, investors in the Sri Lankan stock market cannot safeguard their domestic investments by including global market assets in their portfolios during normal and crisis periods.

4.3. Hedge Ratios, Optimal Portfolio Weights, and Hedging Effectiveness

Table 7 shows the hedge ratios (long/short), optimal weights in the portfolios, and hedging effectiveness for the pairs of global financial asset classes and assets in South Asian stock markets. The results of the hedge ratio column (second column) demonstrate that the cost of hedging for the pairs of global equity assets and Indian stock market assets is significantly larger, ranging from USD 0.31 to 0.36 at 15% to 39% levels of hedging effectiveness, meaning that USD 0.31 to 0.36 is essential to hedge the respective pairs for a USD 1 investment. However, in the remaining pairs—the assets of global markets and stock markets in Bangladesh, Pakistan, and Sri Lanka—we notice a lower level of insignificant hedging cost (almost close to 0) along with somewhat zero effectiveness, confirming that global equity and bond assets are cheap hedges for equity markets in these regions' stock markets.

Table 7. Hedge ratios, optimal portfolio weights, and hedging effectiveness.

	H_a	W_b	HE_a	HE_b
Assets of global financial market/assets of Bangladeshi stock market				
Δln(DJSW)/Δln(DSEB)	0.00	0.41 *	0.01	0.64
Δln(DJSW)/Δln(DSEXS)	0.00	0.40 *	0.01	0.65
Δln(S&PGB)/Δln((DSEB)	0.01	0.90	−0.03	0.05
Δln(S&PGB)/Δln(DSEXS)	0.00	0.76 *	−0.03	0.25
Δln(S&PG1200)/Δln(DSEB)	0.00	0.60 **	0.01	0.08
Δln(S&PG1200)/Δln(DSEXS)	0.01	0.42 *	0.01	0.65
Δln(S&PICB)/Δln(DSEB)	0.01	0.78 *	−0.02	0.10
Δln(S&PICB)/Δln(DSEXS)	0.00	0.61 *	−0.02	0.40
Assets of global financial market/assets of Indian stock market				
Δln(DJSW)/Δln(BSES30)	0.36 *	0.62 *	0.21	0.15
Δln(DJSW)/Δln(NFTY50)	0.36 *	0.63 *	0.21	0.16
Δln(S&PGB)/Δln(BSES30)	0.02	0.53 *	0.03	0.39
Δln(S&PGB)/Δln(NFTY50)	0.02	0.92 ***	0.03	0.07
Δln(S&PG1200)/Δln(BSES30)	0.31 *	0.43 *	0.17	0.39
Δln(S&PG1200)/Δln(NFTY50)	0.31 *	0.68 *	0.17	0.37
Δln(S&PICB)/Δln(BSES30)	0.06 ***	0.83 *	0.08	0.14
Δln(S&PICB)/Δln(NFTY50)	0.06 ***	0.84 *	0.07	0.12
Assets of global financial market/assets of Pakistani stock market				
Δln(DJSW)/Δln(KRH100)	0.08	0.61 *	0.01	0.43
Δln(DJSW)/Δln(KRH30)	0.08	0.66 *	0.02	0.35
Δln(S&PGB)/Δln(KRH100)	0.01	0.76	0.02	0.26
Δln(S&PGB)/Δln(KRH30)	0.01	0.91 *	0.01	0.09
Δln(S&PG1200)/Δln(KRH100)	0.07	0.42 *	0.01	0.66
Δln(S&PG1200)/Δln(KRH30)	0.07	0.63 *	0.01	0.45
Δln(S&PICB)/Δln(KRH100)	0.03	0.61 *	0.03	0.41
Δln(S&PICB)/Δln(KRH30)	0.03	0.81 *	0.03	0.16
Assets of global financial market/assets of Sri Lankan stock market				
Δln(DJSW)/Δln(CSEAS)	0.07	0.40 *	0.02	0.63
Δln(DJSW)/Δln(S&PS20)	0.03	0.51 *	−0.03	0.41
Δln(S&PGB)/Δln(CSEAS)	0.01	0.90 **	−0.02	0.10
Δln(S&PGB)/Δln(S&PS20)	0.01	1.00	−0.01	0.00
Δln(S&PG1200)/Δln(CSEAS)	0.06	0.64 *	0.02	0.16
Δln(S&PG1200)/Δln(S&PS20)	0.02	0.27 *	−0.03	0.76
Δln(S&PICB)/Δln(CSEAS)	0.02	0.80 *	−0.01	0.15
Δln(S&PICB)/Δln(S&PS20)	0.01	0.00 *	0.00	0.57

Notes: H_a and W_b represent the hedge ratios and optimal weights, respectively. HE_a and HE_b indicate hedging effectiveness for the hedge ratios and optimal weights, respectively. *, **, and *** specify the significance at the 1%, 5%, and 10% levels, respectively.

Furthermore, the outcomes of the optimal portfolio weights (see the third column) show that the optimal weights for the pairs of global bond assets (both green and non-green) and South Asian equity assets are higher, ranging from 53% to 91%, except for the S&PICB-S&PS20 pair. The aforementioned findings suggest that most funds should be invested in global bond assets, but the hedging efficiency in these combinations is modest and minor. However, to achieve supreme hedging effectiveness, investors of Bangladeshi, Indian, Pakistani, and Sri Lankan stock markets should invest approximately 40 to 60 percent of their funds in global equity markets in order to reduce the return variance by around 08% to 76%. Moreover, the magnitude of the outcomes in the optimal portfolio weights indicates that, on the one hand, investors in Bangladeshi and Sri Lankan stock markets may reduce more return variance by investing in global green equity assets than investing in global conventional equity assets, while investors in the Indian and Pakistani stock markets may lessen the same thing by investing in global conventional equity markets.

Our arrangements regarding hedge ratios and optimal weights are grounded in a systematic analysis that incorporates dynamic correlation assessments and rigorous optimization techniques, thereby reinforcing the validity of our findings and their relevance to effective portfolio management.

5. Conclusions

Investment liberalization and financial market integration are perceived as keys to inspiring investors to invest in diverse financial assets in different markets worldwide. In addition, the need for investors to create optimal portfolios to protect their investments against unforeseen shocks has increased because of frequent global and regional catastrophes. Despite the abundance of data demonstrating the dynamic interconnectedness between different financial markets, South Asian stock markets have insufficient evidence that limits investors from diversifying their investments at the global level. Therefore, the main objective of this study is to search for potential hedging strategies and safe haven properties of global financial markets against the assets of South Asian stock markets. In doing so, VaR and CVaR estimations were used to reveal the possible downside risk of each studied asset class. Subsequently, the DCC-GJR-GARCH model is employed to exhibit the time-varying volatility connectedness between the four diverse assets from global financial markets and eight equity assets from the four major countries in the South Asian continent. Finally, we compute the hedge ratio, optimal portfolio weights, and hedging effectiveness to estimate whether investments in global markets are cost-effective for South Asian investors.

The results of the VaR and CVaR calculations reveal that the downside risk of stock markets in India, Pakistan, and Sri Lanka is higher; however, this risk is relatively lower for investors in the Bangladeshi stock market. The dynamic time-varying correlation method shows that the volatility of returns between global non-green (both equity and bond) markets and stock markets of Bangladesh and Pakistan is more adverse in the case of negative shocks than in the case of positive shocks, while the same effects are observed only between global equity markets and the Indian stock market. In addition, the volatility spillover shocks of Pakistani and Sri Lankan stock markets from the global markets are extreme over the long run; however, the Indian stock market experiences both short- and long-run volatility spillover effects from the global equity markets and, exceptionally, the Bangladeshi stock market does not experience any significant volatility spillover effect from global marketplaces.

Furthermore, we also reveal that global financial markets provide safe haven roles and hedging effectiveness against the assets of the Bangladeshi stock market for the negative correlation between these market dynamics over the long-run period; however, these markets only provide safe haven benefits to investors in the Pakistani stock market during the crisis period, as the respective asset pairs are negatively correlated to each other in the short-run period. By contrast, investors in the Sri Lankan stock market neither achieve safe haven benefits nor hedging opportunities from the global financial markets for the positive time-varying connectedness between the assets of global financial markets and the assets of the Sri Lankan stock market throughout the study period. Meanwhile, during times of market turbulence caused by geopolitical issues, internal issues, and epidemic circumstances, the global bond markets provide safe haven benefits for investors in the Indian stock market; however, during the Russia–Ukraine invasion, only green bond markets safeguard the investment of Indian equity investors.

Our cost of hedging effectiveness tools demonstrate that global markets and Indian stock market pairs incur higher hedging costs, while cheap hedging costs are witnessed for the pairs of global assets and assets in Bangladeshi, Pakistan, and Sri Lankan stock markets. Additionally, the optimal portfolio weights indicate that South Asian investors would have significant hedging effectiveness if they invested more funds in global equity assets. However, global green equity markets are favorable for investors in the Bangladeshi and Sri Lankan stock markets, whereas counter assets are auspicious for investors in the Indian and Pakistani stock markets to formulate optimal portfolios.

Theoretical Implications

The findings of this research contribute significantly to the existing literature on emerging market volatility by highlighting the differential downside risks associated with stock markets in South Asia. Specifically, the higher downside risk observed in India, Pakistan, and Sri Lanka compared to Bangladesh necessitates a more nuanced understanding of country-specific factors influencing market behavior. Additionally, the study underscores the importance of dynamic time-varying correlations in financial markets, revealing that negative shocks tend to have a more pronounced impact on return volatility than positive shocks. This asymmetry suggests that financial theories must incorporate the conditional nature of risk propagation in emerging markets. Furthermore, the identification of safe haven roles and varying levels of hedging effectiveness among the stock markets emphasizes the need for a refined theoretical framework that addresses how global financial markets interact with regional assets, particularly during periods of market turbulence.

Managerial Implications

From a managerial perspective, the insights derived from this research underscore the necessity for portfolio managers in South Asia to adopt tailored investment strategies based on the unique risk profiles of their respective markets. Managers should exercise caution when investing in Indian, Pakistani, and Sri Lankan stocks, particularly during periods of global volatility, while simultaneously recognizing the potential benefits of allocating assets to the Bangladeshi market. The findings also highlight the importance of dynamic correlation analyses in risk management frameworks, enabling managers to better prepare for asymmetric market responses. Moreover, the research suggests that investment managers should focus on global equity markets for effective hedging, particularly for Bangladeshi and Sri Lankan investors, and should consider market timing strategies that align with geopolitical events to optimize asset allocation and minimize hedging costs. By integrating these insights, managers can enhance their investment decision-making processes and improve overall portfolio performance.

Limitations and Future Research

While this study provides valuable insights into the dynamics of hedging strategies and safe haven properties of global financial markets in relation to South Asian stock markets, several limitations should be acknowledged. Firstly, the research is confined to a specific set of South Asian countries and asset classes, which may not fully capture the complexity of regional market behaviors or the broader implications for other emerging markets. Additionally, the reliance on historical data for VaR and CVaR estimations may not account for sudden market changes or structural breaks, limiting the predictive power of the models used. Future research could expand the scope by incorporating additional countries, asset types (e.g., gold, commodity, and cryptocurrencies), and alternative risk measures or methodologies (e.g., wavelet transform, TVP-VAR, Q-VAR, QQ regression, and t copulas) to enhance the robustness of findings. Furthermore, exploring the impact of behavioral finance factors on investment decisions in South Asian markets could provide deeper insights into investor behavior during periods of volatility. Lastly, longitudinal studies examining the effects of recent geopolitical events and global economic shifts on hedging strategies would further enrich the understanding of the evolving landscape of financial markets in South Asia.

Author Contributions: Conceptualization, M.N.; data curation, M.N., S.K.S., M.A.K., F.K. and A.R.b.S.S.; funding acquisition, M.A.I.G., M.B.A., F.K., A.R.b.S.S. and L.E.; investigation, M.A.I.G., M.N., S.K.S., M.B.A., M.A.K., F.K. and L.E.; methodology, M.N.; project administration, M.A.I.G.; resources, M.A.I.G., M.N., S.K.S., M.B.A., M.A.K., F.K., A.R.b.S.S. and L.E.; software, M.N.; supervision, M.B.A.; validation, M.N., M.B.A., M.A.K., A.R.b.S.S. and L.E.; visualization, S.K.S.; writing—original

draft, M.A.I.G. and M.N.; writing—review and editing, M.A.I.G., M.N., S.K.S. and M.B.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the University of Debrecen Program for Scientific Publication and also supported by the INTI International University, Malaysia.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data of this study will be available upon reasonable request.

Acknowledgments: The authors extend their appreciation to the Deanship Research and Graduate Studies at King Khalid University for funding this work through a large-group Research Project under grant number (RGP.2/107/45)".

Conflicts of Interest: The study's authors affirm that there were no financial or commercial ties that might be seen as a potential conflict of interest throughout its execution.

Notes

1 Available at: https://www.forbes.com/sites/forbesfinancecouncil/2022/09/23/understanding-the-importance-of-investment-diversification/?sh=66a9720a6a88 (accessed on 5 October 2022).

2 Available at: https://www.oecd.org/environment/cc/Green%20bonds%20PP%20[f3]%20[lr].pdf (accessed on 8 April 2023).

3 We also calculate the Gaussian Parametric VaR and CVaR but we choose not to present the results of this model, because the outcomes are nearly identical.

4 Available at: https://www.ndtv.com/business/sensex-crashes-1-000-points-amid-global-selloff-rupee-hits-66-49-1210269 (accessed on 5 October 2022).

5 Available at: https://www.firstpost.com/business/sensex-crashes-1624-points-the-biggest-ever-market-fall-explained-in-seven-graphics-2405610.html (accessed on 5 October 2022).

6 Available at: https://indianexpress.com/article/business/market/bse-sensex-crash-stick-to-the-course/ (accessed on 5 October 2022).

7 Available at: https://www.livemint.com/Politics/zPTEhX52q0NPmZy41ZQAZP/LTCG-imposed-to-check-tax-base-erosion-boost-manufacturing.html (accessed on 5 October 2022).

8 Available at: https://zeenews.india.com/world/pakistan-stock-market-crashes-become-asias-third-worst-performing-stock-market-2472279.html (accessed on 6 October 2022).

9 Available at: https://economictimes.indiatimes.com/markets/stocks/news/pakistan-stocks-crash-after-top-court-disqualified-pm-nawaz-sharif-on-graft-charges/articleshow/59805393.cms (accessed on 6 October 2022).

References

Ackermann, Josef. 2008. The subprime crisis and its consequences. *Journal of Financial Stability* 4: 329–37. [CrossRef]

Ahmed, Danish, Hu X Hua, and Umair Saeed Bhutta. 2024. Innovation through Green Finance: A thematic review. *Current Opinion in Environmental Sustainability* 66: 101402. [CrossRef]

Ahmed, Shaker, Mostafa M. Hasan, and Md Rajib Kamal. 2022. Russia–Ukraine crisis: The effects on the European stock market. *European Financial Management* 29: 1078–118. [CrossRef]

Akhtaruzzaman, Md., Sabri Boubaker, and Ahmet Sensoy. 2021. Financial contagion during COVID–19 crisis. *Finance Research Letters* 38: 101604. [CrossRef]

Al Mamun, Md., Gazi Salah Uddin, Muhammad Tahir Suleman, and Sang Hoon Kang. 2020. Geopolitical risk, uncertainty and Bitcoin investment. *Physica A: Statistical Mechanics and Its Applications* 540: 123107. [CrossRef]

Aloui, Riadh, Mohamed Safouane Ben Aïssa, and Duc Khuong Nguyen. 2011. Global financial crisis, extreme interdependences, and contagion effects: The role of economic structure? *Journal of Banking & Finance* 35: 130–41. [CrossRef]

Ameer, Rashid. 2006. Integration of the South and East Asian Stock Markets: How Long to Go? *Journal of Financial Reporting and Accounting* 4: 61–102. [CrossRef]

Argentiero, Amedeo, Giovanni Bonaccolto, and Giulio Pedrini. 2023. Green finance: Evidence from large portfolios and networks during financial crises and recessions. *Corporate Social Responsibility and Environmental Management* 31: 2474–95. [CrossRef]

Arif, Muhammad, Muhammad Abubakr Naeem, Saqib Farid, Rabindra Nepal, and Tooraj Jamasb. 2022. Diversifier or more? Hedge and safe haven properties of green bonds during COVID-19. *Energy Policy* 168: 113102. [CrossRef]

Artzner, Philippe, Freddy Delbaen, Jean-Marc Eber, and David Heath. 1999. Coherent Measures of Risk. *Mathematical Finance* 9: 203–28. [CrossRef]

Arya, Vandana, and Shveta Singh. 2022. Dynamics of relationship between stock markets of SAARC countries during COVID-19 pandemic. *Journal of Economic and Administrative Sciences*, *ahead-of-print*. [CrossRef]

Aysan, Ahmet Faruk, Ender Demir, Giray Gozgor, and Chi Keung Marco Lau. 2019. Effects of the geopolitical risks on Bitcoin returns and volatility. *Research in International Business and Finance* 47: 511–18. [CrossRef]

Azimli, Asil. 2024. Is gold a safe haven for the U.S. dollar during extreme conditions? *International Economics* 177: 100478. [CrossRef]

Balcilar, Mehmet, Huseyin Ozdemir, and Busra Agan. 2022. Effects of COVID-19 on cryptocurrency and emerging market connectedness: Empirical evidence from quantile, frequency, and lasso networks. *Physica a Statistical Mechanics and Its Applications* 604: 127885. [CrossRef]

Banerjee, Ameet Kumar, Ahmet Sensoy, and John W. Goodell. 2024. Connectivity and spillover during crises: Highlighting the prominent and growing role of green energy. *Energy Economics* 129: 107224. [CrossRef]

Banga, Josué. 2019. The green bond market: A potential source of climate finance for developing countries. *Journal of Sustainable Finance and Investment* 9: 17–32. [CrossRef]

Baur, Dirk G., and Brian M. Lucey. 2010. Is Gold a Hedge or a Safe Haven? An Analysis of Stocks, Bonds and Gold. *Financial Review* 45: 217–29. [CrossRef]

Beirne, John, Guglielmo Maria Caporale, Marianne Schulze-Ghattas, and Nicola Spagnolo. 2010. Global and regional spillovers in emerging stock markets: A multivariate GARCH-in-mean analysis. *Emerging Markets Review* 11: 250–60. [CrossRef]

Belaïd, Fateh, Aisha Al-Sarihi, and Raed Al-Mestneer. 2023. Balancing climate mitigation and energy security goals amid converging global energy crises: The role of green investments. *Renewable Energy* 205: 534–42. [CrossRef]

Boubakri, Salem, and Cyriac Guillaumin. 2015. Regional integration of the East Asian stock markets: An empirical assessment. *Journal of International Money and Finance* 57: 136–60. [CrossRef]

Bouri, Elie, Peter Molnár, Georges Azzi, David Roubaud, and Lars Ivar Hagfors. 2017. On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier? *Finance Research Letters* 20: 192–98. [CrossRef]

Broadstock, David C., Roman Matousek, Martin Meyer, and Nickolaos G. Tzeremes. 2020. Does corporate social responsibility impact firms' innovation capacity? *The indirect link between environmental & social governance implementation and innovation performance. Journal of Business Research* 119: 99–110. [CrossRef]

Brownlees, Christian, Robert Engle, and Bryan Kelly. 2011. A practical guide to volatility forecasting through calm and storm. *Journal of Risk* 14: 3–22. [CrossRef]

Caballero, Ricardo J., and Arvind Krishnamurthy. 2008. Collective Risk Management in a Flight to Quality Episode. *The Journal of Finance* 63: 2195–230. [CrossRef]

Cappiello, Lorenzo, Robert F. Engle, and Kevin Sheppard. 2006. Asymmetric Dynamics in the Correlations of Global Equity and Bond Returns. *Journal of Financial Econometrics* 4: 537–72. [CrossRef]

Chowdhury, Biplob, Mardi Dungey, Moses Kangogo, Mohammad Abu Sayeed, and Vladimir Volkov. 2019. The changing network of financial market linkages: The Asian experience. *International Review of Financial Analysis* 64: 71–92. [CrossRef]

Claessens, Stijn, Giovanni Dell'Ariccia, Deniz Igan, and Luc Laeven. 2010. Cross-country experiences and policy implications from the global financial crisis. *Economic Policy* 25: 267–93. [CrossRef]

Corbet, Shaen, Yang (Greg) Hou, Yang Hu, Les Oxley, and Danyang Xu. 2021. Pandemic-related financial market volatility spillovers: Evidence from the Chinese COVID-19 epicentre. *International Review of Economics & Finance* 71: 55–81. [CrossRef]

Derbali, Abdelkader, and Ali Lamouchi. 2020. Global financial crisis, foreign portfolio investment and volatility. *Pacific Accounting Review* 32: 177–95. [CrossRef]

Dhanaraj, Sowmya, Arun Kumar Gopalaswamy, and Suresh Babu M. 2013. Dynamic interdependence between US and Asian markets: An empirical study. *Journal of Financial Economic Policy* 5: 220–37. [CrossRef]

Dickey, David A., and Wayne A. Fuller. 1981. Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root. *Econometrica* 49: 1057–72. [CrossRef]

Dimic, Nebojsa, Vitaly Orlov, and Vanja Piljak. 2015. The political risk factor in emerging, frontier, and developed stock markets. *Finance Research Letters* 15: 239–45. [CrossRef]

Dungey, Mardi, and Dinesh Gajurel. 2014. Equity market contagion during the global financial crisis: Evidence from the world's eight largest economies. *Economic Systems* 38: 161–77. [CrossRef]

Edey, Malcolm. 2009. The Global Financial Crisis and Its Effects. *Economic Papers: A Journal of Applied Economics and Policy* 28: 186–95. [CrossRef]

Elliott, Graham, Thomas J. Rothenberg, and James H. Stock. 1996. Efficient Tests for an Autoregressive Unit Root. *Econometrica* 64: 813–36. [CrossRef]

Engle, Robert. 2002. Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models. *Journal of Business & Economic Statistics* 20: 339–50. Available online: http://www.jstor.org/stable/1392121 (accessed on 26 October 2024).

Feder-Sempach, Ewa, Piotr Szczepocki, and Joanna Bogołębska. 2024. Global uncertainty and potential shelters: Gold, bitcoin, and currencies as weak and strong safe havens for main world stock markets. *Financial Innovation* 10: 67. [CrossRef]

Ferrer, Román, Rafael Benítez, and Vicente J. Bolós. 2021. Interdependence between green financial instruments and major conventional assets: Awavelet-based network analysis. *Mathematics* 9: 900. [CrossRef]

Flavin, Thomas J., Ciara E. Morley, and Ekaterini Panopoulou. 2014. Identifying safe haven assets for equity investors through an analysis of the stability of shock transmission. Journal of International Financial Markets. *Institutions and Money* 33: 137–54. [CrossRef]

Foglia, Matteo, and Peng-Fei Dai. 2022. "Ubiquitous uncertainties": Spillovers across economic policy uncertainty and cryptocurrency uncertainty indices. *Journal of Asian Business and Economic Studies* 29: 35–49. [CrossRef]

Gandhi, Tanya, and Shahid Ahmed. 2020. Dissecting the Economic Integration in South-Asia: Trends and Analysis. *Journal of International Economics* 11: 19–38.

Gazi, Md. Abu Issa, Md. Nahiduzzaman, Iman Harymawan, Abdullah Al Masud, and Bablu Kumar Dhar. 2022a. Impact of COVID-19 on Financial Performance and Profitability of Banking Sector in Special Reference to Private Commercial Banks: Empirical Evidence from Bangladesh. *Sustainability* 14: 6260. [CrossRef]

Gazi, Md. Abu Issa, Md. Nahiduzzaman, Jakhongir Shaturaev, Bablu Kumar Dhar, and Md. Abdul Halim. 2022b. Dynamic Nexus between macroeconomic factors and CO_2 emissions: Evidence from oil-producing countries. *Frontiers in Environmental Science* 10: 1005814. [CrossRef]

Gazi, Md. Abu Issa, Rejaul Karim, Abdul Rahman bin S Senathirajah, A. K. M Mahfuj Ullah, Kaniz Habiba Afrin, and Md. Nahiduzzaman. 2024. Bank-Specific and Macroeconomic Determinants of Profitability of Islamic Shariah-Based Banks: Evidence from New Economic Horizon Using Panel Data. *Economies* 12: 66. [CrossRef]

Glosten, Lawrence R., Ravi Jagannathan, and David E. Runkle. 1993. On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks. *The Journal of Finance* 48: 1779–801. [CrossRef]

Goh, Kim-Leng, Yoke-Chen Wong, and Kim-Lian Kok. 2005. Financial Crisis and Intertemporal Linkages Across the ASEAN-5 Stock Markets. *Review of Quantitative Finance and Accounting* 24: 359–77. [CrossRef]

Gopalaswamy, A. K., C. H. Huang, and M. Batareddy. 2010. *Price Spillover Effects from Developed to Asian Emerging Stock Markets: Wavelet Analysis*. Working Paper Series; Pathum Thani: Asian Institute of Technology.

Grisse, Christian, and Thomas Nitschka. 2015. On financial risk and the safe haven characteristics of Swiss franc exchange rates. *Journal of Empirical Finance* 32: 153–64. [CrossRef]

Gulzar, Saqib, Ghulam Mujtaba Kayani, Hui Xiaofeng, Usman Ayub, and Amir Rafique. 2019. Financial cointegration and spillover effect of global financial crisis: A study of emerging Asian financial markets. *Economic Research-Ekonomska Istrazivanja* 32: 187–218. [CrossRef]

Habiba, Umm E., Shen Peilong, Wenlong Zhang, and Kashif Hamid. 2020. International stock markets Integration and dynamics of volatility spillover between the USA and South Asian markets: Evidence from Global financial crisis. *Journal of Asia Business Studies* 14: 779–94. [CrossRef]

Haddad, Sama. 2023. Global Financial Market Integration: A Literature Survey. *Journal of Risk and Financial Management* 16: 495. [CrossRef]

Hasan, Md. Bokhtiar, M. Kabir Hassan, Md. Mamunur Rashid, and Yasser Alhenawi. 2021. Are safe haven assets really safe during the 2008 global financial crisis and COVID-19 pandemic? *Global Finance Journal* 50: 100668. [CrossRef]

Hosking, J. R. M. 1980. The Multivariate Portmanteau Statistic. *Journal of the American Statistical Association* 75: 602–8. [CrossRef]

Hung, Ngo Thai. 2019. Return and volatility spillover across equity markets between China and Southeast Asian countries. *Journal of Economics, Finance and Administrative Science* 24: 66–81. [CrossRef]

Janani Sri, S., Parthajit Kayal, and G. Balasubramanian. 2022. Can Equity be Safe-haven for Investment? *Journal of Emerging Market Finance* 21: 32–63. [CrossRef]

Johansson, Anders C. 2011. Financial markets in East Asia and Europe during the global financial crisis. *The World Economy* 34: 1088–105. [CrossRef]

Kabir, Md. Ahsan, Yu Liping, Sanjoy Kumar Sarker, Md. Nahiduzzaman, and Tanmay Borman. 2023. Portfolio optimization and valuation capability of multi-factor models: An observational evidence from Dhaka stock exchange. *Frontiers in Applied Mathematics and Statistics* 9: 1271485. [CrossRef]

Kapar, Burcu, and Steven Buigut. 2020. Effect of Qatar diplomatic and economic isolation on Qatar stock market volatility: An event study approach. *Applied Economics* 52: 6022–30. [CrossRef]

Karanasos, M., S. Yfanti, and J. Hunter. 2021. Emerging stock market volatility and economic fundamentals: The importance of US uncertainty spillovers, financial and health crises. *Annals of Operations Research* 313: 1077–116. [CrossRef]

Khan, M. N., N. Tantisantiwong, S. G. M. Fifield, and D. M. Power. 2015. The relationship between South Asian stock returns and macroeconomic variables. *Applied Economics* 47: 1298–313. [CrossRef]

Khan, Saleheen, and Kwang Woo (Ken) Park. 2009. Contagion in the stock markets: The Asian financial crisis revisited. *Journal of Asian Economics* 20: 561–69. [CrossRef]

Kharbanda, Varuna, and Archana Singh. 2018. Futures market efficiency and effectiveness of hedge in Indian currency market. *International Journal of Emerging Markets* 13: 2001–27. [CrossRef]

Kido, Yosuke. 2018. The transmission of US economic policy uncertainty shocks to Asian and global financial markets. *The North American Journal of Economics and Finance* 46: 222–31. [CrossRef]

Kim, Bong-Han, Hyeongwoo Kim, and Bong-Soo Lee. 2015. Spillover effects of the U.S. financial crisis on financial markets in emerging Asian countries. *International Review of Economics & Finance* 39: 192–210. [CrossRef]

Kim, Suk-Joong, and Michael D. McKenzie. 2007. Chapter 1 Introduction to Asia-Pacific financial markets: Integration, innovation and challenges. *International Finance Review* 8: 3–13. [CrossRef]
Kose, M. Ayhan, Eswar S. Prasad, and Marco E. Terrones. 2003. Financial Integration and Macroeconomic Volatility. *IMF Staff Papers* 50: 119–42. [CrossRef]
Kuang, Wei. 2021. Are clean energy assets a safe haven for international equity markets? *Journal of Cleaner Production* 302: 127006. [CrossRef]
Kumar, Rakesh, and Raj S. Dhankar. 2017. Financial instability, integration and volatility of emerging South Asian stock markets. *South Asian Journal of Business Studies* 6: 177–90. [CrossRef]
Kundurthy, Anirudh, and Milad Nozari. 2024. Global Diversification: Unveiling the Benefits of International Asset Investments. *Journal of Student Research* 13: 1. [CrossRef]
Lakdawala, Aeimit. 2021. The growing impact of US monetary policy on emerging financial markets: Evidence from India. *Journal of International Money and Finance* 119: 102478. [CrossRef]
Laurent, Sébastien, Jeroen V. K. Rombouts, and Francesco Violante. 2012. On the forecasting accuracy of multivariate GARCH models. *Journal of Applied Econometrics* 27: 934–55. [CrossRef]
Lee, Hahn Shik, and Woo Suk Lee. 2020. Network Connectedness among Northeast Asian Financial Markets. *Emerging Markets Finance and Trade* 56: 2945–62. [CrossRef]
Liang, Chin-Chia, Ming-Yung Chen, and Cheng-Hua Yang. 2015. The Interactions of Stock Prices and Exchange Rates in the ASEAN-5 Countries: New Evidence Using a Bootstrap Panel Granger Causality Approach. *Global Economic Review* 44: 324–34. [CrossRef]
Lintner, John. 1965. The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. *The Review of Economics and Statistics* 47: 13. [CrossRef]
Liu, Jian, Yue Hu, Li-Zhao Yan, and Chun-Ping Chang. 2023. Volatility spillover and hedging strategies between the European carbon emissions and energy markets. *Energy Strategy Reviews* 46: 101058. [CrossRef]
Liu, Lu. 2013. International stock market interdependence: Are developing markets the same as developed markets? *Journal of International Financial Markets, Institutions and Money* 26: 226–38. [CrossRef]
Li, Wai Keung, and A. Ian McLeod. 1981. Distribution of the Residual Autocorrelations in Multivariate Arma Time Series Models. *Journal of the Royal Statistical Society Series B (Methodological)* 43: 231–39. [CrossRef]
Ljung, Greta M., and George E. P. Box. 1978. On a measure of lack of fit in time series models. *Biometrika* 65: 297–303. [CrossRef]
Longstaff, Francis A. 2010. The subprime credit crisis and contagion in financial markets. *Journal of Financial Economics* 97: 436–50. [CrossRef]
Lucey, Brian M., and Qiyu Zhang. 2010. Does cultural distance matter in international stock market comovement? Evidence from emerging economies around the world. *Emerging Markets Review* 11: 62–78. [CrossRef]
Markowitz, Harry. 1952. Portfolio selection. *The Journal of Finance* 7: 77–91.
Mazur, Mieszko, Man Dang, and Miguel Vega. 2021. COVID-19 and the march 2020 stock market crash. Evidence from S&P1500. *Finance Research Letters* 38: 101690. [CrossRef]
Mensi, Walid, Syed Jawad Hussain Shahzad, Shawkat Hammoudeh, Rami Zeitun, and Mobeen Ur Rehman. 2017. Diversification potential of Asian frontier, BRIC emerging and major developed stock markets: A wavelet-based value at risk approach. *Emerging Markets Review* 32: 130–47. [CrossRef]
Mohsin, Hasan Muhammad, and Patrick A. Rivers. 2011. Financial Market Integration of South Asian Countries: Panel Data Analysis. *International Journal of Economics and Finance* 3: 2. [CrossRef]
Mohti, Wahbeeah, Andreia Dionísio, Isabel Vieira, and Paulo Ferreira. 2019. Regional and global integration of Asian stock markets. *Research in International Business and Finance* 50: 357–68. [CrossRef]
Mossin, Jan. 1966. Equilibrium in a Capital Asset Market. *Econometrica* 34: 768–83. [CrossRef]
Mukherjee, Paramita, and Suchismita Bose. 2008. Does the Stock Market in India Move with Asia?: A Multivariate Cointegration-Vector Autoregression Approach. *Emerging Markets Finance and Trade* 44: 5–22. [CrossRef]
Naeem, Muhammad Abubakr, and Sitara Karim. 2021. Tail dependence between bitcoin and green financial assets. *Economics Letters* 208: 110068. [CrossRef]
Narayan, Paresh, Russell Smyth, and Mohan Nandha. 2004. Interdependence and dynamic linkages between the emerging stock markets of South Asia. *Accounting & Finance* 44: 419–39. [CrossRef]
Niveditha, P. S. 2024. Identifying Safe Haven Assets: Evidence from Fractal Market Hypothesis. *Computational Economics*. [CrossRef]
Olstad, Aleksander, George Filis, and Stavros Degiannakis. 2021. Oil and currency volatilities: Co-movements and hedging opportunities. *International Journal of Finance & Economics* 26: 2351–74. [CrossRef]
Park, Cyn-Young, and Jong-Wha Lee. 2011. Financial integration in emerging Asia: Challenges and prospects. *Asian Economic Policy Review* 6: 176–98. [CrossRef]
Perera, Anil, and J. Wickramanayake. 2012. Financial integration in selected South Asian countries. *South Asian Journal of Global Business Research* 1: 210–37. [CrossRef]
Phillips, Peter C. B., and Pierre Perron. 1988. Testing for a unit root in time series regression. *Biometrika* 75: 335–46. [CrossRef]
Rahman, Md. Lutfur, and Jashim Uddin. 2009. Dynamic Relationship between Stock Prices and Exchange Rates: Evidence from Three South Asian Countries. *International Business Research* 2: 167–74. [CrossRef]

Rehman, Mobeen Ur, Nasir Ahmad, Syed Jawad Hussain Shahzad, and Xuan Vinh Vo. 2022. Dependence dynamics of stock markets during COVID-19. *Emerging Markets Review* 51: 100894. [CrossRef]

Rusmita, Sylva Alif, Dian Filianti, Ega Nuriayu Mayasani, and Khairunnisa Abd Samad. 2024. Gold characteristics as safe haven and assets diversification for Sharia stocks in Indonesia. *Journal of Islamic Accounting and Business Research*. [CrossRef]

Samitas, Aristeidis, and Ioannis Tsakalos. 2013. How can a small country affect the European economy? The Greek contagion phenomenon. *Journal of International Financial Markets, Institutions and Money* 25: 18–32. [CrossRef]

Shahzad, Syed Jawad Hussain, Memoona Kanwal, Tanveer Ahmed, and Mobeen Ur Rehman. 2016. Relationship between developed, European and South Asian stock markets: A multivariate analysis. *South Asian Journal of Global Business Research* 5: 385–402. [CrossRef]

Sharpe, William F. 1964. Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk. *The Journal of Finance* 19: 425–42. [CrossRef]

Shi, Yujie. 2022. What influences stock market co-movements between China and its Asia-Pacific trading partners after the Global Financial Crisis? *Pacific-Basin Finance Journal* 72: 101722. [CrossRef]

Shu, Chang, Dong He, Jinyue Dong, and Honglin Wang. 2018. Regional pull vs global push factors: China and US influence on Asian financial markets. *Journal of International Money and Finance* 87: 112–32. [CrossRef]

Siddique, Md. Abubakar, Haitham Nobanee, Md. Bokhtiar Hasan, Gazi Salah Uddin, and Md. Nahiduzzaman. 2024. Is investing in green assets costlier? Green vs. non-green financial assets. *International Review of Economics & Finance* 92: 1460–81. [CrossRef]

Silvennoinen, Annastiina, and Timo Teräsvirta. 2009. *Multivariate GARCH Models*. Berlin/Heidelberg: Springer eBooks, pp. 201–29. [CrossRef]

Singhania, Monica, and Jugal Anchalia. 2013. Volatility in Asian stock markets and global financial crisis. *Journal of Advances in Management Research* 10: 333–51. [CrossRef]

Singhania, Monica, and Shachi Prakash. 2014. Volatility and cross correlations of stock markets in SAARC nations. *South Asian Journal of Global Business Research* 3: 154–69. [CrossRef]

Sokhanvar, Amin, and Shawkat Hammoudeh. 2024. Comparative analysis of responses of risky and safe haven assets to stock market risk before and after the yield curve inversions in the U.S. *International Review of Economics & Finance* 94: 103376. [CrossRef]

Sriananthakumar, Sivagowry, and Seema Narayan. 2015. Are prolonged conflict and tension deterrents for stock market integration? The case of Sri Lanka. *International Review of Economics & Finance* 39: 504–20. [CrossRef]

Syed, Aamir Aijaz, and Muhammad Abdul Kamal. 2024. Do cryptocurrency and commodities markets affect stock market performance in South Asia An empirical investigation during the COVID-19 pandemic. *International Journal of Economics and Business Research* 27: 673–92. [CrossRef]

Tissaoui, Kais, and Taha Zaghdoudi. 2021. Dynamic connectedness between the U.S. financial market and Euro-Asian financial markets: Testing transmission of uncertainty through spatial regressions models. *The Quarterly Review of Economics and Finance* 81: 481–92. [CrossRef]

Tiwari, Aviral Kumar, Arif Billah Dar, Niyati Bhanja, and Aasif Shah. 2013. Stock Market Integration in Asian Countries: Evidence from Wavelet multiple correlations. *Journal of Economic Integration* 28: 441–56. [CrossRef]

Tiwari, Aviral Kumar, Emmanuel Joel Aikins Abakah, David Gabauer, and Richard Adjei Dwumfour. 2022. Dynamic spillover effects among green bond, renewable energy stocks and carbon markets during COVID-19 pandemic: Implications for hedging and investments strategies. *Global Finance Journal* 51: 100692. [CrossRef]

Uddin, Gazi Salah, Muhammad Yahya, Gour Gobinda Goswami, Brian Lucey, and Ali Ahmed. 2022. Stock market contagion during the COVID-19 pandemic in emerging economies. *International Review of Economics and Finance* 79: 302–9. [CrossRef]

Umar, Zaghum, Onur Polat, Sun-Yong Choi, and Tamara Teplova. 2022. The impact of the Russia-Ukraine conflict on the connectedness of financial markets. *Finance Research Letters* 48: 102976. [CrossRef]

UNCTAD. 2022. *Foreign Investment in Developing Asia Hit a Record $619 Billion in 2021*. Bridgetown: United Nations Conference on Trade and Development.

Wang, Yu, and Lei Liu. 2016. Spillover effect in Asian financial markets: A VAR-structural GARCH analysis. *China Finance Review International* 6: 150–76. [CrossRef]

World Bank. 2012. Global Economic Prospects June 2012, South Asian Region. Available online: https://www.worldbank.org/content/dam/Worldbank/GEP/GEParchives/GEP2012b/GEP12bSAR_RegionalAnnex.pdf (accessed on 12 October 2022).

World Bank. 2024. *Global Economic Prospects, June 2024*. Washington, DC: World Bank. Available online: http://hdl.handle.net/10986/41536 (accessed on 26 October 2024).

Yang, Jian, James W. Kolari, and Insik Min. 2003. Stock market integration and financial crises: The case of Asia. *Applied Financial Economics* 13: 477–86. [CrossRef]

Yarovaya, Larisa, Janusz Brzeszczyński, and Chi Keung Marco Lau. 2016. Volatility spillovers across stock index futures in Asian markets: Evidence from range volatility estimators. *Finance Research Letters* 17: 158–66. [CrossRef]

Yiu, Matthew S., Wai-Yip Alex Ho, and Daniel F. Choi. 2010. Dynamic correlation analysis of financial contagion in Asian markets in global financial turmoil. *Applied Financial Economics* 20: 345–54. [CrossRef]

Yoon, Seong-Min, Md Al Mamun, Gazi Salah Uddin, and Sang Hoon Kang. 2018. Network connectedness and net spillover between financial and commodity markets. *The North American Journal of Economics and Finance* 48: 801–18. [CrossRef]

Younis, Ijaz, Waheed Ullah Shah, Besma Hkiri, Fiza Qureshi, and Cheng Longsheng. 2023. Risk co-movements and portfolio strategies between energy, gold and BRICS markets. *Resources Policy* 82: 103487. [CrossRef]

Yousaf, Imran, Makram Beljid, Anis Chaibi, and Ahmed AL Ajlouni. 2022. Do volatility spillover and hedging among GCC stock markets and global factors vary from normal to turbulent periods? Evidence from the global financial crisis and Covid-19 pandemic crisis. *Pacific-Basin Finance Journal* 73: 101764. [CrossRef]

Zeng, Hongjun, Ran Lu, and Abdullahi D. Ahmed. 2023. Dynamic dependencies and return connectedness among stock, gold and Bitcoin markets: Evidence from South Asia and China. *Equilibrium Quarterly Journal of Economics and Economic Policy* 18: 49–87. [CrossRef]