Trakya Üniversitesi Sosyal Bilimler Dergisi 81
2025 Cilt 27 Özel Sayı (81-106)
DOI: 10.26468/trakyasobed.1515655 Araştırma Makalesi/Research Article

FROM DRAGON TO ELEPHANT: DECODING RECENT SHIFTS BETWEEN CHINA AND INDIA STOCK EXCHANGES[1]

EJDERHA'DAN FİLE: YAKIN DÖNEM ÇİN VE HİNDİSTAN BORSALARI ARASINDAKİ ETKİLEŞİMİN DEŞİFRESİ

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Geliş Tarihi:15.07.2024 (Received) *Kabul Tarihi: 20.02.2025 (Accepted)*

ABSTRACT: This paper investigates the interconnectedness between the Chinese and Indian stock markets using Vector Autoregression (VAR) and Threshold ARCH (TARCH) model (VAR-VECH-TARCH). Our analysis focuses on the dynamic spillover effects, particularly their intensification following the aftermath of Covid-19 pandemic. The empirical results suggest a differentiated short-term volatility transmission. The Indian market exhibits lower dependence on its own past volatility and weaker short-term linkages with other markets compared to China and the US. However, in the long-term, cointegration is evident, implying interconnectedness across all three markets. Furthermore, our findings reveal a positive dynamic conditional correlation between the Chinese and Indian stock markets, reaching its peak during the pandemic period. Interestingly, this correlation converges to zero after July 2022, potentially reflecting a shift in investment strategies. These results contribute to a nuanced understanding of the recent investment shift from China (SHENZHENCSI) to India (BSESENSEX), highlighting the importance of recognizing the unique dynamics of each market and avoiding oversimplified interpretations.

Key Words: VAR-VECH-TARCH, Indian Stock Markets, Volatility spillover effect, dynamic conditional correlation

ÖZ: Bu çalışma, Vektör Otoregresyon (VAR) ile eşik ARCH (TARCH) modelini (VAR-VECH-TARCH) kullanarak Çin ve Hindistan borsaları arasındaki bağlantıyı araştırmaktadır. Analizimiz, Covid-19 salgını sonrası yoğunlaşan dinamik sıçrama etkilerine odaklanmaktadır. Ampirik sonuçlar, farklılaştırılmış kısa vadeli volatilite aktarımına işaret etmektedir. Hindistan pazarı, Çin ve ABD'ye kıyasla kendi geçmiş volatilitesine daha az bağımlılık ve diğer piyasalara da daha zayıf kısa vadeli bağlantı göstermektedir. Ancak, uzun vadede tüm üç pazar da birbirine bağlılığı ima eden eşbütünleşme açıktır. Ayrıca, bulgularımız Çin ve Hindistan borsa piyasaları arasında pozitif bir dinamik koşullu

[1] Bu çalışma 9-11 Mayıs 2024 tarihinde düzenlenen IERFM2024 Kongresinde sunulan bildirinin gözden geçirilmiş ve düzenlenmiş hâlidir.

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korelasyon olduğunu ortaya koymaktadır. Bu korelasyonun pandemi döneminde zirveye ulaşması dikkate değerdir. İlginç bir şekilde, bu korelasyon Temmuz 2022'den sonra sıfıra yakınsarken potansiyel olarak yatırım stratejilerinde bir değişikliği yansıtmaktadır. Bu sonuçlar, Çin'den (SHENZHENCSI) Hindistan'a (BSESENSEX) yapılan son yatırım kaymasını nüanslı bir şekilde anlamaya katkıda bulunmakta ve her bir piyasanın benzersiz dinamiklerini tanımanın ve aşırı basitleştirilmiş yorumlardan kaçınmanın önemini vurgulamaktadır.

Anahtar Kelimeler: VAR-VECH-TARCH, Hindistan borsası, oynaklık yayılım etkisi, dinamik koşullu korelasyon

EXTENDED ABSTRACT

This paper investigates the potential for technological progress to drive convergence between emerging and developed equity markets. Convergence theory suggests that emerging economies can exhibit "catch-up" growth, narrowing the gap with developed markets. We focus on the burgeoning information technology (IT) sectors of India and China as potential catalysts for this convergence within their respective stock exchanges.

India's IT sector has undergone a remarkable transformation since its inception in the late 20th century. Today, the nation boasts a thriving ecosystem of IT giants specializing in software development, outsourcing, and innovative technologies like artificial intelligence and cloud computing. This trajectory underscores India's capacity for technological innovation and adaptation, offering valuable insights for other emerging economies.

The Indian stock market experienced significant growth, particularly aftermath of the COVID-19 pandemic. While various factors contribute to this growth, the undeniable impact of technology companies, particularly those within the IT sector, deserves particular attention. This influence manifests in three key ways. Firstly, the robust performance of IT companies bolstered investor confidence in the Indian economy, attracting increased capital to the stock market. This influx of liquidity positively impacted overall market sentiment, with benefits spilling over to other sectors. Secondly, the success stories of technology companies have fostered the creation of novel investment opportunities. Innovative startups and companies have attracted significant investor interest and funding, diversifying the market and fueling further growth. Thirdly, the IT sector's emphasis on innovation and adaptability has stimulated broader economic development. Digital transformation has yielded long-term economic benefits by enhancing efficiency, productivity, and transparency, ultimately feeding back into the stock market.

China has emerged as a global tech powerhouse, driven by a potent combination of government initiatives and robust domestic demand. From e-commerce giants like Alibaba and JD.com to fintech innovators and AI pioneers, China's tech landscape boasts impressive depth and scale. However, potential investors must carefully consider the evolving regulatory landscape and associated privacy concerns.

Following the initial stages of the pandemic recovery, the Sensex 50 outperformed the CSI 300. This outperformance can be attributed to factors such as India's young population, rising domestic consumption, and a flourishing tech sector. While China initially held the lead during the recovery phase, it has since encountered headwinds like regulatory pressures and a slowdown in the property market. Of course, addressing this only to investor shift from China would be an oversimplification.

This study employs Vector Autoregression (VAR) and Threshold ARCH (TARCH) models to elucidate the linkage between the Chinese and Indian stock markets. The VAR-VECH-TARCH model incorporates the volatility of both markets and their interdependence. VAR models capture the relationships between multiple time series variables, while VECH refers to a specific method for representing the model's covariance matrix. TARCH models, on the other hand, capture the dynamics of volatility within time series data. In this context, the VAR-VECH-TARCH model is a well-established and robust approach for analyzing the relationship between two stock exchanges, as it can capture the interdependence between multiple time series variables, in this case, the returns of both stock exchanges.

The empirical results reveal contrasting patterns of short-term volatility transmission. The Indian market exhibits a lower dependence on its own past volatility and short-term linkages with other markets. However, in the long run, all markets exhibit interconnectedness. The findings point to a positive dynamic conditional correlation that peaked during the pandemic and subsequently approached zero by July 2022. This potentially reflects a shift in investment strategies.

The empirical findings suggest that the Indian stock market (BSESENSEX) demonstrates lower susceptibility to its own past volatility and weaker short-term volatility linkages with other markets compared to its Chinese and US counterparts. However, long-term interconnectedness persists across all markets, with positive news triggering volatility across the board.

In conclusion, the Chinese and Indian markets offer distinct investment opportunities and challenges. While smaller than the US market, the Indian market boasts greater diversification and significant growth potential. Although currently trading at a premium, the market's relative stability suggests investor confidence in continued positive performance. The Indian market presents a compelling investment opportunity, albeit not without inherent risks. Overall, the results indicate that the Indian equity market (BSESENSEX) exhibits lower sensitivity to its own historical volatility and weaker short-term volatility linkages with other markets compared to the Chinese and US markets. However, long-term interconnectedness across all markets is evident, with positive news capable of triggering volatility across the board.

1. INTRODUCTION

The enticing vision of financial convergence – shrinking gaps in stock market depth, liquidity, and valuation metrics between developed and emerging economies – has captivated investors and policymakers alike. While economic models suggest the possibility of "catch-up" growth for developing nations, the path towards convergence remains a complex and multifaceted challenge. This paper examines the role of technological advancement, with a specific focus on the burgeoning IT sectors of India and China, as potential drivers of convergence for emerging market exchanges.

From its humble beginnings in the late 20th century, India's IT sector has witnessed explosive growth, propelling the nation to the forefront of the global digital landscape. Today, a vibrant ecosystem of IT giants, renowned for expertise in software development, outsourcing, and pioneering technologies like AI and cloud computing, thrives in India. This remarkable journey underscores the nation's capacity for innovation and technological adaptation, offering valuable insights for other emerging markets aspiring to close the gap with developed markets.

The Indian stock market experienced a significant hike in recent years, particularly since the COVID-19 pandemic. While various factors contributed to this growth, the undeniable impact of technology companies, particularly those in the Information Technology (IT) sector, cannot be overstated. This article delves into the multifaceted ways in which these tech titans have driven the Indian stock market, propelling it towards new heights.

The impact of the tech sector goes beyond its own performance. It has demonstrably driven the broader market in several ways. Firstly, the strong performance of IT companies bolstered investor confidence in the Indian economy, attracting more capital into the stock market. This influx of liquidity fueled the overall market sentiment, leading to positive spillover effects across other sectors. Secondly, the success of tech companies encouraged the creation of new investment opportunities. Start-ups and innovative ventures in various fields, not just IT, attracted funding and interest from investors, further diversifying the market and offering new avenues for growth. Thirdly, the tech sector's focus on innovation and adaptability has spurred wider economic development. The digital transformation it drives across industries improves efficiency, productivity, and transparency, leading to long-term economic benefits that ultimately feed back into the stock market.

Consequently, China presents another compelling case study. Its tech sector, fueled by government initiatives and vast domestic demand, has emerged as a global force. From e-commerce giants like Alibaba and JD.com to fintech innovators and artificial intelligence pioneers, China's tech landscape boasts impressive depth and scale. However, concerns over regulatory uncertainty and data privacy pose challenges that require careful consideration.

The world's gaze often swings between the established giants of the East, comparing the economic trajectories of China and India. This is reflected in the performance of their key stock market indices: the Shanghai Shenzhen CSI 300 and the S&P BSE Sensex 50. While both have experienced significant post-pandemic rebounds, their recent journeys diverge, offering intriguing insights into investor sentiment and economic realities.

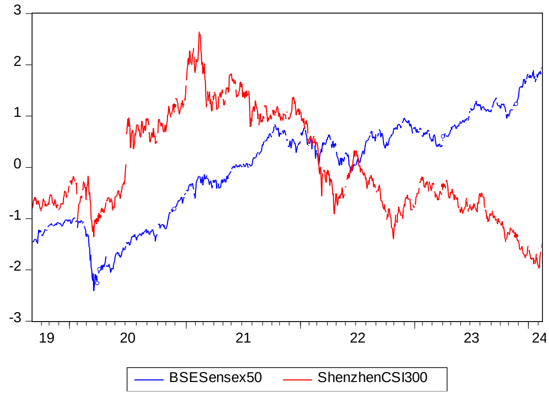

Figure 1: Normalized Returns of BSE Sensex 50 and Shenzhen CSI 300 Indices

It's true that since the pandemic's depths, the Sensex 50 has outpaced the CSI 300, fueled by India's young population, rising domestic consumption, and a booming tech sector (Figure 1). China, initially excelling in the recovery phase, has faced headwinds from regulatory crackdowns and a property market slowdown. However, attributing this solely to a mass investor exodus from China is misleading.

India's tech sector has been a key differentiator. The pandemic accelerated digitization, boosting demand for tech solutions across industries. India's large talent pool and supportive government policies have further fueled this growth. However, China's tech sector, while facing regulatory hurdles, remains a global powerhouse with immense potential. The true story lies in understanding the intricate dance between global economic forces, domestic policies, and sector-specific trends in each market. Both China and India offer distinct investment opportunities and challenges. Investors must avoid oversimplification and conduct thorough due diligence before making investment decisions.

Since the depths of the Covid-19 crisis in March 2020, the CSI 300 has climbed a formidable 61%, riding the wave of China's initial economic recovery and government stimulus measures. However, concerns over regulatory crackdowns and a slowing property market have dampened recent enthusiasm, leading to a 12% correction in 2023. In contrast, the Sensex 50 has soared 120% since March 2020, fueled by India's demographic dividend, rising domestic consumption, and a booming tech sector. While recent volatility has trimmed gains, the Sensex 50 still outperforms its Chinese counterpart.

While definitive conclusions are difficult, some argue for a potential shift in investor sentiment from China to India. This could be driven by regulatory uncertainty in China. China's recent regulatory tightening in tech and other sectors has made investors cautious, seeking stability and transparency in other markets. Also, India's growth potential is another issue. India's young population, rising disposable incomes, and government initiatives to attract foreign investment paint a compelling picture for long-term growth. Moreover, India's tech sector, buoyed by digitization and a supportive regulatory environment, has attracted significant investor interest, fueling the Sensex 50's rise.

However, others caution against oversimplification. China's vast consumer base and infrastructure investments remain potent growth drivers, and the CSI 300 could rebound with renewed policy clarity.

India's tech sector has been a key driver of the Sensex 50's post-pandemic surge. Companies like Infosys, Wipro, and HCL Technologies have seen surging valuations, benefiting from digital transformation, strong talent pool and government support as well. The pandemic accelerated India's digital adoption, creating demand for tech solutions across industries. Moreover, India boasts a large pool of skilled IT professionals, making it a cost-effective outsourcing destination for global companies. Also, the Indian government's initiatives like Digital India and Startup India have fostered innovation and entrepreneurship in the tech sector.

While the current narrative suggests a potential shift in investor focus from China to India, it's crucial to avoid simplistic interpretations. Both economies possess unique strengths and challenges, and their stock markets will likely continue to exhibit individual dynamics. The true story lies in understanding the complex interplay of global economic forces, domestic policies, and sector-specific trends that shape their individual trajectories. As these factors evolve, the relationship between the Shanghai Shenzhen CSI 300 and the S&P BSE Sensex 50 promises to remain a fascinating case study for investors and analysts alike.

2. LITERATURE REVIEW

Over the past thirty years, emerging markets have undergone significant financial deregulation and increased integration with global financial markets (Mishra et al., 2021). This integration has been facilitated by advancements in technology (Habibe et al., 2021). Such developments are particularly beneficial for emerging markets that experience a savings deficit. However, as financial integration progresses, the correlation between financial markets also rises (Baela, 2005; Singh et al., 2015), making it easier for shocks in one market to spread to others.

To analyze market integration, the stock market serves as a crucial indicator, often considered a barometer of the entire economy (Bensiedo et al., 2018). In this context, examining stock market volatility is essential, as the transmission of information through the volatility channel is more significant than through the return channel (first moment) (Ross, 1989; Syropoulos et al., 2015). Consequently, high stock market volatility spillover fundamentally indicates a high level of integration (Zhang and Liu, 2021).

The literature on stock market volatility in emerging markets is relatively recent. Earlier studies primarily detected volatility spillover between the stock markets of developed countries (Hamao et al., 1990; Gerard et al., 2003). More recent research on stock market volatility has focused on the integration of developed markets with developing ones (Worthington and Higgs, 2004; Joshi, 2011; Abounnouri and Tour, 2019; Alfredi, 2019; Bala and Takamatu, 2018; Özdemir, 2018; Uludağ and Kurshid, 2019; Huang, 2019; Vo and Tran, 2020).

Earlier studies suggested a weak financial integration (Agmon, 1972; Hilliard, 1979). However, as mentioned earlier, with the implementation of liberalization policies worldwide, the deregulation of financial markets, and technological improvements, this integration has been significantly enhanced. This is also empirically verified (Jebran and Iqbal, 2016; Li and Giles, 2015; Jung and Maderitsch, 2015). According to Liu et al. (2021) and Zehri et al. (2021), the spillover effect has increased with the Covid-19 pandemic.

India and China remain crucial players in the global stock market landscape, leading to numerous studies focusing on each country respectively. Early research primarily investigated the integration of these stock markets with developed markets. For instance, Moon and Yu (2010) utilized the GARCH model to detect financial integration between the stock markets of China and the US, finding both symmetrical and asymmetrical relationships. Conversely, Li (2007) concentrated on China, Hong Kong, and the USA from 1993 to 2001, employing the EGARCH model but did not find significant volatility spillover between the US and China. In a more recent study, Yu (2017) applied symmetrical and asymmetrical GARCH models to detect stock market spillover between the US and China for the period 1999-2007, uncovering strong evidence of stock market volatility. Guimores-Filho and Hang (2016) asserted that the financial integration of China into the global financial markets has increased since 2015, highlighting China as a new source of shock. According to Vuong et al. (2022), during the pandemic, there was a significant volatility spillover from Chinese to US stock markets.

India's stock market is more integrated with global markets compared to China's. Kumar and Mukhopadhyay (2002) investigated the stock market spillover between India and the US for the period 1999-2001 using the GARCH methodology and found a high spillover between the markets. Sakthivel et al. (2012) studied the market spillover effect between India and developed markets (US, UK, Japan, Australia) between 1998-2011 using a bivariate GARCH model. Their findings indicated a bidirectional volatility spillover between India and the US.

Syropoulos et al. (2015) employed a VAR-GARCH approach to analyze the period from 2005 to 2013, aiming to calculate the volatility spillover from the US to BRICS countries during times of financial crisis. They uniquely used disaggregated indexes, focusing on industrial and financial sectors. Their findings indicated that while India is highly integrated with the US, the Chinese economy remains relatively isolated. Similarly, Batareddy et al. (2012) used time-varying cointegration to study the period from 1998 to 2008. They argued that integration among Asian emerging markets with the US and Japan has increased. Specifically, India is well integrated with global financial markets, but China shows limited integration with both Japan and the US.

With the financial integration of emerging Asian countries facilitated by deregulation, stock market volatility in these regions becomes increasingly significant. Numerous studies focus on modeling the spillover effects in these markets. Lee (2009) utilized the VAR-GARCH methodology to detect volatility spillover among six Asian countries (India, Hong Kong, South Korea, Japan, Singapore, and Thailand), finding a high spillover effect. Mukherjee and Mishra (2010) investigated the financial integration between India and major Asian markets using the VAR-GARCH model for the period 1997-2008, suggesting a positive bidirectional linkage between markets, except for Sri Lanka. Similarly, Chen et al. (2015) analyzed financial market integration between China and ASEAN-5 countries using recursive cointegration analysis for the period 1994-2002, finding that China's financial integration with ASEAN countries has been increasing but remains limited. Zhang and Liu (2018) analyzed dynamic conditional correlation using MGARCH models, focusing on China and Southeast Asian markets, and suggested a positive correlation that peaked during the Asian Crisis and the Global Financial Crisis.

Analyzing the integration of the Indian and Chinese markets is crucial due to their status as economic competitors, making it important to determine the stock market volatility spillover between these economies. Lobo et al. (2006) utilized a Fractionally Integrated Vector Error Correction Model (FIVECM) augmented with multivariate GARCH to detect the integration of the stock markets in the US, India, and China. They found that the Indian and Chinese markets are fractionally integrated, with India leading in volatility transmission. Joshi (2011), employing the GARCH-BEKK methodology to study Asian stock markets from 2007 to 2010, found a unidirectional volatility spillover from China to India. Jebran and Iqbal (2016) focused on three East Asian and three South Asian countries between 1999 and 2014, using the EGARCH methodology. They observed a spillover effect from India to China but did not find a significant spillover effect from China to India.

Uludağ and Kurshid (2019) applied the VAR-GARCH methodology to detect volatility transmission from China to G7 and E7 countries between 1995 and 2015, finding a positive spillover from China to India but not the reverse. Habiba et al. (2021) examined China, India, Indonesia, South Korea, Malaysia, Pakistan, the Philippines, and Taiwan between 2002 and 2017, discovering a unidirectional spillover from China to India. Mishra et al. (2022) investigated the integration of the Indian markets with developed and selected Asian countries using the GARCH-BEKK methodology, concluding that the Indian and Chinese markets are integrated. Vlasova and Luo (2022) detected the stock market spillover effect in the US, Russia, India, and China between 2010 and 2019 using the GARCH-BEKK model, finding that Indian markets react to shocks from Chinese markets.

3. METHODOLOGY

Financial data shows periods of varying risk. Volatility models, like those using standard deviation, help with risk analysis in finance, including portfolio building and pricing derivatives (Engle et al. 1982, 1993). An intriguing phenomenon observed in asset pricing is the asymmetric volatility response to positive and negative returns. This is manifested as a statistically significant negative correlation between contemporaneous returns and future volatility, implying a tendency for volatility to decrease with increasing returns and conversely, increase with decreasing returns. This well-documented effect, known as the leverage effect, is further illustrated in the following figure. Here, "new information" refers to the size of a variable (ε_{t-1}). When ε_{t-1} is 0, expected volatility is also 0.

A model by Glosten, Jaganathan, and Runkle (1993) allows for different impacts of positive and negative news on volatility. In simpler terms, εt-1 acts as a threshold. Shocks (new information) above this threshold have a different effect on volatility compared to shocks below it. This model is called the Threshold-GARCH (TARCH) process:

$$h_{t=}\alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \lambda_1 d_{t-1}\varepsilon_{t-1}^2 + \beta_1 h_{t-1} \qquad [1]$$

where the TARCH model incorporates a dummy variable, d_{t-1}, to capture the asymmetric effects of past shocks (ε_{t-1}) on volatility (h_t). This variable takes a value of 1 when the shock is negative ($\varepsilon_{t-1} < 0$) and 0 when it's non-negative ($\varepsilon_{t-1} \geq 0$). The key idea is that positive shocks have no impact on volatility ($d_{t-1} = 0$ if $\varepsilon_{t-1} \geq 0$). Consequently, their effect on h_t is negligible. In contrast, negative shocks ($\varepsilon_{t-1} < 0$) trigger d_{t-1} to become 1, allowing them to influence volatility (h_t). The strength of this influence depends on the parameter λ_1. If λ_1 is positive ($\lambda_1 > 0$), negative shocks have a greater impact on volatility compared to positive shocks. This highlights the model's ability to capture the asymmetric nature of volatility responses to positive and negative shocks.

3.1. VAR-VECH-TARCH Model

This approach builds upon the VAR-GARCH model introduced by Ling and McAleer (2003). It allows for a detailed analysis of both conditional returns and volatility thanks to its well-defined parameters. This two-part method combines a VAR model with an asymmetric VECH-TARCH model. The VAR portion, extending the traditional AR model to a vector framework, considers multiple financial markets as interconnected variables. This enables the examination of contagion and spillover effects, where fluctuations in one market impact others.

The VAR-VECH-TARCH model suggests that it considers the volatility of both markets and their interdependence. VAR (Vector Autoregression) models capture the relationship between multiple time series variables, VECH refers to a specific way of representing the covariance matrix of the model, and TARCH models capture the volatility dynamics in time series data. In this context, VAR-VECH-TARCH model is a valid and commonly used approach for analyzing the relationship between two stock exchanges since it can capture the interdependence between multiple time series variables, in this case, the returns of both stock exchanges. The TARCH component allows it to account for the heteroscedasticity often observed in financial data, where volatility fluctuates over time while model estimates the conditional correlation between the two markets, taking past information into account, providing a more nuanced understanding than simple correlation measures. It can be easily extended to include additional variables, like global economic indicators or sector-specific data, to further enhance the analysis.

For analyzing stock exchange relationships, VAR-VECH-TARCH shines brightly. It delves deeper than simple correlations, capturing how shocks in one market ripple through the other ("spillover effects"). By analyzing volatility dynamics, it empowers risk management and portfolio diversification strategies. Additionally, by uncovering lead-lag relationships and conditional correlations, it unveils potential hedging opportunities for savvy investors seeking to protect their positions across markets.

The basic mathematical expression of the VAR model is as follows:

$$R_t = C + A_1 R_{t-1} + A_2 R_{t-2} + \cdots + A_k R_{t-k} + \varepsilon_t \qquad [2]$$

$$\varepsilon_t \mid I_{t-1} \sim N(0, H_t)$$

The model employs a Vector Autoregression (VAR) framework to analyze the relationship between endogenous variables (represented by the vector R_t at time *t*. A constant term (C) and a coefficient matrix (A) are estimated to capture the influence of past values (represented by the lag operator k) on the current state of the variables.

The model assumes the residuals (ε_t) to be normally distributed with zero mean and constant variance. Additionally, it incorporates market information available at the previous time step (d_{t-1}) to account for potential news or event impacts. The optimal lag order (k) for the VAR structure is determined using established criteria like AIC, FPE, and LR.

This approach allows for the investigation of news spillovers between different markets through a three-dimensional model, the specific structure of which will be presented subsequently:

$$\varepsilon_{i,t} = \upsilon_{i,t}.h_{i,t}, \quad \upsilon_{i,t} \sim N(0,1) \qquad [3]$$

$$h_{i.t} = c_i + a_i\varepsilon_{t-1}^2 + \beta_i h_{i,t-1} \qquad [4]$$

$$H_t = C^T C + A^T \varepsilon_{t-1}\varepsilon_{t-1}^T A + B^T H_{t-1} B \qquad [5]$$

Equation [3] models the relationship between the residual term, denoted by $\varepsilon_{i.t}$, and the conditional variance, $h_{i.t}.\upsilon_{i.t}$ which is assumed to be normally distributed with a mean of zero and a constant variance. The conditional variance-covariance matrix is represented by $H_{i,t}$. α and β denote coefficients within the equation. It is important to note that C represents a lower triangular matrix, and both A and B are square matrices. The positive definiteness of C^TC (C transposed multiplied by C) is a necessary condition for it to be almost positive definite.

$$H_t = \begin{bmatrix} h_{11,t} & h_{12,t} & h_{13,t} \\ h_{12,t} & h_{22,t} & h_{23,t} \\ h_{31,t} & h_{32,t} & h_{33,t} \end{bmatrix}$$

$$C = \begin{bmatrix} c_{11} & c_{12} & c_{13} \\ c_{21} & c_{22} & c_{23} \\ c_{31} & c_{32} & c_{33} \end{bmatrix} \quad A = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \quad B = \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix}$$

Within the context of the model, the conditional variances are denoted by the diagonal elements ($h_{11,t}$, $h_{22,t}$, $h_{33,t}$) of matrix H_t. Matrix A, containing the ARCH coefficients (a_{11}, a_{22}, a_{33}), captures the ARCH effects, while matrix B, with the GARCH coefficients (b_{11}, b_{22}, b_{33}), represents the GARCH effects in the model.

To account for the asymmetric effect, the diagonal VECH is applied, resulting in the following expression:

$$H_t = A_0 + \sum_{i=1}^{p} A_i \otimes H_{t-i} + \sum_{i=1}^{q} B_i \otimes \varepsilon_{t-1}\varepsilon_{t-1}^T \qquad [6]$$

In which the equation governing the conditional variance-covariance matrix of a bivariate TARCH model takes the following structure:

$$VECH(H_t) = C + AVCEH(\varepsilon_{t-1}\varepsilon_{t-1}') + BVECH(H_{t-1}H_{t-1}') + DVECH(\varepsilon_{t-1}\varepsilon_{t-1}')(d_{t-1}) \qquad [7]$$

where the last term on the RHS of equation [7] depicts the asymmetries. In this context the diagonal bivariate VECH model is as follows:

$$h_{11,t} = C_{01} + a_{11}\varepsilon_{1,t-1}^2 + b_{11}h_{11,t-1} \qquad [8]$$

$$h_{12,t} = C_{02} + a_{33}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + b_{22}h_{12,t-1} \qquad [9]$$

$$h_{22,t} = C_{03} + a_{33}\varepsilon_{2,t-1}^2 + b_{33}h_{22,t-1} \qquad [10]$$

Within the model, the coefficient α_{11} captures the ARCH (Autoregressive Conditional Heteroskedasticity) process in the residuals of asset *i*. This coefficient reflects the volatility clustering evident in the asset's returns, implying that large (or small) shocks tend to be followed by periods of similarly large (or small) fluctuations. The ARCH effect, as measured by α_{11}, represents short-term persistence in the volatility of asset *i*. In contrast, GARCH models (Generalized ARCH) capture longer-term persistence, which is not explicitly discussed here. Similarly, the coefficient α_{33} represents the ARCH process in the residuals of the second asset (asset *j*).

It's important to note that these coefficients, α_{11} and α_{33}, are specific to each asset and do not directly capture the relationship between asset i and asset j. The time-varying beta coefficient, whose calculation is not provided here, would be the appropriate measure for such inter-asset dynamics.

$$\beta_{it}^{BG} = \hat{h}_{12,t}/\hat{h}_{22,t} \quad [11]$$

where the symbol ^ indicates the estimated values of conditional variance.

4. DATA AND EMRPICAL RESULTS

The study leverages a dataset comprised of four variables. These variables encompass the S&P BSE Sensex 50 (BSESensex), the Shanghai Shenzhen CSI 300 (ShenzhenCSI), the Nasdaq 100 (Nasdaq), and the Dollar Index (DXY). They are subsequently employed within two distinct model systems.[1] between 01.09.2019 and 22.02.2024, which covers the Covid-19 and aftermath period. The return of each market is calculated as follows:

$$ln(P_t) - ln(P_{t-1}) \quad [12]$$

where the return series of RBSESensex, RShenzhenCSI, RNasdaq, and RDXY, which represent relevant market variables. Figure 1 depicts the time series behavior of the daily returns for these markets. The time-varying nature and volatility clustering characteristics of the returns are visually evident in Figure 2.

[1] In this research, the author explores the economic characteristics of BRICS nations, with a particular focus on China and India. To achieve this, stock market indices from MOEX (Russia), BOVESPA (Brazil), and JSE (South Africa) were collected for a consistent time period, providing a basis for preliminary analysis and identification of unique features of China and India relative to other BRICS members. Subsequently, a Vector Autoregression (VAR) model incorporating a Vector Error Correction Mechanism (VECM) and a Threshold Autoregressive Conditional Heteroskedasticity (TARCH) structure was employed for further investigation. The analysis revealed that only China and India displayed dynamics relevant to the research objective, leading to the exclusion of the remaining BRICS economies from the subsequent stages of the study.

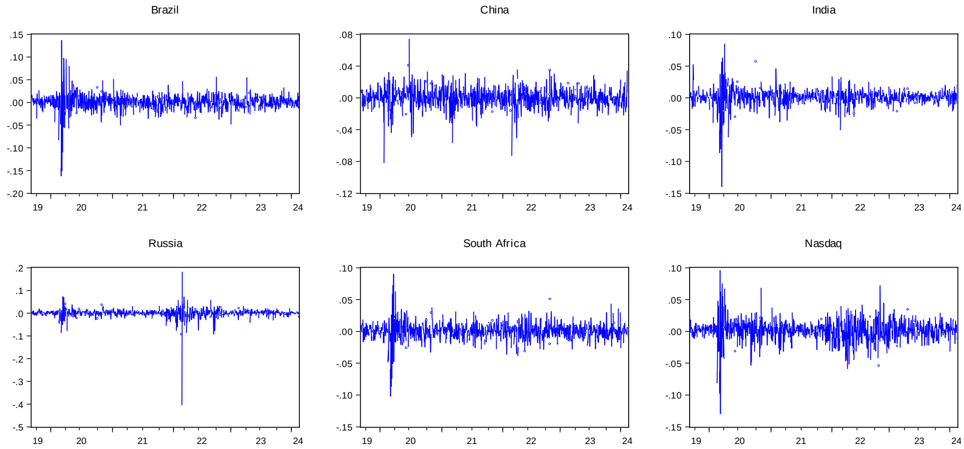

Figure 2: Normalized Returns of BSE Sensex 50 and Shenzhen CSI 300 Indices

The Sensex, established in 1986, is the most longstanding stock market index in India. It functions as a barometer for the performance of 30 prominent and financially robust companies, representing crucial sectors of the economy, listed on the Bombay Stock Exchange (BSE). Managed by Standard & Poor's (S&P), the Sensex employs free-float market capitalization to select constituents, signifying that a company's influence on the index's movement is directly proportional to the number of its shares readily available for trading. The financial sector, encompassing banks and non-banking financial companies (NBFCs), holds the most significant weighting within the Sensex, followed by the information technology (IT) sector..

Coherently, The Shenzhen CSI 300 index's performance over the past five years has been significantly influenced by a couple of key sectors. Technology, particularly companies involved in consumer electronics, internet services, and semiconductors, has been a major driver of growth. Additionally, healthcare and consumer staples have also played a role, as these sectors often show resilience during economic fluctuations. It's important to note that the CSI 300's composition can change over time, so the relative weight of each sector's influence can fluctuate as well.

Table 1 represents Country Complexity Comparisons of BRICS and USA. Country Complexity Comparisons of China is 14 and quite higher than India which is 42, however, BSE Sensex is crowding out Shenzhen CSI in the recent period thanks to its valuable technology companies. One of the main reasonings is that emerging economies can jump ahead in tech compared to traditional industries. Unlike factories and established businesses, tech thrives on innovation, allowing them to use the latest global developments without needing everything built locally. This leapfrog effect lets them compete with developed countries much quicker. Successful tech companies in these economies become investment magnets. This influx of capital strengthens their financial markets, making them even more attractive for future investments. Remember, a strong financial system is crucial for a healthy economy. The beauty of tech is its global reach from the get-go. These companies can tap into a vast international user base and generate significant income even before their domestic economy fully develops. This international success fuels their home financial system, accelerating its growth. Overall, Table 1 suggests that China has achieved the most significant economic development among the BRICS countries. Russia, South Africa, and Brazil have shown slower progress, while India's development has been more moderate.

Table 1: Country Complexity Comparisons (Rankings)[2]

Country	1995	2000	2005	2010	2021
China	46	39	29	24	18
Russia	51	28	39	55	53
South Africa	47	44	48	56	68
Brazil	25	26	34	46	70
India	60	43	50	54	42
USA	9	6	8	12	14

Source: Harvard Growth Lab's

We begin by presenting the impulse response functions (IRFs) that capture the dynamic response of the S&P BSE Sensex 50 Index to one-standard-deviation shocks applied to Shanghai Shenzhen CSI 300 (ShenzhenCSI), Nasdaq 100 (Nasdaq), and the Dollar Index (DXY). This analysis (Figure 3) reveals a statistically significant, albeit temporary, negative influence on the linear specification of Indian and Chinese stock returns exerted by their own past performance (lagged terms), the Brazilian market, the US dollar index, and each other's stock market indices. Conversely, the responses of the Indian and Chinese stock returns to shocks from

[2] Economic development hinges on the accumulation of knowledge that can be applied to production. This productive knowledge is then leveraged to expand into increasingly complex industries. The Harvard Growth Lab utilizes the Economic Complexity Index (ECI) to evaluate a nation's current level of productive knowledge. This index is based on the variety and intricacy of products a country successfully exports. In essence, nations can elevate their ECI by diversifying and increasing the complexity of their exports.

Russia, South Africa and US are positive but temporary.

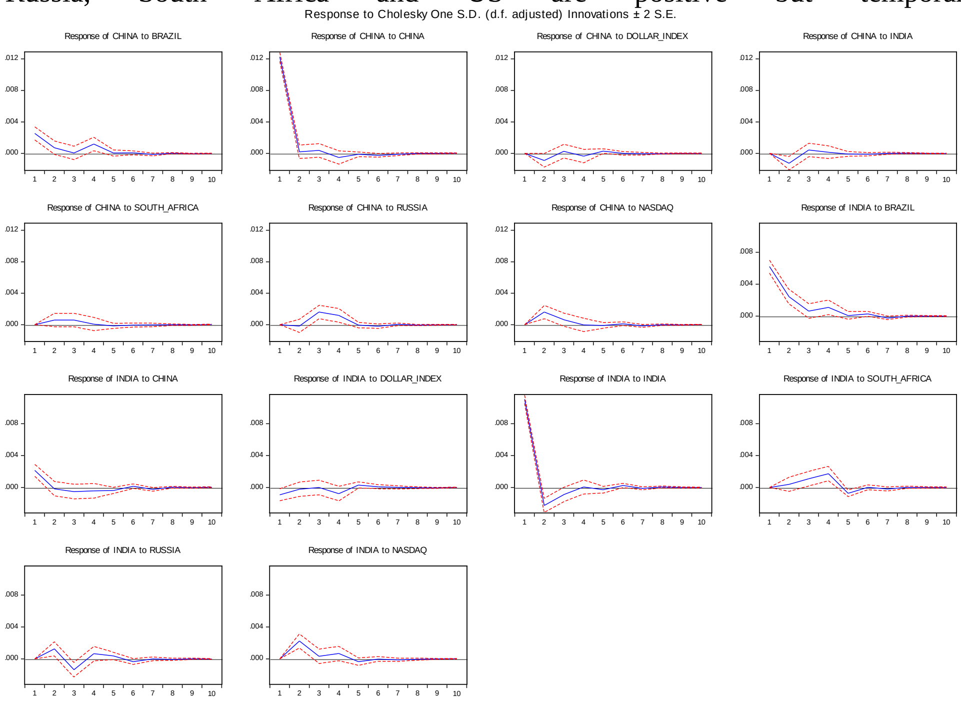

Figure 3: Impulse Response Analysis of China and India

Empirical evidence from a variance decomposition analysis (Figure 4) gives us more insight. Briefly, variance decomposition is a statistical technique that allows researchers to break down the variance of a variable (such as the return of a stock index) into the contributions of different factors. This is useful for understanding what factors are most important for driving the movement of the variable. The largest contributor to the variance of India is itself, followed by Brazil. This means that changes in these factors have the biggest impact on the movement of BSE Sensex 50. On the other hand, the largest contributor to the variance of China is itself, followed by Nasdaq and Brazil. This suggests that the Shenzhen CSI index is also self-driven like the BSE Sensex 50, but both indices are still influenced by external factors.

As illustrated in Figure 1, a discernible shift emerges in the performance correlation between the Indian and Chinese stock markets following July 2022. To investigate this shift further, the data analysis window was narrowed to encompass the period between July 2022 and February 2024, as depicted in Figure 5. Notably, the revised analysis reveals the Nasdaq and the US dollar index as the second-most significant factors influencing Indian stock market movements. This suggests a potential influx of investment funds into the Indian market during the recent period.

Additionally, the influence of the Brazilian market on Indian stocks appears to have diminished within this timeframe. In contrast, the results for the Chinese market remain largely consistent with those obtained using the full data set. This observation implies a potentially stronger preference for Indian equities among investment funds during the specified period.

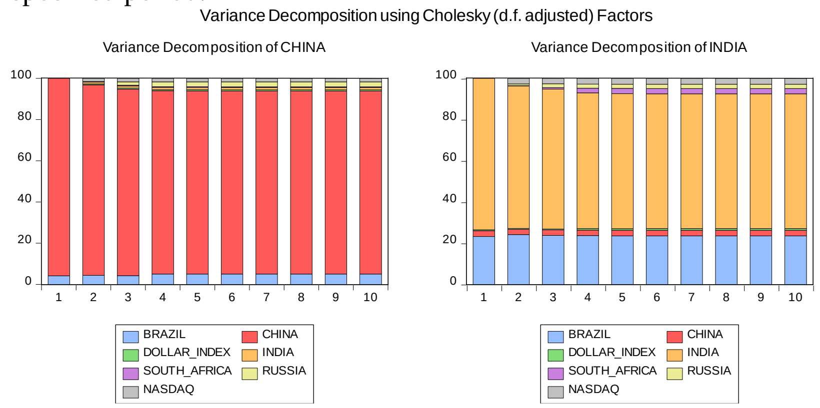

Figure 4: Variance Decomposition Graphs

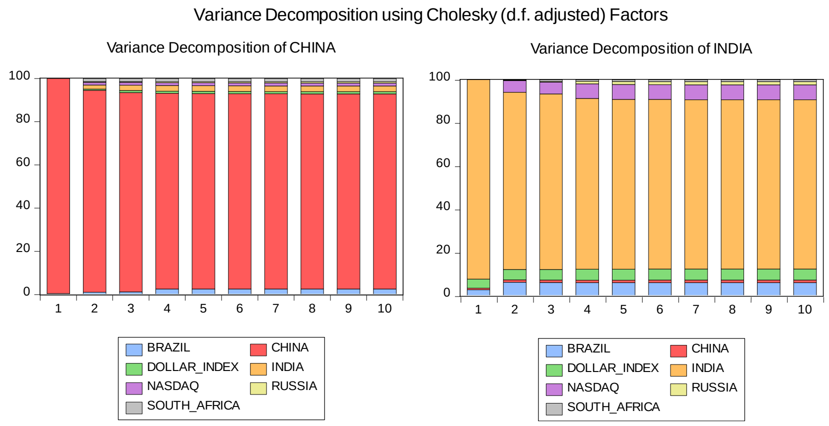

Figure 5: Variance Decomposition Graphs (01.07.2022-22.02.2024)

Simple covariance is sensitive to outliers, which can significantly distort the estimated relationship. Conditional covariance models often use more robust estimation techniques, making them less susceptible to outliers and providing more reliable results. Moreover, when comparing potential future changes, conditional covariance can provide more accurate forecasts than simple covariance. By incorporating information about past relationships and volatility clustering, it can better capture the dynamic nature of the market and predict future co-movements more effectively. Coherently, our model incorporates a Vector Autoregression

(VAR) model which allows the VAR-VECH-TARCH to capture the feedback loops between the variables' returns. In simpler terms, it considers how past returns of one variable can affect not only its own future volatility but also the volatility of other variables in the set. Moreover, The VECH-TARCH part allows for modeling asymmetric volatility effects. This means it can differentiate between how positive and negative shocks impact volatility. For example, a stock market crash might have a more significant impact on volatility than a similar sized gain. In this context, we constructed three different model systems with two different VAR system specifications which are as follows:

VAR System Specification: [13]

$$\begin{aligned} \mathrm{RBSESENSEX_t} = {} & \alpha_1 + \beta_1 \mathrm{RBSESENSEX_{t-1}} + \cdots \beta_5 \mathrm{RBSESENSEX_{t-5}} \\ & + \beta_6 \mathrm{RSHENZHENCSI_{t-1}} + \cdots \beta_{10} \mathrm{RSHENZHENCSI_{t-5}} + \beta_{11} \mathrm{RDXY_{t-1}} \\ & + \cdots \beta_{15} \mathrm{RDYX_{t-5}} + \beta_{16} \mathrm{RNASDAQ_{t-1}} + \cdots \beta_{20} \mathrm{RNASDAQ_{t-5}} \end{aligned}$$

$$\begin{aligned} \mathrm{RDXY_t} = {} & \alpha_2 + \beta_{21} \mathrm{RBSESENSEX_{t-1}} + \cdots \beta_{25} \mathrm{RBSESENSEX_{t-5}} + \beta_{26} \mathrm{RSHENZHENCSI_{t-1}} \\ & + \cdots \beta_{30} \mathrm{RSHENZHENCSI_{t-5}} + \beta_{31} \mathrm{RDXY_{t-1}} + \cdots \beta_{35} \mathrm{RDYX_{t-5}} \\ & + \beta_{36} \mathrm{RNASDAQ_{t-1}} + \cdots \beta_{40} \mathrm{RNASDAQ_{t-5}} \end{aligned}$$

$$\begin{aligned} \mathrm{RNASDAQ_t} = {} & \alpha_3 + \beta_{41} \mathrm{RBSESENSEX_{t-1}} + \cdots \beta_{45} \mathrm{RBSESENSEX_{t-5}} \\ & + \beta_{46} \mathrm{RSHENZHENCSI_{t-1}} + \cdots \beta_{50} \mathrm{RSHENZHENCSI_{t-5}} + \beta_{51} \mathrm{RDXY_{t-1}} \\ & + \cdots \beta_{55} \mathrm{RDYX_{t-5}} + \beta_{56} \mathrm{RNASDAQ_{t-1}} + \cdots \beta_{60} \mathrm{RNASDAQ_{t-5}} \end{aligned}$$

$$\begin{aligned} & \mathrm{RSHENZHENCSI}_t \\ & = \alpha_4 + \beta_{61} \mathrm{RBSESENSEX_{t-1}} + \cdots \beta_{65} \mathrm{RBSESENSEX_{t-5}} \\ & + \beta_{66} \mathrm{RSHENZHENCSI_{t-1}} + \cdots \beta_{70} \mathrm{RSHENZHENCSI_{t-5}} + \beta_{71} \mathrm{RDXY_{t-1}} \\ & + \cdots \beta_{75} \mathrm{RDYX_{t-5}} + \beta_{76} \mathrm{RNASDAQ_{t-1}} + \cdots \beta_{80} \mathrm{RNASDAQ_{t-5}} \end{aligned}$$

Table 2: Estimation Results of Returns-VAR-VECH-TARCH (1,1) Model

	Coefficient	Std. Error	z-Statistic	Prob.
M(1,1)	0.0000	0.0000	4.5795	0.0000
M(1,2)	0.0000	0.0000	-1.1514	0.2496
M(1,3)	0.0000	0.0000	1.6582	0.0973
M(1,4)	0.0000	0.0000	1.3042	0.1922
M(2,2)	0.0000	0.0000	2.2763	0.0228
M(2,3)	0.0000	0.0000	-0.4917	0.6229
M(2,4)	0.0000	0.0000	-0.2646	0.7913
M(3,3)	0.0000	0.0000	4.3020	0.0000
M(3,4)	0.0000	0.0000	0.4216	0.6733
M(4,4)	0.0000	0.0000	4.1419	0.0000
A1(1,1)	0.0121	0.0159	0.7627	0.4457
A1(1,2)	0.0248	0.0170	1.4604	0.1442
A1(1,3)	0.0496	0.0199	2.4975	0.0125
A1(1,4)	0.0293	0.0186	1.5760	0.1150
A1(2,2)	0.0739	0.0181	4.0888	0.0000
A1(2,3)	0.0443	0.0114	3.8795	0.0001
A1(2,4)	0.0078	0.0090	0.8700	0.3843
A1(3,3)	0.0414	0.0209	1.9822	0.0475
A1(3,4)	0.0034	0.0082	0.4142	0.6787
A1(4,4)	0.0721	0.0144	5.0083	0.0000
D1(1,1)	0.1342	0.0284	4.7236	0.0000
D1(2,2)	-0.0029	0.0215	-0.1360	0.8918
D1(3,3)	0.0746	0.0236	3.1634	0.0016
D1(4,4)	0.0679	0.0231	2.9449	0.0032
B1(1,1)	0.8814	0.0161	54.7848	0.0000
B1(1,2)	0.8698	0.0932	9.3344	0.0000
B1(1,3)	0.8640	0.0556	15.5289	0.0000
B1(1,4)	0.8916	0.0639	13.9636	0.0000
B1(2,2)	0.9096	0.0183	49.7170	0.0000
B1(2,3)	0.9362	0.0183	51.2947	0.0000
B1(2,4)	0.9805	0.0360	27.2710	0.0000
B1(3,3)	0.8957	0.0171	52.5262	0.0000
B1(3,4)	0.9808	0.0404	24.3044	0.0000
B1(4,4)	0.8182	0.0282	29.0237	0.0000

According to the model results in Table 2, the relationship between BSESENSEX, SHENZHENCSI, DXY and NASDAQ is analyzed. The own conditional ARCH effects (a_{ii}) is significant even at the %1 level for DXY and SHENZHENCSI, significant for NASDAQ at 5% level, but not significant for BSESENSE even at 10% level. These results indicate Chinese markets, Dollar Index and Nasdaq are influenced by the volatility of their own markets while India is not. However, there is high volatility spillover over effects between India-Nasdaq and Nasdaq-Dollar Index pairs in the short term since a_{13} *and* a_{23} are statistically significant at the 1% level while India-China spillover, a_{14}, is barely significant at 11% level.

Moreover, the conditional GARCH effects (b_{ii})in matrix B are all significant at %1 level for all related markets in the model. Consequently, for the long-term volatility spillovers, the volatility spillover between BSESENSEX, SHENZHENCSI, DXY and NASDAQ are all significant at 1% level that are $b_{12}, b_{13}, b_{14}, b_{23}, b_{24}$ *and* b_{34}. As a result, we can conclude that a volatility spillover between the mentioned markets strongly exists in the long term. Finally, the D matrix refers to the asymmetric coefficients of all India, Nasdaq and China are positive and significant at 1% level. Positive coefficients mean that good news increase the volatility for all markets in the model.

Overall, results suggests that the Indian stock market (BSESENSEX) is less influenced by its own past volatility and has weaker short-term volatility linkages with the other markets compared to the Chinese and US markets. However, in the long term, all the markets seem to be interconnected, and positive news can trigger volatility across all these markets.

Both India and China have large, young populations driving domestic consumption. This creates a strong internal market for businesses to sell to. Additionally, both nations have been undergoing economic reforms for decades, making them more attractive to foreign investors. Technology companies played a big role in the rise of these markets. In China, giants like Alibaba and Tencent are major players on the Shanghai and Shenzhen Stock Exchanges, which are captured by the CSI 300 index. These tech companies boomed during the pandemic as people turned to online shopping, communication, and entertainment. Similarly, Indian tech firms listed on the Bombay Stock Exchange (BSE), reflected in the S&P BSE Sensex 50, thrived as India's digital economy surged. The growth of these tech companies fueled the overall performance of the Chinese and Indian stock markets. COVID-19 did cause an initial plunge in both the Chinese and Indian stock markets, just like most markets around the world. This was due to the general panic and uncertainty surrounding the pandemic's economic impact. However, the strong domestic economies and the tech sector's resilience helped them recover faster. In China, for instance, the government's stimulus packages and focus on domestic consumption aided the rebound. In India, the rise of the digital economy, with people relying more on online services during lockdowns, benefitted tech companies listed on the BSE Sensex, propelling the market's recovery. So, while COVID-19 did deliver a blow, the underlying strengths of the Chinese and Indian economies, coupled with the tech sector's growth, ultimately helped these markets weather the storm and outperform many others.

Figure 6 shows the conditional covariances which seem to be positive for most of the period shown. This suggests that the two indices tend to move in the same direction, although there are some periods where they move in opposite directions. The conditional variances of all indices seem to be higher in Covid-19 pandemic period and then decreases over time. This suggests that the volatility of some index pairs has decreased over time[3]. Especially the conditional covariance of India and China fluctuates around zero band after July 2022[4].

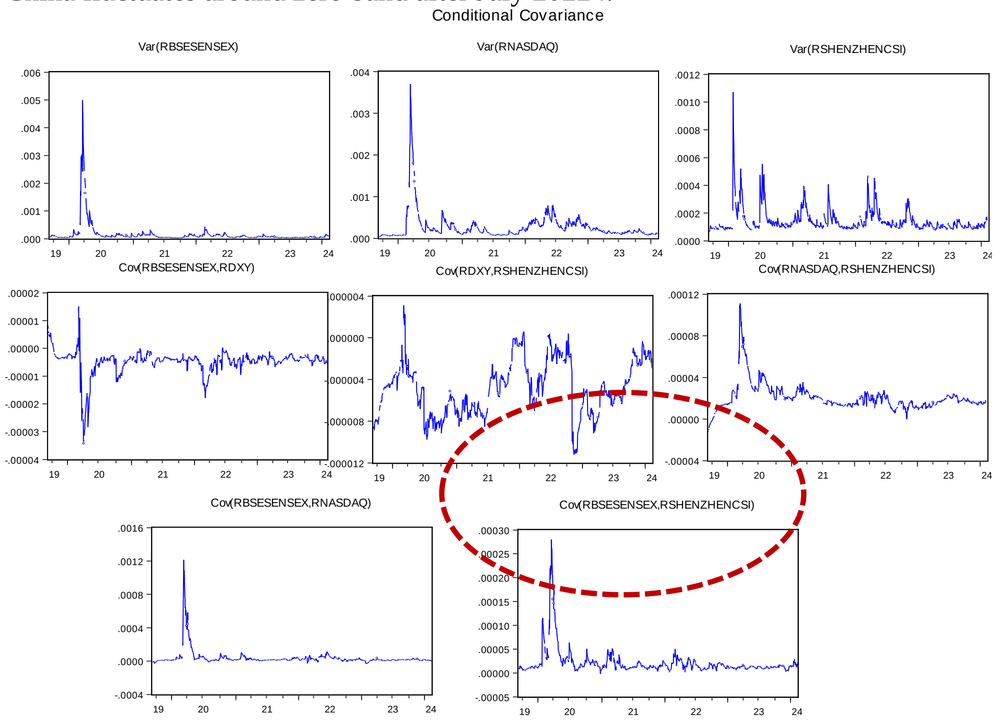

Figure 6: Conditional Covariances

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[3] It's important to note that this graph only shows the conditional covariance between the two indices. It does not necessarily mean that one index causes the other to move. There could be other factors that affect both indices, such as global economic conditions or investor sentiment.

[4] dotted circled graph.

Conditional correlation is often a better measure than simple correlation when comparing changes in two stock exchanges, especially for several reasons. First, simple correlation assumes a static relationship between the two exchanges, meaning the correlation stays the same throughout the observed period. However, in reality, the correlation between stock markets can change over time, especially during periods of high volatility or crisis. Conditional correlation models this dynamic nature by allowing the correlation to vary based on past information, providing a more accurate picture of the current relationship. On the other hand, simple correlation can be misleading when dealing with clustered volatility, where the markets tend to move together during certain periods and diverge in others. Conditional correlation models address this issue by incorporating the volatility of each exchange into the correlation calculation, leading to a more robust measure. Moreover, conditional correlation can help identify potential financial contagion, where a shock in one market spills over to another, leading to increased correlation. By analyzing how the correlation changes during different market conditions, you can gain insights into the interconnectedness of the two exchanges. Finally, for investors and risk managers, understanding the dynamic relationship between different markets is crucial. Conditional correlation provides valuable information for portfolio diversification, risk assessment, and hedging strategies, leading to more informed investment decisions.

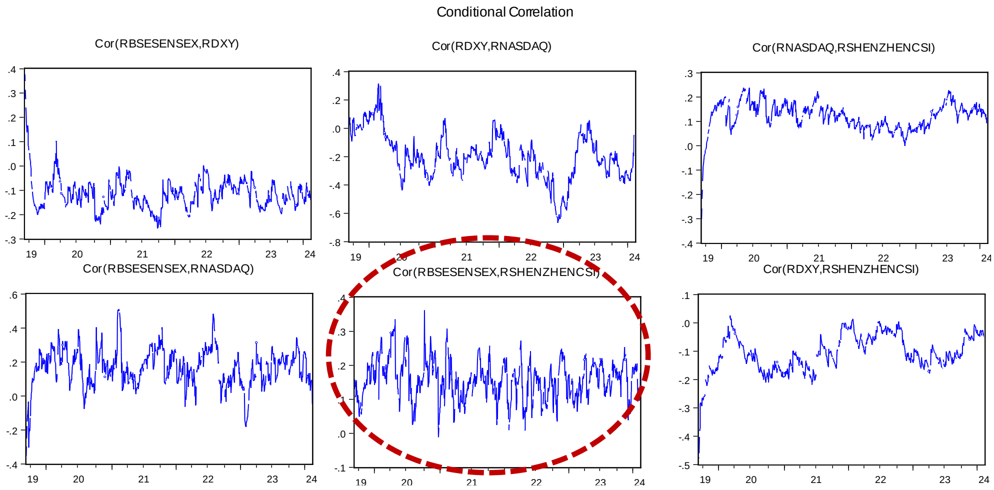

Figure 7: Conditional Correlations

In this context, Figure 7 likely shows the conditional correlation between the Indian and Chinese stock exchanges over time, after accounting for the past performance of both markets. In simpler terms, it measures how closely the two markets move together, given their past movements. The value closer to 1 indicates a strong positive correlation, while a value closer to -1 indicates a strong negative correlation. Figure 7 indicates that the correlation between the two indexes is changing over time. For example, there seems to be a period around pandemic where the correlation is positive, but then it converges to zero. This suggests that during that time, the two indexes moved in the same direction (positive correlation) but then later started to move in opposite directions.

5. CONCLUSIONS

While capital flight from China may be contributing to inflows, the primary driver of growth appears to be a burgeoning domestic investor base. This is fueled by rising disposable incomes and a growing "equity culture," as evidenced by the tripling of targeted investment plans over the past decade. India's market stands in stark contrast to the US. Here, a surge in publicly listed companies (up by a factor of five) coincides with a decline in the US (down by a quarter). This suggests a more competitive landscape in India, potentially fostering innovation and diversification. Notably, India boasts the highest number of companies experiencing a threefold value increase this decade, surpassing even the US.

However, the surge in retail investor participation raises concerns about potential market excesses. The high volume of short-term option trades indicates speculative behavior, prompting regulatory warnings about significant investor losses. Despite its smaller size compared to the US, the Indian market exhibits greater diversity and holds significant growth potential. While valuations are currently high, the market's relative stability suggests investor confidence in continued positive performance. The Indian market presents a unique investment opportunity, albeit not without inherent risks. Overall, results suggests that the Indian stock market (BSESENSEX) is less influenced by its own past volatility and has weaker short-term volatility linkages with the other markets compared to the Chinese and US markets. However, in the long term, all the markets seem to be interconnected, and positive news can trigger volatility across all these markets.

Ethical Declaration

In this study, all the rules stated in the "Higher Education Institutions Scientific Research (Türkiye) and Publication Ethics Directive" were followed.

Ethics Committee

Approval The author declare that the research is one of the studies that does not require ethical committee approval.

Conflict of Interest and Funding

No conflict of interest and funding has been declared by the authors.

Authorship Contribution Declaration

All stages of the study were designed and prepared by the authors. First Author %50, Second Author %30, Thirth Author %20.

REFERENCES

Abounoori, Esmaiel and Mansour Tour. "Stock market interactions among Iran, USA, Turkey, and UAE. *Physica A: Statistical Mechanics and its Applications*, *524*, 297-305, 2019.

Agmon, Tamir. "The Relations Among Equity Markets: A Study Of Share Price Comovements in the United States, United Kingdom, Germany, and Japan" *Journal of Finance*, 27(3), 839-855, 1972.

Alfreedi, Ajab A. "Shocks and Volatility Spillover Between Stock Markets of Developed Countries and GCC Stock Markets." *Journal of Taibah University for Science*, *13*(1), 112-120, 2019.

Baele, Lieven. "Volatility Spillover Effects in European Equity Markets" *Journal of Financial and Quantitative Analysis*, 40(2), 373–401. 2005.

Bala, Dahiru A and Tara Takimoto. "Stock Markets Volatility Spillovers During Financial Crises: A DCC-MGARCH with Skewed-T Density Approach". *Borsa Istanbul Review*, 17(1): 25-48, 2017.

Balcilar, Mehmet and Zeynel A. Ozdemir. *The Volatility Effect On Precious Metals Prices in A Stochastic Volatility in Mean Model with Time-Varying Parameters* (No. 15-34), 2018.

Batareddy, Murali. Gopalaswamy, Arun K and Chai-Hsang Huang. "The Stability of Long-Run Relationships: A Study on Asian Emerging and Developed Stock Markets (Japan And US)". *International Journal of Emerging Markets*, 7(1): 31-48, 2018.

BenSaïda, Ahmet, Boubaker, Sabri and Duc Khong Nguyen. "The Shifting Dependence Dynamics Between the G7 Stock Markets". *Quantitative Finance*, 18(5), 801–812, 2018.

Chen, Heng, Lobo, Bento. J., and Wing Keung Wong. "Links Between the Indian, US and Chinese Stock Markets." *National University of Singapore, Department of Economics, Working Paper*, *602*, 2006.

Chen, Qiang, Zheng, Xu, and Zihuyan Pan. "Asymptotically Distribution-Free Tests for the Volatility Function of a Diffusion". *Journal of Econometrics*, *184*(1), 124-144, 2015.

Gérard, Bruno., Thanyalakpark, Kessara and Jonathan V Batten. "Are The East Asian Markets Integrated? Evidence from The ICAPM." *Journal of Economics and Business,* 55(5-6): 585-607, 2003.

Glosten, Lawrance R, Jagannathan, Ravi and David E. Runkle. "On The Relation Between the Expected Value and the Volatility of the Nominal Excess Return on Stocks." *The Journal of Finance*, 48(5), 1779-1801, 1993.

Guimaraes-Filho, Roberto and Gee Hee, Hong. "Dynamic Connectedness of Asian Equity Markets." *International Monetary Fund (IMF) Working Paper*, WP/16/57, 2016.

Habiba, Umm E., Peilong, Shen, Zhang, Wenlong and Kashif Hamid. "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(5), 779-794, 2020.

Hamao, Yasushi, Masulis, Ronald W. and Victor Ng. "Correlations in Price Changes and Volatility Across International Stock Markets". *The Review of Financial Studies*. 3(2): 281-307, 1990.

Hilliard, Jimmy E. "The Relationship Between Equity Indices on World Exchanges." *The Journal of Finance*, *34*(1), 103-114, 1979.

Hung, Ngo T. "Return and Volatility Spillover Across Equity Markets Between China and Southeast Asian Countries." *Journal of Economics, Finance and Administrative Science*. 24(47): 66-81. 2019.

Jebran, Khalil and Amjad Iqbal. "Dynamics of Volatility Spillover Between Stock Market and Foreign Exchange Market: Evidence from Asian Countries." *Financial Innovation*, *2*, 1-20, 2016.

Jebran, Khalil Chen, Shihua., Ullah, Irfan and Sultan S. Mirza. "Does Volatility Spillover Among Stock Markets Varies from Normal to Turbulent Periods? Evidence from Emerging Markets of Asia." *The Journal of Finance and Data Science*, 3(1-4): 20-30, 2017.

Joshi, Prashant. "Return and Volatility Spillovers among Asian Stock Markets". *Sage Open*, 1(1): 2158244011413474, 2011.

Kirkulak Uludag, Berna and Muzammil Khurshid. "Volatility Spillover from the Chinese Stock Market to E7 and G7 Stock Markets." *Journal of Economic Studies*, 46(1), 90-105, 2019.

Kumar, Kiran K. and Chiranjit C. Mukhopadyay. "Equity Market Interlinkages: Transmission of Volatility-A Case of US and India. NSE*"*. *India Research paper*, Source: www. nseindia. com. 2002

Lee, Byung-Joo. "Asian Financial Market Integration and the Role of Chinese Financial Market." *International Review of Economics & Finance*, 59, 490-499, 2019.

Li, Matthew C. "Wealth, Volume and Stock Market Volatility: Case of Hong Kong (1993–2001)." *Applied Economics*, 39(15), 1937-1953, 2007.

Li, Yanan and David E. Giles. "Modelling Volatility Spillover Effects Between Developed Stock Markets and Asian Emerging Stock Markets." *International Journal of Finance & Economics*, 20(2): 155-177, 2015.

Ling, Siqhing and Micahael McAleer. "Asymptotic Theory for a Vector ARMA-GARCH Model.*" Econometric Theory,* 19(2), 280-310, 2003.

Liu, Ziefeng, Huynh, Toaan. L. D., and Peng-Fei Dai "The impact of COVID-19 on the stock market crash risk in China". *Research in international Business and Finance*, *57*, 101419. 2021.

Mishra, Alok K., Rath, Badri N and Aruna K. Dash. (2021). "Does The Indian Financial Market Nosedive Because Of The COVID-19 Outbreak, In Comparison to After Demonetisation and The GST?", *Research on Pandemics* (pp. 30-48). Routledge, 2021.

Moon, Gyu-Hen, and Choun Yu Wei. "Volatility Spillovers Between the US and China Stock Markets: Structural Break Test with Symmetric and Asymmetric GARCH Approaches." *Global Economic Review*, 39(2), 129-149, 2010.

Mukherjee, Kedar and Ram K. Mishra. "Stock Market Integration and Volatility Spillover: India and Its Major Asian Counterparts" *Research in International Business and Finance*, 24(2), 235-251,2010.

Ross, Stephen A. "Information and Volatility: The No-Arbitrage Martingale Approach to Timing and Resolution Irrelevancy." *The Journal of Finance*, 44(1), 1-17, 1989.

Sakthivel, P., Bodkhe, N. and B. Kamaiah "Correlation and Volatility Transmission Across International Stock Markets: A Bivariate GARCH Analysis". *International Journal of Economics and Finance*, *4*(3), 253-264, 2012.

Syriopoulos, Theodore., Makram, Beljid, and Boubaker, Adel "Stock Market Volatility Spillovers and Portfolio Hedging: BRICS and the Financial Crisis." *International Review of Financial Analysis*, 39, 7-18, 2015.

Singh, Pardeep., Kumar, Arnav and CA Deepak. "Volatility Spillover Across Major Equity Markets: A Critical Review of Literature." *International Journal of Research in Commerce & Management*, 6(4), 2015.

Vlasova, E. and D. Luo."Volatility Spillover Between the Russia–India–China Triad and The United States: A Multivariate Generalized Autoregressive Conditional Heteroscedasticity Analysis." *The New Economic Association,* 111, 2022.

Vo, Xuan V. and Thi Tuan A. Tran. “Modelling Volatility Spillovers from The US Equity Market to ASEAN Stock Markets.” *Pacific-Basin Finance Journal*. 59:101246, 2020.

Vuong, Giang Thi H., Nguyen, Manh H. and Anh Ngoc Q. Huynh “Volatility Spillovers from the Chinese Stock Market to The US Stock Market: The Role of the COVID-19 Pandemic.” *The Journal of Economic Asymmetries*, 26, e00276, 2022.

Worthington, Andrew and Hellen Higgs. “Random Walks and Market Efficiency in European Equity Markets.” *The Global Journal of Finance and Economics*, *1*(1), 59-78, 2004.

Zehri, Chokri. “Stock Market Comovements: Evidence from the COVID-19 Pandemic.” *The Journal of Economic Asymmetries*. 24: e00228, 2021.

Zhang, Guofu, and Wei Liu. “Analysis of the International Propagation of Contagion Between Oil and Stock Markets.” *Energy*, 165, 469-486, 2018.

Zhong, Yi. and Jiapeng Liu. “Correlations and Volatility Spillovers Between China and Southeast Asian Stock Markets” *The Quarterly Review of Economics and Finance*. 81: 57-69, 2021.