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Dynamics of Price and Volatility Spillovers among Stock Markets and Foreign Exchange Markets: Evidence from South Asia

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Abstract

This study examines the volatility spillover interplay between the foreign exchange and equity markets in three key South Asian countries: India, Pakistan, and Sri Lanka. Drawing on time-series data from 2001 to 2023 and utilizing the DCC-GARCH model, distinct market dynamics emerge. India stands out with pronounced short-term and long-term bidirectional spillovers, revealing an integrated financial landscape. Conversely, Pakistan demonstrates heightened sensitivity to short-term market shocks with muted long-term correlations. Sri Lanka's financial landscape reveals an absence of short-term spillovers while manifesting pronounced long-term interdependencies. This study underscores South Asia's financial heterogeneity, offering pivotal insights for regional economic strategies, investment paradigms, and future academic studies.

Keywords: DCC-GARCH model, Foreign exchange markets, Regional heterogeneity, South Asian equity markets, Volatility spillover

Introduction

The interplay between stock valuations and exchange rate fluctuations has been the focal point of increased scholarly and professional attention, mainly due to its profound impact on economic trajectories (Chkili et al., 2012). Wong (2017) emphasized the intricate relationship between these financial components, suggesting profound implications for the strategies underlying both monetary and fiscal policies. The mutual interdependence of these sectors is further underscored by the observation that disturbances in one market can rapidly spill over into another, as evidenced by contagion effects (Chkili & Nguyen, 2014). Global financial crisis in 2007 serves as a testament to the potential repercussions of such unexpected intermarket volatilities.

The burgeoning trend in both domestic and international equity investments has led to amplified dynamics in the foreign currency market, establishing a discernible correlation between equity returns and foreign exchange rates (Cantu C., 2019). This intertwined relationship has crucial bearings on matters of portfolio diversification, financial stability, and the broader implications for economic growth. Consequentially, the rise in volatility transmission intensifies the international portfolio risks for investors, potentially leading to diminished returns.

The relationship between share prices and foreign exchange rates can be understood through two primary theoretical lenses: flow-oriented and stock-oriented models. Dornbusch and Fischer (1980) advocate for the flow-oriented model, positing a direct correlation between exchange rates and stock prices, grounded in a country's trade balance. On the other hand, the stock-oriented model, presented by Branson (1985) and Frankel (1983), underscores the equilibrium dynamics between the supply and demand of financial assets, like equities and bonds. Within this framework, there's a distinction between a monetary model and a portfolio-balance model, with the latter suggesting an inverse relationship between stock prices and exchange rates.

Technological advancements in financial econometrics have furnished scholars with sophisticated tools for delving into the complex interlinkages between stock and foreign exchange markets. Predominantly, GARCH-BEKK and DCC-GARCH models have been instrumental in the analysis of numerous studies (Chkili et al., 2012; Andreou et al., 2013; Kumar, 2013; Caporale et al., 2014; Kim et al., 2015; Moore & Wang, 2014; Wong, 2017; Panda & Nanda, 2018). These tools elucidate the multifaceted nature of returns' interconnectedness and the ensuing volatility spillovers.

For instance, the empirical study by Kanas (2000) leveraged the Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) model and non-parametric cointegration tests to gauge volatility spillovers between stock and foreign exchange markets, spanning six developed nations from 1986-1998. The study illuminated asymmetric volatility spillover effects from stock returns to foreign exchange rate shifts, excluding Germany. Aloui (2007) echoed these findings, underscoring significant spillovers in Europe post the euro era from 1991-2005. The Dynamic Conditional Correlation (DCC) GARCH model is a widely recognized and extensively used framework for estimating time-varying correlations, making it especially suitable for examining the spillover effects between financial markets, such as the stock market and exchange rates. The spillover effect refers to the transmission of shocks or fluctuations from one market to another. Engle (2002) introduced the DCC GARCH model, highlighting its efficacy in capturing the dynamic nature of correlations between different financial time series, which is critical when studying spillover effects. Given the complex interactions between stock markets and foreign exchange markets, the DCC GARCH provides a robust methodology. It allows for the conditional variances and correlations to evolve over time, enabling the capture of potential volatility clustering and changing relationships, which are common phenomena in financial markets. Diebold and Yilmaz (2009, 2012) further emphasized the importance of understanding spillover effects using methodologies like DCC GARCH, as these interlinkages have profound implications for portfolio management, risk management, and macroeconomic policy decisions.

In this treatise, our objective is to delve into the interconnected returns and volatility spillovers between stock markets and foreign exchange arenas across South Asia. Adopting the DCC GARCH model, we aim to demystify the asymmetric volatility transmission dynamics in three South Asian nations: India, Sri Lanka, and Pakistan, selected due to data availability. Our findings are poised to offer valuable insights for policymakers, keen on understanding contagion mechanisms and enhancing market regulations, as well as investors and fund managers aiming to hedge investment risks in the region.

The remainder of this paper is structured as follows: Section two delves into the extant theoretical and empirical literature. Sections three elucidates the adopted methodology. Section four delves into the empirical findings, culminating in the concluding remarks in section five.

Literature Review

The interplay of volatility spillovers between stock markets and exchange rates is a nuanced and highly researched area in empirical finance. A consistent theme underscored by various studies, including those of Basher, Haug, and Sadorsky (2016), and Prasad Bal and Narayan Rath (2015), is the pivotal role of oil prices in the dynamism of exchange rates. The results suggest that global demand shocks, primarily driven by oil prices, have discernible repercussions on exchange rates. These studies, differing in their regional focus and time frames, emphasize the imperative nature of oil price movements and their consequential effects on financial markets.

A key methodological advancement that has emerged in this realm of research is the adoption of the Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model. As Gamba-Santamaria et al. (2017) illustrate, the DCC-GARCH model is adept at exploring the intricate volatility relations among an array of assets. Their work supports the foundational studies of Bollerslev (1990) and Engle (1993), reiterating the model's suitability in understanding time-varying asset price correlations in financial time series. Further buttressing the efficacy of this model, Kumar (2013) utilized it to examine volatility transmission in the stock markets and foreign exchange rates, particularly for the IBSA nations (India, South Africa, Brazil). Not only did the model detect bidirectional volatility transmission, but it also spotlighted the dominance of stock markets in driving this spillover.

However, while there's a consensus on the central role of oil prices, the methodologies and outcomes present divergent paths. Prasad Bal and Narayan Rath (2015) employed nonlinear Granger causality, revealing distinct relationships for India and China. The feedback relationship observed for India juxtaposed with the unidirectional causality for China is a testament to the region-specific intricacies inherent in these spillovers. On a different spectrum, Choudhry, Hassan, and Shabi (2015) using a nonlinear approach detected bidirectional causality among varied countries. Such findings accentuate the significance of adopting diverse methodologies that cater to the unique economic landscapes of different regions.

Region-specific studies, especially those focused on the BRICS nations, offer a mosaic of insights. The US financial crisis's contagion effect on these economies, as highlighted by Aloui et al. (2011), Syriopoulos et al. (2015), and Dimitriou et al. (2013), presents a range of outcomes. While Aloui et al. and Syriopoulos et al. confirmed the contagion effect, Dimitriou et al. offered a contrasting perspective, underscoring the disparities possibly arising from variations in methodologies, sample periods, or unaccounted regional economic elements.

Furthermore, beyond the prominent focus on oil prices, the literature also gravitates towards the symbiotic relationship between gold prices, exchange rates, and stock markets. Works by Sari et al. (2010), Tully and Lucey (2007), and Sjaastad (2008) shine a light on these interrelations, with findings ranging from gold price volatility influences by macroeconomic variables to weak asymmetric relationships between gold and oil prices.

Recent spillover Studies

The turbulence in crude oil prices has been closely linked to risk spillovers across commodity, stock, and foreign exchange sectors (Luo and Ji, 2018; Wu et al., 2020; Huang et al., 2020). Such spillovers, and the mechanisms driving them, can amplify systemic risks, potentially resulting in deeper financial disturbances (Nyman et al., 2021). In a detailed exploration of oil price fluctuations and their impact on global stock returns, Mokni (2020) highlighted a distinction between supply and demand shocks. While supply shocks generally exerted a minimal negative effect, demand shocks consistently yielded notable positive implications for stock returns. Additionally, Wu et al. (2020) shed light on the nuanced, wave-like reactions of exchange rates in oil-exporting countries to oil price shifts, particularly during periods of global financial unrest.

Antonakakis et al. (2014) utilized the Economic Policy Uncertainty (EPU) index to investigate the evolving relationship among U.S. stock returns, implied volatility, and economic policy uncertainty. Their findings highlight the reciprocal relationship where stock market volatility intensifies economic policy uncertainty, and conversely, economic uncertainty can amplify stock market volatility. Furthermore, the study emphasized the significant role of international crude oil prices in influencing stock prices, mainly through mechanisms like expected cash flows and capital costs.

External shocks, particularly sudden and extreme events like the COVID-19 pandemic, have surged to the forefront of cross-market contagion effects research (Fu and Gregory, 2019; Baker et al., 2020; Haddad et al., 2021). Such unanticipated events introduce heightened volatility spillovers between financial markets (Glasserman and Peyton Young, 2016; Roncoroni et al., 2021). Ji et al. (2020) examined the repercussions of the pandemic on financial markets, suggesting that traditional safe-haven currencies might have lost their quintessential asset allocation functionalities, with other inherent financial market functions being equally perturbed.

As market interconnections continue to evolve, so do the methodologies to decipher their intricacies. Using the Copula-GARCH model, Aloui et al. (2013) unveiled pronounced risk interdependencies between WTI, Brent crude oil prices, and the USD exchange rate. Progressing from there, Du and He (2015) tapped into the Granger causality test to discern notable risk spillover dynamics between the S&P 500 and WTI crude oil futures. Expanding the boundaries of this research, Ji et al. (2018) delved into the spillover of extreme risks between energy commodities, such as crude oil, and the agricultural sector.

Leveraging the potential of big data and advanced computational techniques, scholars have increasingly veered towards machine learning and deep learning for risk assessments. Kinkyo (2020) adopted random forests and deep learning techniques, positioning them as potent tools for early warnings across financial markets. This growing trend was further underscored by Li et al. (2022) who proposed an intricate forecasting model (ICEEMDAN-SSCE-TVMD-GTO-KELM), emphasizing its accuracy in predicting crude oil prices.

The relationship between stock markets and exchange rates has been the subject of numerous academic investigations. As global financial systems become increasingly interconnected, understanding these relationships becomes crucial for policymakers, investors, and scholars alike. Future research may seek to explore the effects of specific macroeconomic policies on these dynamics, adding another layer to this multifaceted field of study.

Methodology

Data and Sample

The primary objective of this research is to investigate the volatility spillover between foreign exchange and stock markets, with an emphasis on the dynamics of the financial instruments' pricing, particularly in the context of the South Asian region. Employing time-series data, this research examines daily stock indices and exchange rates. The data range starts from 1st January 2001 for India and Pakistan, while for Sri Lanka, it commences from 20th December 2004, dictated by the data availability for the S&P 20 Index. The dataset extends up to 11th August 2023, which marks the latest date at the point of this investigation.

The data set incorporates information from three prominent stock exchanges in South Asia: Bombay Stock Exchange (BSE) in India, Karachi Stock Exchange (KSE) in Pakistan, and Colombo Stock Exchange (CSE) in Sri Lanka. Given the inherent susceptibility of these stocks to market information, the indices chosen for analysis represent the most liquid and financially robust stocks within each market. Specifically, the indices under consideration include the S&P BSE SENSEX 30 Index for India, the KSE100 Index for Pakistan, and the S&P Sri Lanka 20 for Sri Lanka.

Owing to the significant demand for US Dollars (USD) required to sustain economic activities in the South Asian region, this research emphasizes the exchange rate of the local currency against the USD for each respective country. As such, the exchange rates utilized in this study are the Indian Rupee to the United States Dollar (USDINR), the Pakistani Rupee to the United States Dollar (USDPKR), and the Sri Lankan Rupee to the United States Dollar (USDLKR). To ensure consistency and accurately capture volatility transmission, the research employs day-closing prices for both the foreign currency exchange and stock markets in the aforementioned countries.

Econometric Models

The DCC-GARCH model, as formulated by Engle (2009), is designed to investigate the shifting correlations amidst two or more data series. Essentially, a Vector Autoregression (VAR) model is applied to the series, and the ensuing residuals are standardized by segmenting them by their respective GARCH conditional standard deviations. This process of standardization, coined as "De-GARCHing" by Engle (2009), paves the way for the DCC model to subsequently estimate the Dynamic Conditional Correlations between the series. To examine the volatility spillover effects in the stock and foreign exchange markets of the selected countries, daily data were employed. The computation of returns was conducted in accordance with methodologies delineated in prior studies, such as Mishra et al. (2007), Mitra (2017), and Sahadudheen (2015).

$$R_{S,t} = \ln S_t - \ln S_{t-1} \quad (1)$$

$$R_{X,t} = \ln X_t - \ln X_{t-1} \quad (2)$$

In the aforementioned context:

$R_{S,t}$ denotes the return on the stock index pertinent to the specific country.
$R_{X,t}$ represents the return on the exchange rate relevant to the designated exchange rate.
The terms t and $t-1$ respectively indicate the current period and the preceding period.
S signifies the stock index relevant to the particular country.
X alludes to the exchange rate of the specified country.

Univariate GARCH Models for Each Series:

For each return series $R_{S,t}$ and $R_{X,t}$ a GARCH (1,1) model is fitted,

For the Stock Index:

$$R_{S,t} = \mu_S + \epsilon_{S,t} \quad (3)$$

$$\epsilon_{S,t} = \sigma_{S,t} \times z_{S,t} \quad (4)$$

$$\sigma^2{}_{S,t} = \omega_S + \alpha_S \epsilon^2{}_{S,t-1} + \beta_S \sigma^2{}_{S,t-1} \quad (5)$$

And for the Exchange Rate:

$$R_{X,t} = \mu_X + \epsilon_{X,t} \quad (6)$$

$$\epsilon_{S,t} = \sigma_{X,t} \times z_{X,t} \quad (7)$$

$$\sigma^2{}_{X,t} = \omega_X + \alpha_X \epsilon^2{}_{X,t-1} + \beta_X \sigma^2{}_{X,t-1} \quad (8)$$

Where:

μ is the mean return.
ϵ is the innovation or shock at time t.
σ is the conditional volatility at time t.
z is a white noise error term, usually assumed to be iid and follows a standardized distribution (like Normal or Student's t-distribution).
$\omega, \alpha,$ and β are parameters to be estimated.

DCC Specification:

Once the univariate GARCH models are estimated, standardized residuals are to be derived:

$$q_{S,t} = \frac{\epsilon_{S,t}}{\sigma_{S,t}} \quad (9)$$

$$q_{X,t} = \frac{\epsilon_{X,t}}{\sigma_{X,t}} \qquad (10)$$

Then, the joint dynamics of these standardized residuals are to be modelled:

$$Q_t = (1 - a - b)\bar{Q} + a(q_{t-1}q_{t-1}') + bQ_{t-1} \qquad (11)$$

Where;

Q_t is the conditional covariance matrix[1] of the standardized residuals[2].

$\bar{Q}$ is the unconditional covariance matrix[3] of the standardized residuals.

a and b are parameters to be estimated.

The dynamic conditional correlation matrix[4] R_t is derived from Q_t:

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[1] $Q_t = \begin{bmatrix} {\sigma^2}_{S,t} & q_{S,t}q_{X,t} \\ q_{X,t}q_{S,t} & {\sigma^2}_{X,t} \end{bmatrix}$

[2] $q_t = \begin{bmatrix} q_{S,t} \\ q_{X,t} \end{bmatrix}$

[3] This matrix is essentially the long-run average or expected value of Q_t:

$$\bar{Q} = E[Q_t]$$

For our two-variable system:

$$\bar{Q} = \begin{bmatrix} E[{\sigma^2}_{S,t}] & E[q_{S,t}q_{X,t}] \\ E[q_{X,t}q_{S,t}] & E[{\sigma^2}_{X,t}] \end{bmatrix}$$

[444] Derivation

$$Let\ \boldsymbol{A} = \ diag(Qt)^{-0.5} = \begin{bmatrix} \frac{1}{\sqrt{q_{S,t}^2}} & 0 \\ 0 & \frac{1}{\sqrt{q_{X,t}^2}} \end{bmatrix}$$

$$Let\ \boldsymbol{B} = \ Q_t diag(Qt)^{-0.5} = \begin{bmatrix} {\sigma^2}_{S,t} & q_{S,t}q_{X,t} \\ q_{X,t}q_{S,t} & {\sigma^2}_{X,t} \end{bmatrix} \begin{bmatrix} \frac{1}{\sqrt{q_{S,t}^2}} & 0 \\ 0 & \frac{1}{\sqrt{q_{X,t}^2}} \end{bmatrix} = \begin{bmatrix} 1 & \frac{q_{S,t}q_{X,t}}{\sqrt{q_{X,t}^2}} \\ \frac{q_{X,t}q_{S,t}}{\sqrt{q_{S,t}^2}} & 1 \end{bmatrix}$$

Then $\mathbf{A}.\mathbf{B}$ gives

$$\mathbf{A}.\mathbf{B} = \ R_t = \begin{bmatrix} 1 & \frac{q_{S,t}q_{X,t}}{\sqrt{q_{S,t}^2 q_{X,t}^2}} \\ \frac{q_{X,t}q_{S,t}}{\sqrt{q_{S,t}^2 q_{X,t}^2}} & 1 \end{bmatrix}$$

Here, the off-diagonal elements are the dynamic conditional correlations between the two series, S and X. The diagonal elements are always 1 since the correlation of a series with itself is 1.

$$R_t = diag(Qt)^{-0.5} Q_t diag(Qt)^{-0.5} \qquad (12)$$

Where:

R_t is a matrix that contains the time-varying conditional correlations between S and X.

Descriptive Statistics

The table presents the descriptive statistics of index returns and exchange rate returns across three countries: India, Pakistan, and Sri Lanka. India's RBSESN30, representing the BSESN30 index return, demonstrates a mean return of approximately 0.000501. This value, while appearing modest, gains significance when compared with its standard deviation of 0.014609. Such a deviation indicates considerable fluctuation, suggesting that the Indian stock market, during the observed period, experienced notable volatility. The range, illustrated by the minimum and maximum values (-0.14102 and 0.120539, respectively), further emphasizes this volatility. On the other hand, the RUSDINR, denoting the USD/INR exchange rate return, has a more contained standard deviation of 0.004108, hinting at comparatively less tumultuous movements in the currency market than the stock market.

Turning our attention to Pakistan, the RKSE100 index return reveals an average return of 0.00062, slightly higher than India's primary index. However, its volatility, as inferred from a standard deviation of 0.012714, is somewhat lower than the Indian counterpart. The USD/PKR exchange rate return (RUSDPKR) has an average return of 0.000285, more than double that of India's currency return, indicating more frequent adjustments or potential interventions in the foreign exchange market. Sri Lanka's financial landscape, represented by the RSP20 and RUSDLKR, is characterized by a narrower gap between the index and currency returns compared to the other countries. Both returns hover around the 0.00025 to 0.000276 range. However, the RSP20 demonstrates a pronounced maximum deviation, with the difference between its maximum and minimum values being quite stark, emphasizing significant market swings during certain periods.

Regarding the normality of the series, the skewness and kurtosis joint tests were conducted for each variable. A p-value less than the conventional significance level of 0.05 would reject the hypothesis of normality. The results for all variables from each country have p-values of 0.0000, thus strongly suggesting non-normality in their distributions. This implies that for each series under investigation, the data does not follow a normal distribution, which is a crucial insight for subsequent econometric analyses.

Table I: Descriptive statistics of Index returns and exchange rate returns

Country	Variable	N	Mean	Standard Dev.	Min	Max	Skewness and kurtosis joint tests for normality Adj chi2(2)	Prob>chi2
India	RBSESN30	5,598	0.000501	0.014609	-0.14102	0.120539	984.14	0.0000
	RUSDINR	5,598	0.000103	0.004108	-0.0355	0.036936	708.19	0.0000
Pakistan	RKSE100	5,579	0.00062	0.012714	-0.07741	0.085071	480.09	0.0000
	RUSDPKR	5,579	0.000285	0.004418	-0.0541	0.079599	236.87	0.0000
Sri Lanka	RSP20	4,445	0.000276	0.01254	-0.21044	0.112149	437.84	0.0000
	RUSDLKR	4,445	0.00025	0.004894	-0.06062	0.119529	268.23	0.0000

Note: RBSESN30 refers to the return of BSESN30 index return (India), RUSDINR refers to USD/INR exchange rate return (India), RKSE100 refers to KSE100 index return (Pakistan), RUSDPKR refers to USD/PKR exchange rate return, RSP20 refers to S&P20 returns (Sri Lanka) and RUSDLKR refers to USD/LKR exchange rate return (Sri Lanka)

Unit Root Tests

Before applying any econometric model to time series data, it's paramount to ascertain the stationarity of the data. The unit root test[5] serves as a standard tool in determining the presence or absence of stationarity within time series data. For this purpose, the Augmented Dickey–Fuller (ADF) test was employed to investigate the stationarity of the data under consideration.

Table II showcases the ADF test results for the stock markets of selected countries, also elucidating the number of lagged difference terms utilized in the test. At a 5% significance level, the null hypothesis—that the time series data possesses a unit root—cannot be rejected for both the stock index and foreign exchange rate, irrespective of whether a deterministic trend is incorporated. However, upon differencing the series once, they were found to be stationary based on the ADF test results. Consequently, this research infers that all the considered stock indexes and exchange rates are integrated of order 1 (I(1)

[5] H0 = Data series is non-stationary

Table II: Unit Root test for Stock Indices and Exchange Rates

Country	I(0) Level	ADF test statistics	I(1) First difference	ADF test statistics
India	BSESN30	1.8190	d.BSESN30	-58.9440***
	USDINR	0.3880	d.USDINR	-55.7930***
Pakistan	KSE100	1.3940	d.KSE100	-52.0100***
	USDPKR	3.9270	d.USDPKR	-52.9860***
Sri Lanka	SP20	-0.8470	d.SP20	-45.4590***
	USDLKR	1.1370	d.USDLKR	-121.2690***

Note: d refers to the first difference series (I(1)). *** indicates 1% level of significance

ARCH-LM Test: Heteroscedasticity

To determine the appropriateness of employing GARCH models, the Lagrange Multiplier (LM) test was applied to examine the presence of autoregressive conditional heteroskedasticity (ARCH) effects in the data. The results of the LM test conclusively rejected the null hypothesis[6] that the time series data is void of ARCH effects, doing so at a 5% significance level for all selected countries, encompassing both exchange rates and stock indices. The evident ARCH-LM effects in the stock market returns and exchange rates of the surveyed countries support the foundational presumptions of the ARCH model family. Based on these findings, it's scholarly valid to employ GARCH modeling for the stock index returns and exchange rates in these countries. Detailed ARCH-LM test outcomes have been excluded for conciseness.

Analysis of Foreign Exchange and Stock Market Volatility Using DCC-GARCH Methodology.

Table III presents the results of the DCC-GARCH models for each country. The BSESN30 index of India, a representative of the country's equity market's vitality, showcases a mean daily return of 0.000927. This figure is statistically significant at the 1% significance level, underlining the importance of understanding daily fluctuations in this market. The sum of α_1 and β_1 coefficients, being close to unity, signifies that the volatility in the Indian equity market tends to be persistent. This persistence indicates that shocks, whether positive or negative, have a lasting impact on future volatilities, emphasizing the need for informed hedging and risk management strategies for market participants. In the realm of forex, the USD/INR exchange rate showcases a daily return hovering around -0.000017. While this figure might seem minuscule and it indeed lacks the statistical significance, it's the pronounced volatility clustering, evidenced by the high and significant α_1 and β_1 coefficients, that takes center stage. Such volatility clustering is indicative of the forex market's sensitivity to past shocks. Navigating between these markets, the significant $\boldsymbol{dcc_{a1}}$ coefficient, clocking in at 0.003927 (significant at the 5% level), brings to light short-run spillovers. This emphasizes that shocks in one market can have almost instantaneous repercussions on the other. Furthermore, the $\boldsymbol{dcc_{b1}}$ coefficient, a robust 0.991006 significant at the 1% level, bears testimony to the enduring bidirectional spillovers between these markets, hinting at an intertwined relationship in the longer horizon.

6 H0 = There is no ARCH effect in the stock index and foreign exchange rate.

Moving westward, the Pakistani equity market, represented by the KSE100 index, provides insights into its volatility dynamics. With a mean daily return of 0.001015, significant at the 1% level, the importance of understanding market movements becomes paramount. The statistically significant α_1 and β_1 coefficients elucidate the enduring nature of volatility clustering, much like its Indian counterpart. The USD/PKR exchange rate offers a more tranquil daily mean return at 0.000098. Though this isn't buttressed by statistical significance, the pronounced significance of its volatility persistence coefficients (α_1 and β_1) cannot be overlooked. In the short run, evidenced by a $\boldsymbol{dcc_{a1}}$ of 0.020870 (significant at the 5% level), immediate bidirectional spillovers are present. However, when casting our gaze long-term, the $\boldsymbol{dcc_{b1}}$value of 0.211590 appears less convincing, lacking robust statistical significance. This possibly hints at a weaker long-term correlation between the equity and forex markets in Pakistan.

The Sri Lankan equity market, exemplified by the S&P20 index, showcases a daily return of 0.000282, significant at a modest 10% level. The volatility dynamics, as represented by significant α_1 and β_1 coefficients, point towards an enduring impact of past market shocks. In the currency exchange arena, the USD/LKR exchange rate manifests with a subtle mean return of 0.000029. While this doesn't command statistical significance, the high volatility persistence, signified by its significant coefficients, suggests the influence of historical shocks. The $\boldsymbol{dcc_{a1}}$ coefficient stands at 0.009369, not quite breaching the walls of statistical significance. This suggests that in the short run, the markets might operate with a degree of insulation. However, the long-term paints a different picture. The significant $\boldsymbol{dcc_{b1}}$ of 0.844728, significant at the 1% level, reveals those markets having interdependencies in the longer horizon.

Across the board, India emerges with a pronounced long-term bidirectional spillover, underpinned by a formidable $\boldsymbol{dcc_{b1}}$ coefficient. Pakistan, in contrast, appears responsive to immediate market shocks but hints at potential long-term divergence. Sri Lanka, straddling between these dynamics, presents an interesting blend of short-term market insulation but evident long-term correlations. Such diverse dynamics underscore the region's heterogeneity and the intricate tapestry of market interdependencies in South Asia.

Table III: DCC-GARCH Results

Country	Variable	μ	ω	α_1	β_1	dcc_{a1}	dcc_{b1}
India	RBSESN30	0.000927***	0.000003*	0.110703***	0.878597***	0.003927**	0.991006***
	RUSDINR	-0.000017	0.000000	0.068595***	0.930370***		
Pakistan	RKSE100	0.001015***	0.000007***	0.150737***	0.809170***	0.020870**	0.211590
	RUSDPKR	0.000098	0.000000	0.056487***	0.918984***		
Sri Lanka	RSP20	0.000282*	0.000002	0.147211***	0.851789***	0.009369	0.844728***
	RUSDLKR	0.000029	0.000000	0.229784***	0.769216***		

Note 1: *** refers to 1% level of significance, ** refers to 5% level of significance , * refers to 10% level of significance

Note 2: RBSESN30 refers to the return of BSESN30 index return (India), RUSDINR refers to USD/INR exchange rate return (India), RKSE100 refers to KSE100 index return (Pakistan), RUSDPKR refers to USD/PKR exchange rate return, RSP20 refers to S&P20 returns (Sri Lanka) and RUSDLKR refers to USD/LKR exchange rate return (Sri Lanka)

Note 3: $\boldsymbol{dcc_{a1}}$ refers to the Short run persistence (Short run spillover effect) and $\boldsymbol{dcc_{b1}}$ refers to the long run persistence (long run spillover effect) ($\boldsymbol{dcc_{b1} + dcc_{b1} < 1}$)

Note 4: table III values can be substitutes to the equations presented in section 3 are as follows, for instance consider Pakistan,

Mean Equations:

For RKSE100

$R_{S,t} = 0.001015 + \epsilon_{S,t}$

For RUSDPKR:

$R_{X,t} = 0.000098 + \epsilon_{X,t}$

Variance Equations:

For RKSE100

${\sigma^2}_{S,t} = 0.000007 + 0.150737{\epsilon^2}_{S,t-1} + 0.809170{\sigma^2}_{S,t-1}$

For RUSDPKR:

${\sigma^2}_{X,t} = 0.000000 + 0.056487{\epsilon^2}_{X,t-1} + 0.918984{\sigma^2}_{X,t-1}$

DCC Specification:

$Q_t = (1 - 0020870 - 0.211590)\bar{Q} + 0.020870(q_{t-1}q_{t-1}{}') + 0.211590Q_{t-1}$

Conclusion

The financial landscapes of South Asian economies have long piqued the interest of both scholars and practitioners, largely owing to their unique economic structures, strategic geopolitical positioning, and inherent market volatilities. This research embarked on an exploration into the volatility spillover between foreign exchange and stock markets in the region, specifically focusing on the dynamics of financial instrument pricing in India, Pakistan, and Sri Lanka. By leveraging time-series data from key stock exchanges in these countries and juxtaposing these with pertinent foreign exchange metrics against the US Dollar, the study intended to unearth underlying patterns and correlations that could offer profound insights into market behaviors.

Our findings present a nuanced understanding of the market dynamics in the South Asian financial landscape. India's equity and forex markets stand out, not just for their immediate reactions to market shocks but for the persistence of these volatilities over time. The pronounced bidirectional spillover effects in the Indian context are particularly striking, signaling deeply entrenched interdependencies between the stock and forex markets. This suggests a scenario where an exogenous shock or policy alteration in one domain could ripple through, leaving a lasting footprint in the other. Such intricate interlinkages imply that the Indian markets, while robust in their own right, are entwined in a delicate balance of mutual influence.

Pakistan's market dynamics offer a contrasting narrative. While the short-term spillover effects echo the Indian landscape, revealing immediate market sensitivities, the long-term perspective offers a divergence. The potential weakening of correlation between the equity and forex markets over prolonged periods paints a picture of two markets that might be starting to carve their paths independently. This divergence is critical for investors and policymakers who need to be cognizant of the diverging forces at play in the immediate versus extended time horizons.

Sri Lanka, on the other hand, serves as a compelling case of mixed dynamics. While the short-term suggests a certain degree of insulation between the equity and forex domains, indicating potential resilience to immediate shocks, the long-term view is markedly different. The evident interdependencies in the long run, as showcased by the significant correlation coefficients, indicate a landscape where the long-term strategies and decisions in one market could have cascading effects on the other. This blend of short-term insulation and long-term interdependency highlights the multifaceted nature of the Sri Lankan financial ecosystem and the myriad forces shaping it.

In light of these findings, it becomes clear that South Asia, as a region, presents a heterogeneity of market behaviors and spillover dynamics. Each country, while sharing certain foundational similarities, exhibits unique patterns and correlations, shaped by its historical, economic, and geopolitical contexts.

The implications of short-run and long-run spillover effects in financial markets have been the subject of extensive research and debate. In the short run, spillover effects signify the immediate reaction or adjustment of markets to shocks, reflecting the efficiency and integration of markets. Such effects can potentially lead to herding behavior, where investors rapidly move in the same direction, either buying or selling assets, in response to new information or external events (Bikhchandani & Sharma, 2000). This immediate reaction can exacerbate market volatility and has implications for portfolio management, with investors needing to be wary of these sudden movements (Engle, 2002).

In contrast, long-run spillover effects represent the continued and persistent adjustment of one market due to shocks in another. Such long-term relationships can signify deeper economic linkages between markets or countries and might be attributed to factors such as trade relations, shared economic policies, or similar macroeconomic conditions (Forbes & Rigobon, 2002). Recognizing these long-run spillover effects is crucial for policymakers when designing economic policies, as the repercussions of decisions might spill over borders, affecting global financial stability (Diebold & Yilmaz, 2009).

Limitations and future research

This research, while comprehensive, is not devoid of constraints that need acknowledgment. The temporal bounds, starting from 2001 (and 2004 for Sri Lanka) up to 2023, although expansive, might omit insights from potential structural breaks or regime shifts from earlier periods. The specific choice of indices, while representative, may exclude nuances presented by other economic sectors or smaller-cap entities. Additionally, the DCC-GARCH, despite its sophistication, works within certain assumptions, particularly linear relationships, which might not capture nonlinear interdependencies between markets. Also, potential influential factors such as major global events, geopolitical tensions, and the focus on daily returns might restrict the study's ability to capture all dimensions of volatility spillover. Furthermore, the static nature of the DCC-GARCH parameters, estimated once for the entire sample, might overlook any evolving relationships over time.

Given the recognized limitations, several avenues present themselves for future inquiries. Subsequent studies can expand their scope by incorporating diverse financial indicators, like bond yields or commodities, to deliver a more rounded understanding of spillover effects. Delving into nonlinear models like the Threshold GARCH or incorporating vital macroeconomic indicators could potentially provide a richer contextual backdrop. Moreover, the granularity provided by high-frequency data analysis could unmask intra-day volatility dynamics. To enhance regional understanding, including more South Asian nations might offer a broader panorama of inter-country spillovers. Recognizing the significant influence of global events, future research could focus on structural break analysis to gain a more nuanced perspective. Lastly, with technological advancements, employing deep learning techniques such as recurrent neural networks might pave the way for innovative analyses and predictions on volatility spillovers.

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Appendices

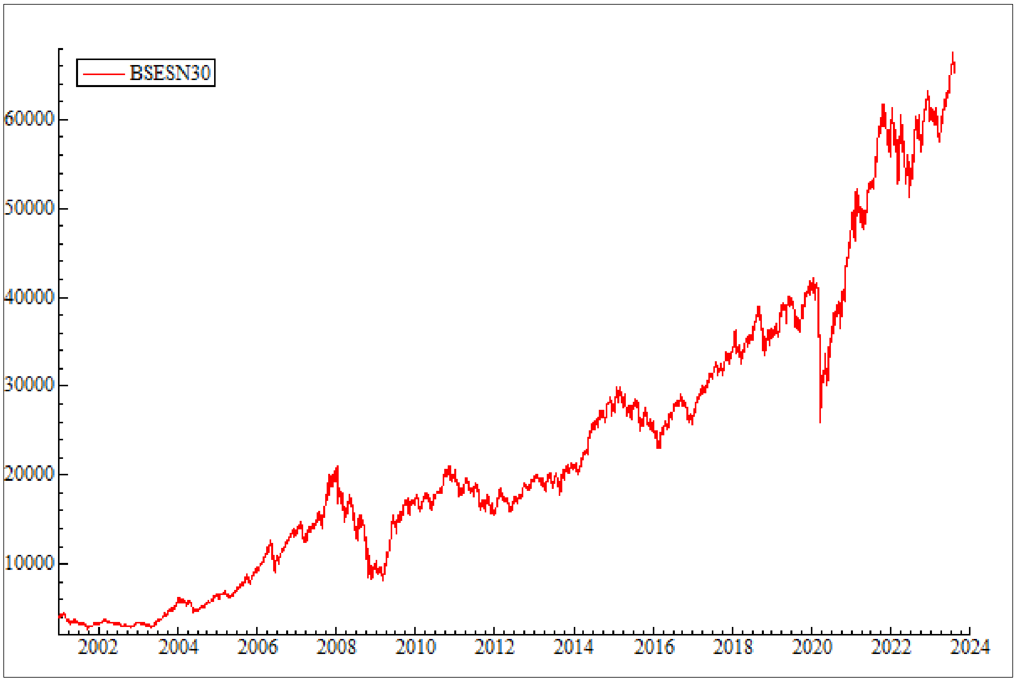

Figure I: India; BSESN30 Index

Figure II: India; USD/INR Exchange Rate

Figure III: Pakistan; KSE100 Index

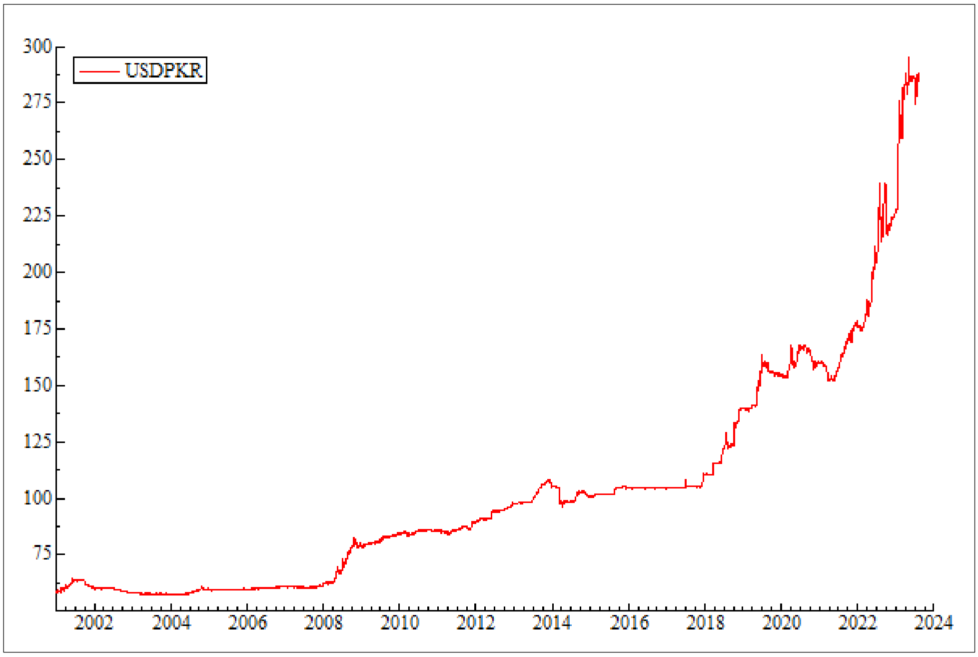

Figure IV: Pakistan; USD/PKR Exchange Rate

Figure V: Sri Lanka; S&P 20 Index

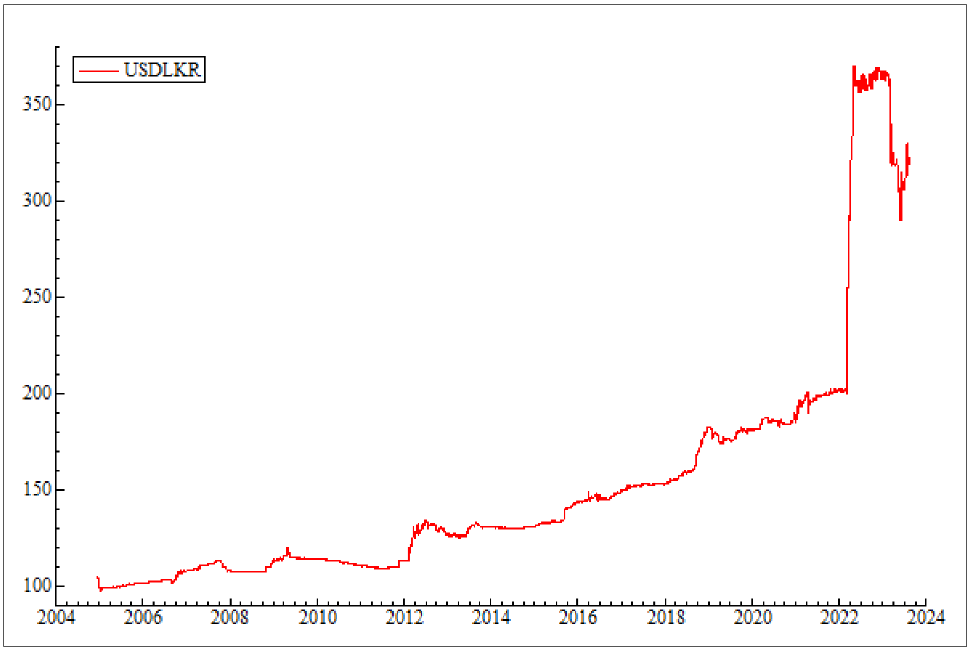

Figure VI: Sri Lanka USD/LKR Exchange Rate

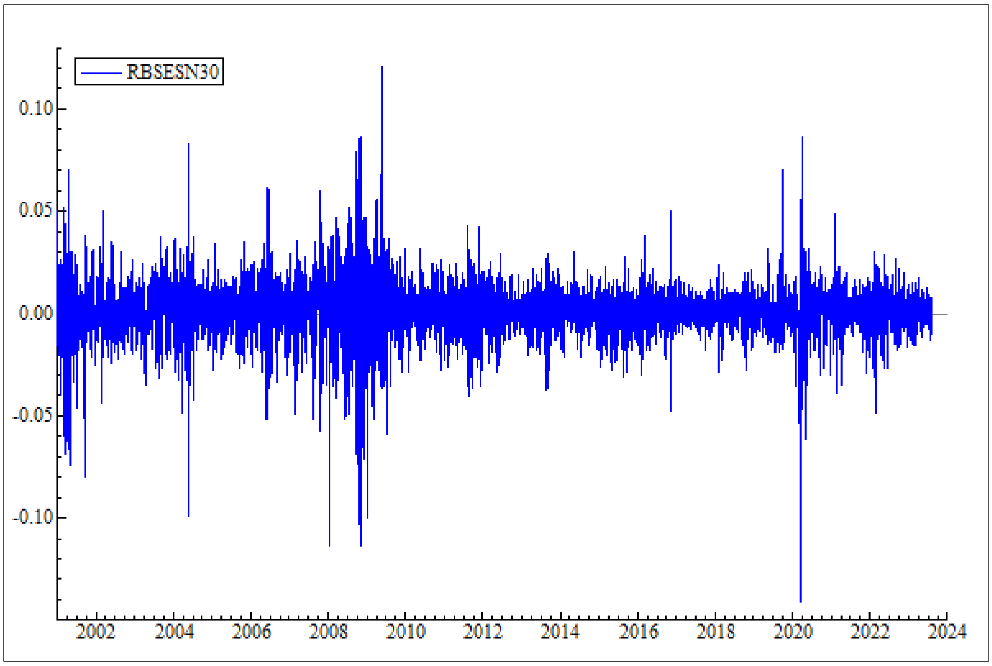

Figure VII: India; BSESN30 Index Return

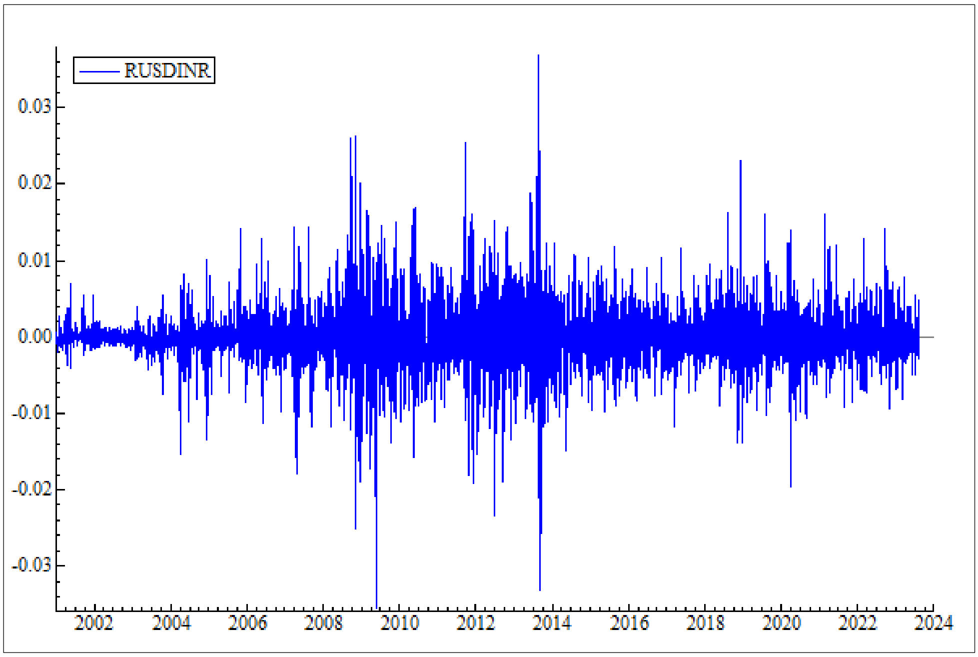

Figure VIII: India; USD/INR Exchange Rate Return

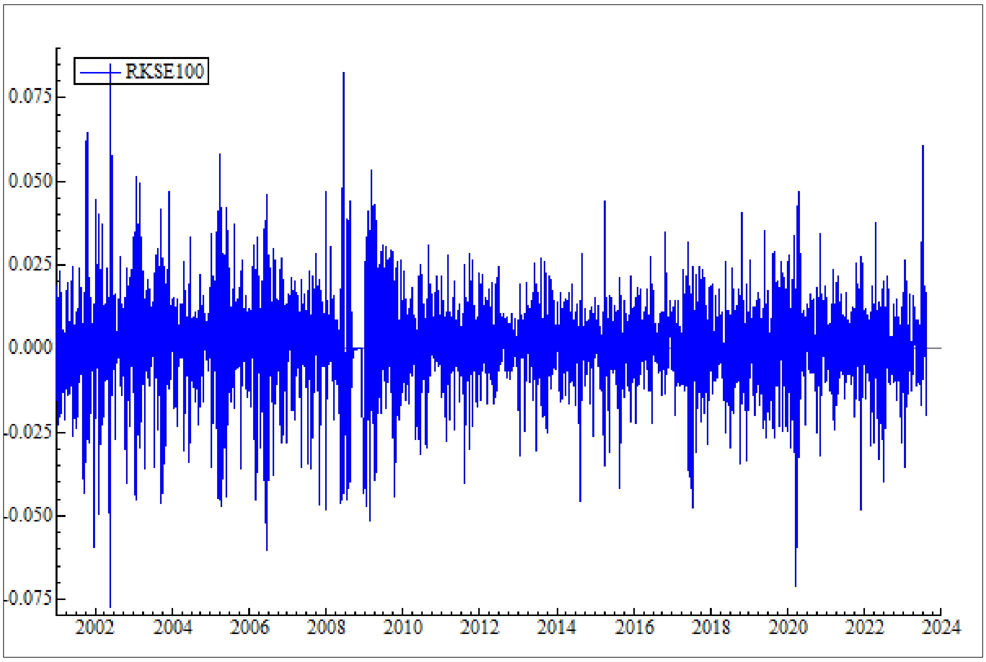

Figure IX: Pakistan; KSE100 Index Return

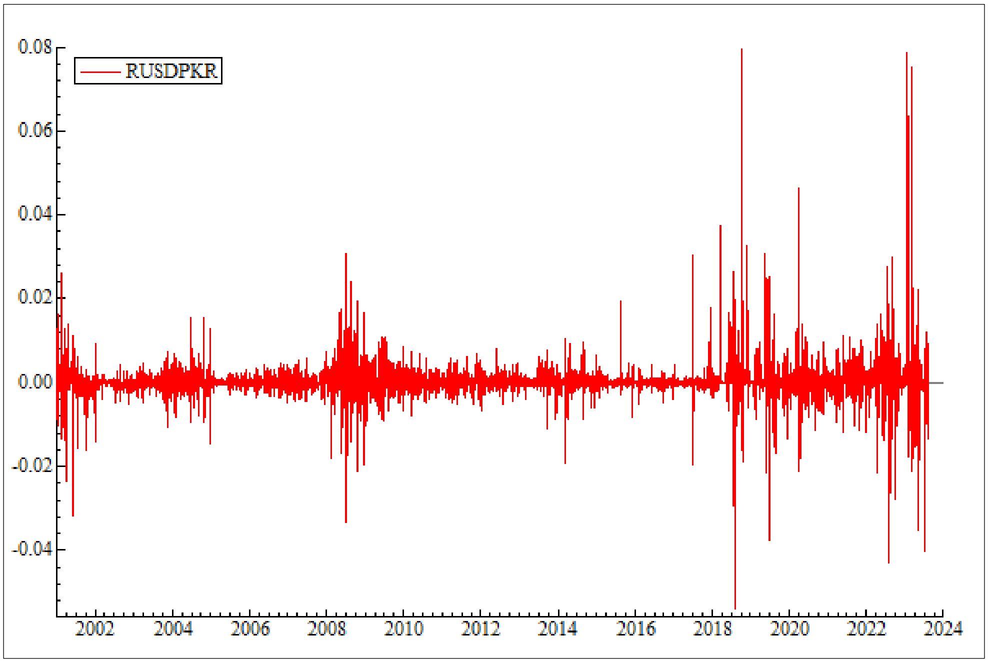

Figure X: Pakistan; USD/PKR Exchange Rate Return

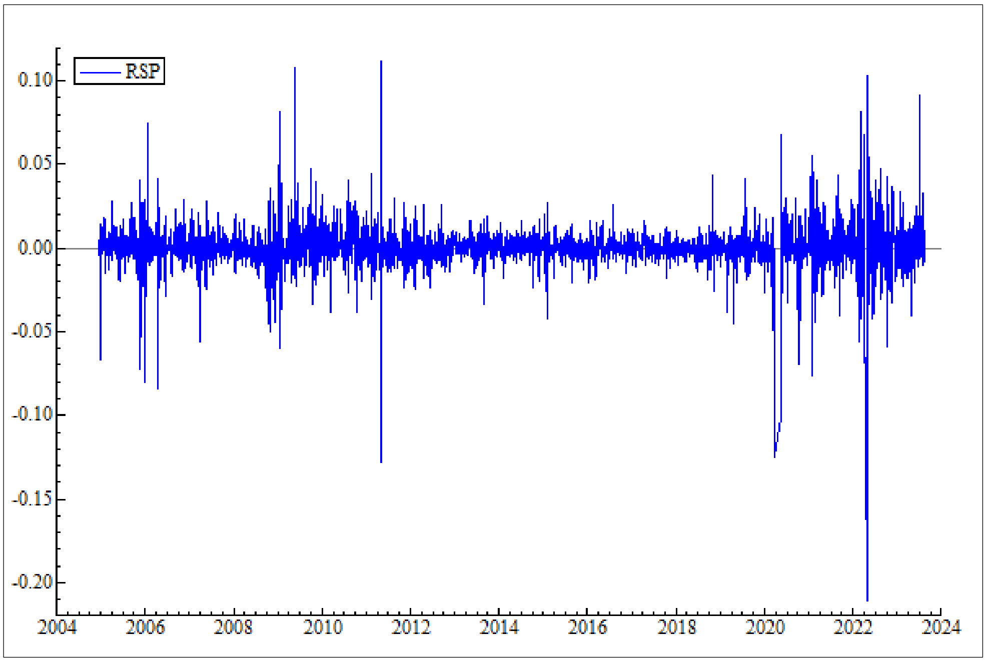

Figure XI: Sri Lanka; S&P 20 Index Return

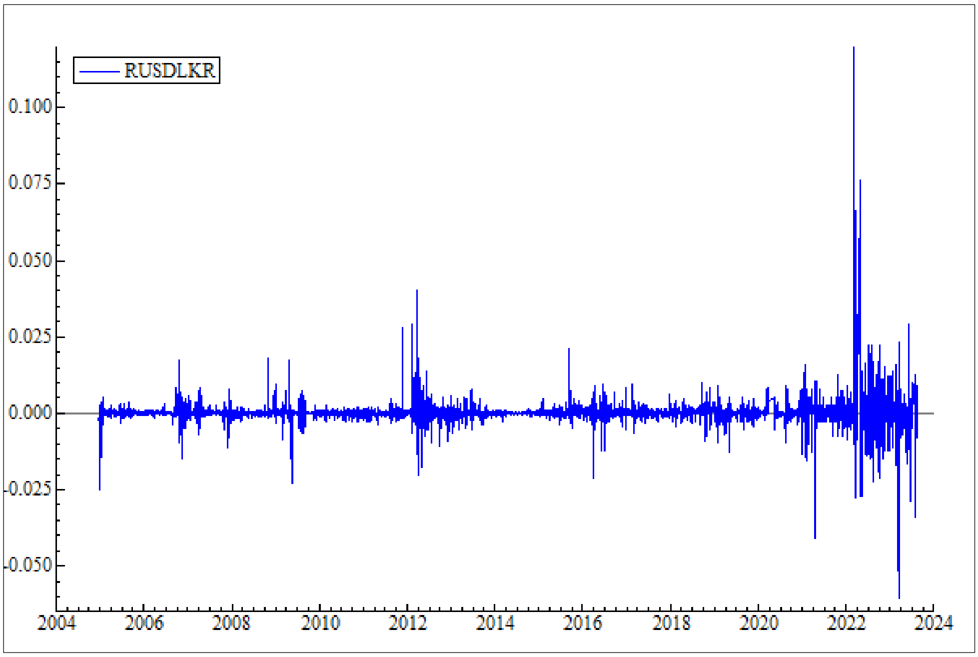

Figure XII: Sri Lanka USD/LKR Exchange Rate Return

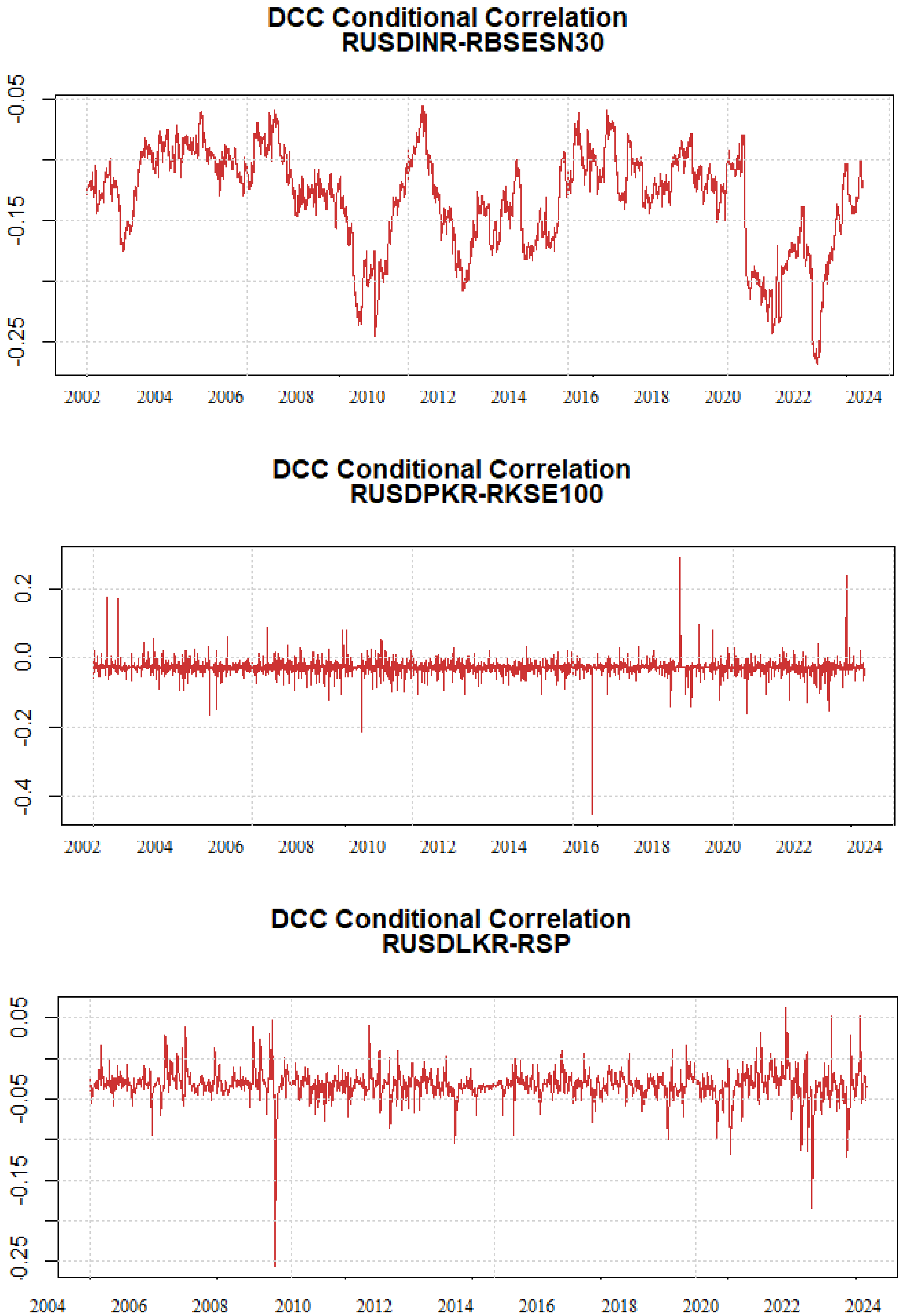

Figure XIII: DCC Conditional Correlations