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Multiple Behavioral Conditions of the Forward Exchange Rates and Stock Market Return in the South Asian Stock Markets During COVID-19: A Novel MT-QARDL Approach

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Abstract: This study examines the short- and long-term effects of multiple quantiles of forward exchange rate premiums (FERPs) and COVID-19 cases on the quantiles of stock market returns (SMRs). We extend the Quantile Autoregressive Distributive Lag (QARDL) model, and the Multiple Threshold Non-linear Autoregressive Distributive Lag (NARDL) model propose a new Multiple Threshold Quantile Autoregressive Distributive Lag (MT-QARDL) approach. Unlike MT-NARDL, QARDL, and NARDL, the MT-QARDL model, which integrates the MT-NARDL model and the quantile regression methodology, captures both short- and long-term locational and sign-based asymmetries. For instance, at lower quantiles for Indian and Sri Lankan SMRs, bearish FERP exerts a positive influence, while bullish FERP has a negative effect during COVID-19. Conversely, bullish FERP negatively affects lower quantiles of SMRs of Bangladesh, India, and Sri Lanka, whereas bearish FERP either yields an opposite effect or remain statistically insignificant during COVID-19. The findings underscore long-term sign-based asymmetries due to the differential bearish and bullish FERP impact during COVID-19. However, in the long term, location-based asymmetries also existed as bullish FERP negative influence the SMRs of India, Bangladesh and Sri Lanka at higher quantiles but SMRs at lower quantiles insignificantly respond to the bullish FERP fluctuations during COVID-19.

Keywords: multiple threshold quantile autoregressive distributive lag model (MT-QARDL); BDS test of non-linearity; forward exchange rate premium (FERP); stock market returns (SMRs); COVID-19 cases; South Asia

1. Introduction

The local currency appreciation leads to higher costs for exports, diminishing international competitiveness, and potentially decreasing future revenues and stock returns for firms reliant on exports [1,2]. In contrast, currency depreciation can enhance export performance by lowering product prices in foreign markets, thereby increasing revenues and positively influencing stock returns[3,4]. COVID-19 has also amplified exchange rate risk for South Asian exporters and importers due to trade restrictions and inflation, driving up interest rates [5]. Kassouri and Altıntaş [6] note that depreciating and appreciating exchange rates can asymmetrically influence the stock market. Exchange rate movements affect market sentiment, with depreciations often signaling economic instability and increasing perceived risk [3]. This heightened risk perception generally exerts a stronger impact on stock returns than the positive sentiment from currency appreciations, thereby strengthening the stance of asymmetrical association between forex and stock returns. In lower stock returns' quantiles, negative sentiment may amplify the effects of currency fluctuations due to panic selling or reduced confidence. Conversely, in higher quantiles, positive sentiment may dampen the adverse effects of currency fluctuations, with investors viewing a strong currency as an economic strength signal, potentially boosting stock prices. The prospect theory suggests investors react more strongly to losses than gains, known as loss aversion [7,8]. Depreciating exchange rates heighten perceived risks, prompting negative reactions as investors sell off stocks to avoid losses. In contrast, currency appreciation elicits a weaker positive response, having a more subdued impact on stock returns and thereby leading to the asymmetrical response of stock returns.

Additionally, the majority of current research on investor sentiment and exchange rate returns has primarily concentrated on mean-to-mean relationships, overlooking the possibility of non-linear tail dependence between these variables [9]. This non-linearity is particularly relevant during economic downturns [10–12] such as COVID-19 [13], as stock return responses to exchange rate fluctuations may vary markedly across quantiles [14], indicating distinct market sentiments and varying degrees of economic resilience. Therefore, multiple quantiles of forward exchange rate premium (FERP) may have an asymmetrical impact on the multiple quantiles of the stock market returns (SMRs).

The COVID-19 pandemic has caused a liquidity crisis in stock markets and a decline in local currencies [15] due to volatile oil prices and inflation [16]. The World Bank's "South Asian Economic Focus" report states that COVID-19 has caused unprecedented economic disruptions in South Asia [17]. The combined effects of the pandemic and rising inflation from the Russia–Ukraine conflict have intensified debt challenges and depleted foreign reserves in Sri Lanka and Pakistan. Sri Lanka is projected to experience a 9.2% contraction in real output growth in 2022, followed by a further 4.2% decline in 2023. Increased commodity prices have also raised inflation in India and reduced Pakistan's reserves, harming its global competitiveness. The pandemic has sharply decreased equity returns in the region, with India seeing a 17.74% drop [18]. Rahman et al. [19] explored the symmetrical impact of COVID-19 on regional equity returns using the panel-based causality method by Dumitrescu and Hurlin [20], and the findings suggested the short-term adverse effect of COVID-19 news. In contrast, Ashraf [21] also utilized the symmetrical econometric approach and found that new COVID-19 cases affect stock indexes more than death toll fluctuations. Furthermore, COVID-19 has depreciated exchange rates, prompting traders to enter forward exchange rate agreements [15]. However, research on the asymmetric influence of forward exchange rate premiums (FERPs) on South Asian stock market returns (SMRs) during COVID-19 is lacking. Several studies also suggested the negative correlation between the health crisis and stock indices, including Baek et al. [22] and Suleman et al. [13]. Ftiti et al. [23] also found that COVID-19 cases asymmetrically influence stock returns by using the daily time series data from 2019 to 2020. Baek et al. [22] used a regime-switching autoregressive model to show that negative COVID-19 news has a more significant adverse effect on equity returns than positive news. Topcu and Gulal [24] found that the crisis impacted stock markets in developing Asian regions more severely than in developed areas. Nonetheless, government stimulus [24], vaccination efforts [25], and firm-specific factors like corporate social responsibility [26] helped mitigate the pandemic's negative effects. Consequently, South Asian equity returns throughout the COVID-19 pandemic may display both downside and upside fluctuations [3], influenced by the negative consequences of the crisis alongside the compensatory measures enacted through stimulus packages by governments.

This furthermore motivates us to examine the short- and long-term asymmetrical impact of multiple (bearish, bullish, and moderate) quantiles of forward exchange rate premium (FERP) and COVID-19 cases on the multiple quantiles of stock market returns (SMRs) as a ***foremost*** research objective. The bearish, moderate, and bullish conditions of equity returns are represented by lower-, median-, and higher-order quantiles [12,27,28]. In order to explore the impact of multiple quantiles of FERP on the multiple SMRs' quantiles for different investment horizons (short and long term), we have integrated the MT-NARDL model by Pal and Mitra [29–31] nd quantile regression by Koenker and Hallock [32] into the novel MT-QARDL approach. Previously, Sim and Zhou [33] combined the quantile regression by Koenker and Hallock [32] and the localized OLS approach into the QQ regression framework. Furthermore, Cho et al. [34] ntegrated the ARDL by Pesaran et al. [35] and the quantile regression approach by Koenker and Xiao [36] into the QARDL framework. However, the QARDL approach can only examine the location-based asymmetries due to the differential response of SMRs at varied quantiles to the mean values of the FERP, whereas the MT-NARDL approach can only examine the sign-based asymmetries due to the differential impact of FERP at different quantiles on the mean values of the SMRs. The recently developed MT-QARDL model allows for an analysis of impact of the multiple quantiles of FERP on the SMRs' multiple quantiles over both the short- and long-term investment periods, thereby capturing both short- and long-term sign- and location-based asymmetries.

This research article offers contributions to the existing body of literature in several key ways.

Firstly, this is the first research article to explore the impact of multiple quantiles of FERP and COVID-19 cases on the multiple quantiles of SMRs under different investment horizons (short and long term) by using the novel MT-QARDL approach. Table A1 shows that while many studies report significant stock market responses to spot currency rates [37–48], others find no such link [49]. Recent research largely overlooks "sign"- and "location"-based asymmetries in stock returns to currency shifts due to reliance on linear models [37,38,46]. This linearity can be misleading, as it misses hidden co-integration [29–31]. Cho et al. [50] argue that linear models may miss hidden co-integration. Only a few studies adopt asymmetrical methods, like TYP-VAR [45], quantile regression [43], panel-based NARDL [42], QARDL [14], and non-linear Granger causality [40], which are limited in exploring extreme quantile connectedness and "sign"- as well as "location"-based asymmetries between FERP and SMRs across varying time horizons. Moreover, all of these studies are outside of the context of the South Asian region (see Table A1). The term "sign"-based asymmetries estimated through the NARDL approach by Shin et al. [51] and the MT-NARDL approach by Pal and Mitra [29–31] assumes the non-linear association between the variables due to the different impact of positive and negative shocks in the independent variable on the dependent variable. In contrast, the QARDL approach by Cho et al. [34] highlights the "location"-based asymmetries due to the asymmetric responses of the dependent variable at varied quantiles to the fluctuations in the independent variable. However, the newly developed MT-QARDL approach has the capability to explore both the "sign"- and "location"-based asymmetries due to the asymmetrical effects of multiple quantiles (bearish, moderate, and bullish) of FERP on the quantile of SMRs as well as the differential response of SMRs at varied quantile levels to the bearish or bullish or moderate FERP. (For the said purpose, we merge the quantile regression methodology introduced by Koenker and Hallock [32] with the Multiple Threshold-based Non-linear Autoregressive Distributive Lag model (MT-NARDL) framework proposed by Pal and Mitra [29–31] to formulate an innovative Multiple Threshold-based Quantile domain Autoregressive Distributive Lag model approach (MT-QARDL). Therefore, the MT-QARDL approach can explore the effect of multiple quantiles of FERP and COVID-19 cases on the multiple quantiles of SMRs during COVID-19).

Secondly, our study also differs from the existing research articles by focusing on the impact of forward exchange rate premiums (FERPs) on stock returns instead of spot forex market rates [41–47,52,53] and categorizing FERPs and COVID-19 cases into distinct thresholds (bearish, bullish, and moderate).

The linear ARDL model proposed by Pesaran et al. [35] does not adequately account for asymmetric responses to changes in cumulative regressors, as highlighted by Shin et al [51]. Additionally, the conventional ARDL and NARDL models introduced by Shin et al. [51] fail to consider latent co-integration across quantiles. Cho et al. [34] address this gap by merging the ARDL approach with the quantile regression model developed by Koenker and Hallock [32], resulting in the QARDL framework, which facilitates the analysis of equity return responses across different quantiles. Pal and Mitra [29–31] enhance the ARDL methodology by breaking down regressors into fixed quantiles to evaluate their asymmetric effects on the mean dependent variable. From an econometric standpoint, the symmetric relationships between FERP and SMRs introduce complexities that complicate the application of standard techniques (e.g., ARDL, NARDL, and QARDL) for estimating their quantile-dependent interactions over both short- and long-term time horizons. Equity returns may respond differently to FERP shocks based on market conditions, with larger shocks affecting equity markets differently than smaller ones, leading to asymmetric responses to lower FERP shocks over time. Consequently, the impact of FERP on SMRs varies depending on the state of stock returns and the nature of the shocks. This study uniquely explores the short- and long-term extreme quantile connections among FERP, COVID-19 cases, and stock market returns, revealing asymmetric effects influenced by (1) stock market quantiles, (2) variations in bearish, bullish, and moderate quantiles of COVID-19 cases and FERP, and (3) different short- and long-term time horizons.

The article is organized as follows: Section 2 reviews the literature on the relationship between stocks and currencies. Sections 3 and 4 discuss the econometric methods employed to estimate the MT-QARDL framework and the information about the data, respectively. Section 5 presents the findings and their implications for exporters, importers, and shareholders, and Section 6 concludes the paper.

2. Literature Review

The two principal theoretical frameworks—the "stock-oriented" model by Branson [54] and the "flow-oriented" model by Dornbusch and Fischer [2]—offer insight into the dynamics between equity and foreign exchange (forex) returns [55]. The flow-oriented model posits that currency depreciation boosts exports and improves the trade balance by enhancing the competitiveness of domestic goods [2]. This, in turn, stimulates local production, sales, and, ultimately, stock prices [4]. However, many domestically traded companies rely on imported inputs and products. As a result, while currency depreciation may benefit exporters, it can negatively impact the profitability of importers [56]. The overall effect on the economies' stock market index thus depends on the relative proportions of importing versus exporting firms. The J-curve phenomenon further introduces a temporal delay in the impact of exchange rate fluctuations on the current account balance, complicating the timing of these effects on stock prices across nations. In response, some researchers have proposed a "Micro-based Flow-oriented model", emphasizing micro-level mechanisms to clarify the causal links between exchange rates and stock prices [44]. This model, refined by Evans and Lyons [57], highlights the role of financial investors who adjust portfolio allocations between domestic and international assets, suggesting that "order flow" from electronic brokerage platforms correlates with immediate or slightly delayed fluctuations in exchange rates influenced by stock prices [44].

In examining BRICS economies, Dahir et al. [58] utilized wavelet techniques to identify direct linkages between exchange rate fluctuations and stock indices in Russia and Brazil while noting inverse, time-varying linkages in India. Conversely, Delgado et al. [59] found a symmetrical inverse relationship between fluctuations in Mexican stock indices and exchange rate uncertainties using a linear VAR model. In contrast, Roubaud and Arouri [60] identified a non-linear relationship between these variables. Similarly, Blau [61] demonstrated that currency fluctuations induce volatility in the stock prices of foreign companies trading on U.S. financial markets. Zhu et al. [43] explored the effects of exchange rates and oil prices on stock market returns in BRICS nations from 2009 to 2020, employing threshold rolling window quantile regression and wavelet decomposition to capture time–frequency effects across various scales. Their findings reveal asymmetrical relationships between foreign currency and equity markets and illustrate how macroeconomic volatility magnifies the impact of fluctuating oil and exchange rates on stock market behavior. Wen and Chang [62] further demonstrate that the relationships between exchange rates, oil prices, and stock prices differ across quantiles through employing a Bayesian Multivariate Quantile-on-Quantile GARCH approach.

Chen et al. [63] examined the influence of oil price movements and exchange rate fluctuations on Chinese stock market indices through conditional value-at-risk (CoVaR) metrics. They found that these indices are particularly sensitive to exchange rate volatility during China's reform period, whereas outside this period, they respond more to oil price shifts than to exchange rate fluctuations. Sokhanvar et al. [55] used ARDL and Granger causality analyses to examine the dynamic relationship between exchange rates and equity returns in developed economies operating as exporters or importers. Their study revealed that, across both pre- and post-Russian–Ukraine conflict periods, causality predominantly flows from stock market indices to currency rates, with no significant distinction between commodity-importing and -exporting nations. In a related analysis, Xiong et al. [53] identified adverse correlation patterns between stock returns and exchange rates. Employing the GARCH-MIDAS-X model to incorporate structural discontinuities, their study also examined the moderating effects of macroeconomic fundamentals, geopolitical uncertainty, and economic instability on these dynamic associations. The findings further suggest that portfolios combining stocks and exchange rates serve as effective risk mitigation strategies, especially in the presence of structural breaks. Xie et al. [40] investigated the heterogeneity and non-linearity in forex stock market returns using bootstrap-based symmetric and non-linear Granger causality techniques. Their findings indicate that exchange rate movements significantly impact stock markets while the reverse effect remains modest. Similarly, Kassouri and Altıntaş [6] argued that conventional econometric approaches fail to capture the asymmetrical co-integration between the Turkish Lira and stock market indices. Additionally, Salisu and Vo [48] utilized panel data methodologies to assess how stock returns respond differently to currency changes in high- and low-interest-rate environments, highlighting the asymmetrical effects of currency fluctuations on stock price volatility.

Khan et al. [46] employed a simulation-based linear autoregressive distributed lag model to demonstrate that the stock market's response to exchange rate fluctuations occurs indirectly and is positively correlated with changes in gold and oil prices. Salisu et al. [42] applied the Panel-based Non-Linear Distributed Lag (PNARDL) method to analyze the stock market's reaction to exchange rate changes, accounting for asymmetries and heterogeneous effects. Their findings show that exchange rate increases positively influence stock prices, while decreases have a negative impact, with benefits generally outweighing drawbacks. This suggests that U.S. equity returns vary substantially in response to positive and negative exchange rate shocks, signaling caution for investors during significant fluctuations. Xu et al. [64] examined the robustness of asymmetrical estimation methods to assess how exchange rate fluctuations moderate the relationship between stock market indices and oil price volatility. Their findings indicate that this moderating effect depends on varying currency growth rates. Huang et al. [45] utilized a time-varying parameter vector autoregressive model to explore the impact of currency fluctuations on stock market movements in BRICS economies, revealing both commonalities and distinctions in exchange rate effects on financial markets. Additionally, Reboredo et al. [65] analyzed structural dependencies between forex and financial market returns using a copula approach, calculating conditional value-at-risk (CoVaR) alongside upward and downward value-at-risk (VaR) metrics.

Previous asymmetric methods, such as the Quantile-on-Quantile (QQ) regression model by Sim and Zhou [33], confined to single investment horizons, inadequately capture extreme tail shocks' effects on forward currency rates, COVID-19 cases, and varying equity returns (upper, lower, medium quantiles) in the short and long term. The econometric techniques like the QQ model [33], NARDL approach [51], QARDL model [34], and copula-based models [65] fail to address both sign- and location-based asymmetries in multivariate regressions across multiple investment horizons (short and long term). The MT-QARDL framework addresses these gaps, analyzing extreme tail dependencies of stock market returns (SMRs) on forward exchange rate premiums (FERPs) and COVID-19 cases at multiple quantiles within multivariate regression and multiple investment horizons (short and long term).

3. Research Methodology: Toward a New Multiple Threshold Quantile Autoregressive Distributive Lag (MT-QARDL) Framework

Building on stock- and flow-oriented frameworks, prior research has focused on the linear responses of average equity returns to mean exchange rate values [66,67]. However, Nusair and Olson [68] and Suleman et al. [3] note that financial market returns respond differently to positive and negative currency shocks due to dependence and non-identically distributed residuals in financial time series. Unlike the NARDL framework by [51], our study decomposes FERP and COVID-19 cases into three thresholds (bearish, bullish, and moderate quantiles). We combine the quantile regression methodology of [32] with the MT-NARDL model by [29–31] to develop the MT-QARDL approach. This expands the ARDL (Equation (1)), NARDL (Equation (2)), and QARDL (Equations (5) and (6)) methodologies into the MT-QARDL framework (Equation (7)). This framework allows us to regress equity returns across various quantiles against the different quantiles of FERP and COVID-19 cases in both short- and long-term scenarios.

The linear form of the ARDL model by Pesaran et al. [35] is presented below:

$$\Delta lnSMI_t = \alpha_1 lnSMI_{t-1} + \beta_1 lnFERP_{t-1} + \beta_2 lnCovid_{19}\ cases_{t-1} + \sum_{i=1}^{p-1}\gamma_{1i}\Delta lnSMI_{t-i} + \sum_{i=1}^{q-1}\gamma_{2i}\Delta lnFERP_{t-i} + \sum_{i=1}^{q-1}\gamma_{3i}\Delta lnCovid_{19}\ cases_{t-i} + \varepsilon_t \quad (1)$$

In Equation (1), the dependent variable ($\Delta lnSMI_t$) represents the logarithmic changes in South Asian stock market indices. The term ($\alpha_1 lnSMI_{t-1}$) indicates the impact of the previous day's indices, while $\beta_1 lnFERP_{t-1}$ and $\beta_2 lnCovid_{19}\ cases_{t-1}$ capture the long-term effects of the forward exchange rate premium (FERP) and COVID-19 cases. Short-term effects are included through γ_1, γ_2, and γ_3.

Equation (1) shows the linear relationship between the regressors and the dependent variable, with specific lag orders determined by the minimum "Akaike Information Criteria" and "Schwarz Information Criteria" (3). To test for long-run co-integration, we can use the Wald test for joint significance of long-run coefficients or the error correction term ($\alpha_1 lnSMI_{t-1}$). A negative α_1 with significance below 0.05 rejects the null hypothesis of no co-integration (H_0: $\alpha_1 = \beta_1 = \beta_2 = 0$). Shin et al. [51] extend the ARDL approach by decomposing the regressors in Equation (1) into cumulative sums of positive and negative shocks. The NARDL model by [63] is provided below in Equation (2).

$$\Delta lnSMI_t = \alpha_0 + \beta_1 lnSMI_{t-1} + {\beta_2}^{+} lnFERP^{+}{}_{t-1} + \beta_3^{-} lnFERP^{-}{}_{t-1} + {\beta_4}^{+} lnCovid_{19}Cases^{+}{}_{t-1} + \beta_5^{-} lnCovid_{19}Cases^{-}{}_{t-1} + \sum_{i=1}^{p-1}\gamma_{1i}\Delta lnSMI_{t-i} + \sum_{i=1}^{q-1}{\gamma_{2i}}^{+}\Delta lnFERP^{+}{}_{t-i} + \sum_{i=1}^{q-1}{\gamma_{3i}}^{-}\Delta lnFERP^{-}{}_{t-i} + \sum_{i=1}^{q-1}{\gamma_{4i}}^{+}\Delta lnCovid_{19}Cases^{+}{}_{t-i} + \sum_{i=1}^{q-1}{\gamma_{5i}}^{-}\Delta lnCovid_{19}Cases^{-}{}_{t-i} + \varepsilon_t \quad (2)$$

In Equation (2), $\Delta lnSMI_t$ represents the first difference of the South Asian stock market indices. $\beta_1 lnSMI_{t-1}$ captures the influence of prior-day stock indices. The terms ${\beta_2}^{+} lnFERP^{+}{}_{t-1}$ and ${\beta_3}^{-} lnFERP^{-}{}_{t-1}$ indicate the long-term impacts of positive and negative FERP shocks, while ${\beta_4}^{+} lnCovid_{19}Cases^{+}{}_{t-1}$ and ${\beta_5}^{-} lnCovid_{19}Cases^{-}{}_{t-1}$ represent long-term effects of positive and negative COVID-19 shocks. However, ${\gamma_{2i}}^{+}, {\gamma_{3i}}^{-}$ and ${\gamma_{4i}}^{+}, {\gamma_{5i}}^{-}$ account for short-term impacts of FERP and COVID-19 cases on the SMR ($\Delta lnSMI_t$). Here, p and q are the lag orders, and ε_t is the error term. The NARDL model addresses sign-based asymmetry, allowing for short-run (${\gamma_{2i}}^{+} \neq {\gamma_{3i}}^{-}$) and long-run (${\beta_{2i}}^{+} \neq {\beta_{3i}}^{-}$) non-linear impact of FERP on the stock returns, assessed via Wald test statistics. The alternative hypothesis for the long-run asymmetrical co-integration ($H_1: \beta_1 \neq {\beta_2}^{+} \neq {\beta_3}^{-} \neq {\beta_4}^{+} \neq {\beta_5}^{-} \neq 0$) is confirmed if F-statistics exceed critical values. However, ARDL and NARDL cannot capture "location"-based asymmetries in stock market responses, addressed by the QARDL model of [34], explained below.

For the QARDL approach, the symmetrical ARDL modeling approach is transformed by applying Equation (1) on the quantile regression settings of [32] and [36], as below:

$$Q_{\Delta SMI_t} = \beta_0 + \sum_{i=1}^{p} \theta_{1i} SMI_{t-i} + \sum_{i=1}^{q} \theta_{2i} FERP_{t-i} + \sum_{i=1}^{q} \theta_{3i} Covid_{19}cases_{t-i} + \varepsilon_t \quad (3)$$

In the above Equation (3), the dependent variable is the multiple quantiles of the stock market indices ($Q_{\Delta SMI_t}$) with 1st difference operator (Δ). However, $\theta_{1i} SMI_{t-i}$ and $\theta_{2i} FERP_{t-i}$ are the 1-day-previous value of the stock market indices and forward exchange rate premium (FERP) values of the individual South Asian economies, respectively. Moreover, $\theta_{3i} Covid_{19}cases_{t-i} and\ \varepsilon_t$ are represented by the one-day-prior values of the COVID-19 cases and error term, respectively.

Furthermore, Cho et al. [34] apply Equation (3) on the quantile settings, and Equation (3) can be transformed as follows:

$$Q_{\Delta SMI_t}(\tau) = \beta(\tau) + \sum_{i=1}^{p} \theta_{1i}(\tau) SMI_{t-i} + \sum_{i=1}^{q} \theta_{2i}(\tau) FERP_{t-i} + \sum_{i=1}^{q} \theta_{3i}(\tau) Covid_{19}cases_{t-i} + \varepsilon_t(\tau) \quad (4)$$

In Equation (4), $\varepsilon_t(\tau)$ is equal to the $SMI_{t-i} - Q_{\Delta SMI_t}(\tau / F_{t-i})$, and $Q_{\Delta SMI_t}(\tau / F_{t-i})$ is equal to the conditional distribution of ΔSMI_{t-i} at τth quantile on the designated information prescribed by F_{t-i} [69]. Therefore, Equation (4) can be re-written as

$$Q_{\Delta SMI_t} = \beta + \rho SMI_{t-1} + \theta_{FERP} FERP_{t-1} + \theta_{covid_{19}cases} Covid_{19}cases_{t-1} + \sum_{i=1}^{p} \delta_i \Delta SMI_{t-i} + \sum_{i=1}^{q} \varphi_i \Delta FERP_{t-i} + \sum_{i=1}^{q} \omega_i \Delta Covid_{19}cases_{t-i} + \nu_t(\tau). \quad (5)$$

In Equation (5), there may be instances of contemporaneous correlation between v and $\Delta FERP$ or v and $\Delta Covid_{19}cases_{t-1}$. Therefore, in order to avoid the correlation, the projection of v is added to the $\Delta Covid_{19}cases_{t-1}$ and $\Delta FERP$ by using the $\nu_t = \gamma \Delta FERP_t + \gamma \Delta Covid_{19}cases_{t-1} + \varepsilon_t$. The QARD-ECM model is provided by Equation (6) below:

$$Q_{\Delta SMI_t}(\tau) = \beta(\tau) + \rho(\tau)(SMI_{t-1} - \theta_{FERP}(\tau) FERP_{t-1} - \theta_{covid_{19}cases}(\tau) Covid_{19}cases_{t-1}) + \sum_{i=1}^{p} \delta_i(\tau) \Delta SMI_{t-i} + \sum_{i=1}^{q} \varphi_i(\tau) \Delta FERP_{t-i} + \sum_{i=1}^{q} \omega_i(\tau) \Delta Covid_{19}cases_{t-i} + \nu_t(\tau). \quad (6)$$

Equations (5) and (6) present the traditional QARDL model proposed by [34]. In the above equations, $Q_{\Delta SMI_t}(\tau)$ is the dependent variable explaining the multiple quantiles of the stock market indices with 1st difference operator (Δ). However, ρSMI_{t-1} is the error correction mechanism (ECM) embedded within the QARDL approach explaining the impact of the one-day-prior value of the stock market indices of the South Asian economies on the stock market returns. Moreover, $\theta_{FERP}(\tau) FERP_{t-1}$ represents the one-day-prior values of the forward exchange rate premiums and is incorporated in Equations (5) and (6) to explain the long-term response of stock returns at multiple quantiles to the fluctuations in forward exchange rate premium. Moreover, $\theta_{covid_{19}cases}(\tau) Covid_{19}cases_{t-1}$ explains the impact of the one-day-prior value of the COVID-19 cases on the multiple quantiles of stock returns of individual South Asian economy in the long term. Furthermore, $\varphi(\tau) \Delta FERP_{t-i}$ and $\omega(\tau) \Delta Covid_{19}cases_{t-i}$ are incorporated in the QARDL approach in order to explain the short-term impact of FERP and COVID-19 cases on the stock returns of the South Asian economies. Furthermore, $\delta(\tau) \Delta SMI_{t-i}$ explains the one-day-previous stock market returns on the current dynamics.

However, one of the drawbacks of the traditional QARDL model is its incapacity to examine the response of the stock market behavior at multiple quantiles to the bullish, moderate, and bearish behavior (quantiles) of the FERP. [29–31] examine whether the dependent variable may respond asymmetrically to the multiple behavioral conditions of regressors and purposed the MT-NARDL framework. However, the MT-NARDL model also shows several deficiencies in examining the influence of regressors at multiple behavioral points (quantiles) to the multiple quantiles of the conditional distribution of the regressand. This is generally because of the incapability of the model to capture the hidden asymmetries arising due to the differential response of the regressand at different behavioral points (quantiles) to the higher, median, and lower quantiles of the regressors. Therefore, to fill this gap, we have combined the MT-NARDL approach by [29–31] and the quantile regression model by [32]. We decomposed the FERP and COVID-19 cases into multiple thresholds in the following way:

$$FERP\xi_{1,t} = \sum_{i=1}^{t} \Delta FERP\xi_{1,i} = \sum_{i=1}^{t} \Delta \mathrm{FERP}_i I\ \{\Delta FERP_i \leq \tau 30\}. \quad (6.1)$$

$$FERP\xi_{2,t} = \sum_{i=1}^{t} \Delta FERP\xi_{2,i} = \sum_{i=1}^{t} \Delta \mathrm{FERP}_i I\ \{\Delta FERP_i \geq \tau 70\}. \quad (6.2)$$

$$FERP\xi_{3,t} = \sum_{i=1}^{t} \Delta FERP\xi_{3,i} = \sum_{i=1}^{t} \Delta \mathrm{FERP}_i I\ \{\tau 30 \leq \Delta FERP_i \leq \tau 70\}. \quad (6.3)$$

The COVID-19 confirmed cases are broken down into multiple thresholds of bearish, bullish, and normal behavioral conditions in the following way:

$$Covid_{19}cases\beta_{1,t} = \sum_{i=1}^{t} \Delta \mathrm{Covid}_{19}cases\beta_{1,i} = \sum_{i=1}^{t} \Delta \mathrm{Covid}_{19}cases_i I\ \{\Delta Covid_{19}cases_i \leq \tau 30\}. \quad (6.4)$$

$$Covid_{19}cases\beta_{2,t} = \sum_{i=1}^{t} \Delta \mathrm{Covid}_{19}cases\beta_{2,i} = \sum_{i=1}^{t} \Delta \mathrm{Covid}_{19}cases_i I\ \{\Delta Covid_{19}cases_i \geq \tau 70\}. \quad (6.5)$$

$$Covid_{19}cases\beta_{3,t} = \sum_{i=1}^{t} \Delta \mathrm{Covid}_{19}cases\beta_{3,i} = \sum_{i=1}^{t} \Delta \mathrm{Covid}_{19}cases_i I\ \{\tau 30 \leq \Delta Covid_{19}cases_i \leq \tau 70\}. \quad (6.6)$$

Therefore, Equations (5) and (6) can be re-written for MT-QARDL as follows:

$$\begin{gathered} Q_{\Delta SMI_t}(\tau) = \beta + \rho SMI_{t-1} + \theta_{FERP} FERP_{t-1}(\xi_1) + \theta_{FERP} FERP_{t-1}(\xi_2) + \theta_{FERP} FERP_{t-1}(\xi_3) + \\ \theta_{covid_{19cases}} Covid_{19}cases_{t-1}(\beta_1) + \theta_{covid_{19cases}} Covid_{19}cases_{t-1}(\beta_2) + \\ \theta_{covid_{19}cases} Covid_{19}cases_{t-1}(\beta_3) + \sum_{i=1}^{p} \delta_i \Delta SMI_{t-i} + \sum_{i=1}^{q} \varphi_i \Delta FERP_{t-i}(\xi_1) + \\ \sum_{i=1}^{q} \varphi_i \Delta FERP_{t-i}(\xi_2) + \sum_{i=1}^{q} \varphi_i \Delta FERP_{t-i}(\xi_3) + \sum_{i=1}^{q} \omega_i \Delta Covid_{19}cases_{t-1}(\beta_1) + \\ \sum_{i=1}^{q} \omega_i \Delta Covid_{19}cases_{t-i}(\beta_2) + \sum_{i=1}^{q} \omega_i \Delta Covid_{19}cases_{t-i}(\beta_3) + \nu_t\ (\tau). \end{gathered} \quad (7)$$

$$\begin{gathered} Q_{\Delta SMI_t}(\tau) = \beta + \rho(\tau)(SMI_{t-1} - \theta_{FERP}(\tau) FERP_{t-1}(\xi_1) - \theta_{FERP}(\tau) FERP_{t-1}(\xi_2) - \\ \theta_{FERP}(\tau) FERP_{t-1}(\xi_3) - \theta_{covid_{19}cases}(\tau) Covid_{19}cases_{t-1}(\beta_1) - \\ \theta_{covid_{19}cases}(\tau) Covid_{19}cases_{t-1}(\beta_2) - \theta_{covid_{19cases}}(\tau) Covid_{19}cases_{t-1}(\beta_3)) + \sum_{i=1}^{p} \delta_i \Delta SMI_{t-i} + \\ \sum_{i=1}^{q} \varphi_i \Delta FERP_{t-i}(\xi_1) + \sum_{i=1}^{q} \varphi_i \Delta FERP_{t-i}(\xi_2) + \\ \sum_{i=1}^{q} \varphi_i \Delta FERP_{t-i}(\xi_3) + \sum_{i=1}^{q} \omega_i \Delta Covid_{19}cases_{t-1}(\beta_1) + \\ \sum_{i=1}^{q} \omega_i \Delta Covid_{19}cases_{t-i}(\beta_2) + \sum_{i=1}^{q} \omega_i \Delta Covid_{19}cases_{t-i}(\beta_3) + \nu_t\ (\tau). \end{gathered} \quad (8)$$

Equations (7) and (8) represent the newly developed Multiple Threshold-based Quantile Autoregressive Distributive Lag (MT-QARDL) model. In the above equations, $Q_{\Delta SMI_t}$ is the dependent variable as multiple quantiles of the stock market indices with 1st difference operator (Δ). ρSMI_{t-1} signifies the impact of one-day-prior stock market indices of the South Asian economies on the current dynamics of the stock market returns and is incorporated in the Equation (7) and (8) as the error correction term (ECT). Furthermore, $\theta_{FERP} FERP_{t-1}(\xi_1), \theta_{FERP} FERP_{t-1}(\xi_2)\ and\ \theta_{FERP} FERP_{t-1}(\xi_3)$ is incorporated in the framework in order to explain the long-term influence of bearish, bullish, and moderate fluctuations in forward exchange rate premiums (FERP) on the stock market returns, respectively.

Moreover, $\varphi\Delta FERP_{t-1}(\xi_1), \sum_{i=1}^{q}\varphi\Delta FERP_{t-1}(\xi_2)$ *and* $\sum_{i=1}^{q}\varphi\Delta FERP_{t-1}(\xi_3)$ explains the short-term impact of bearish, bullish, and moderate influence of FERP on the quantiles of the stock market returns of South Asian economies, respectively. Furthermore, in order to explain the long-term bearish, bullish, and moderate fluctuations of COVID-19 cases' impact on the quantiles of the stock returns of South Asian economies, we incorporate the

$\theta_{covid_{19}cases}(\tau)Covid_{19}cases_{t-1}(\beta_1), \theta_{covid_{19}cases}(\tau)Covid_{19}cases_{t-1}(\beta_2)$ *and* $\theta_{covid_{19cases}}(\tau)Covid_{19}cases_{t-1}(\beta_3))$

into the framework, respectively. Moreover, $\sum_{i=1}^{q}\omega\Delta Covid_{19}cases_{t-1}(\beta_1), \sum_{i=1}^{q}\omega\Delta Covid_{19}cases_{t-1}(\beta_2)$ *and* $\sum_{i=1}^{q}\omega\Delta Covid_{19}cases_{t-1}(\beta_3)$ explains the short-term influence of bearish, bullish, and moderate COVID-19 cases on the stock returns' quantiles of individual South Asian economies.

Hence, the cumulative long-run impact of bearish, bullish, and normal behavioral states of FERP and COVID-19 cases on the stock market are calculated by $\theta_* = \sum_{i=1}^{q=1}\theta_{FERP}(\xi_1)$, $\theta_* = \sum_{i=1}^{q=1}\theta_{FERP}(\xi_2)$, $\theta_* = \sum_{i=1}^{q=1}\theta_{FERP}(\xi_3)$ and $\theta_* = \sum_{i=1}^{q=1}\theta_{Covid_{19}cases}(\beta_1), \theta_* = \sum_{i=1}^{q=1}\theta_{Covid_{19}cases}(\beta_2)$, *and* $\theta_{Covid_{19}cases} = \sum_{i=1}^{q=1}\theta_{Covid_{19}cases}(\beta_3)$, respectively. Similarly, as shown in Equations (7) and (8), the short-run cumulative effect of bearish, bullish, and normal behavioral states of FERP and COVID-19 cases are captured by φ_* and ω_*, respectively, whereas the ρSMR_{t-1} in Equation (8) is incorporated to establish the autoregressive dynamics of the QARDL framework and is classified as the "speed of adjustment" characteristic of the model. The longer-run integration coefficients of bearish, bullish, and normal behavior of COVID-19 cases and FERPs are calculated as $\beta_{Covid_{19}cases} = -\frac{\theta_{Covid_{19}cases}(\beta_1)}{\rho}$, $\beta_{Covid_{19}cases} = -\frac{\theta_{Covid_{19}cases}(\beta_2)}{\rho}$, $\beta_{Covid_{19}cases} = -\frac{\theta_{Covid_{19}cases}(\beta_3)}{\rho}$ and $\beta_{FERP} = -\frac{\theta_{FERP}(\xi_1)}{\rho}$, $\beta_{FERP} = -\frac{\theta_{FERP}(\xi_2)}{\rho}$, $\beta_{FERP} = -\frac{\theta_{FERP}(\xi_3)}{\rho}$, respectively.

Sign and Location-Based Asymmetries

For the location-based asymmetries, the Wald test statistics are utilized to examine the departure from symmetrical distribution by comparing the impact of the bullish or bearish or moderate behavior of the FERP at upper and lower quantile values of SMRs. Because of conditional symmetry, the mean value of two pairs of parameters for symmetrical quantiles about the median equals the value of the parameters at the median. In this way, we have applied the Newey and Powel [70] test of asymmetrical distribution $(\frac{\beta_{0.1}+\beta(1-0.9)}{2} = \beta(1/2))$ by analyzing the coefficient value at the set of two distinct quantiles, i.e., 0.1 and 0.9. The departure from the symmetrical distribution test is conducted for every long- and short-run regressor incorporated in Equations (7) and (8). Wald test statistics can also be utilized to examine the locational asymmetries. Locational asymmetries determine the non-linear response of equity market returns at different quantiles to the bearish or bullish or moderate fluctuations in the forward exchange rate premiums. The locational asymmetries arising due to the long-run asymmetrical pass-through from the bearish forward exchange rate premium $\theta_{FERP}(\xi_1)$ toward the equity returns can be proved by rejecting the null of long-run symmetrical pass-through, i.e., H_0 : $\theta_{FERP}(\xi_1)_{(\tau=0.1)} = \theta_{FERP}(\xi_1)_{\tau=0.2} = \theta_{FERP}(\xi_1)_{\tau=0.3} = \theta_{FERP}(\xi_1)_{\tau=0.7} = \theta_{FERP}(\xi_1)_{\tau=0.8} = \theta_{FERP}(\xi_1)_{\tau=0.9}$. However, the traditional QARDL model cannot estimate the sign-based asymmetries arising due to the joint differential impact of bearish, bullish, and moderate FERP on individual quantiles of the South Asian stock market. The null hypothesis of long-run sign-based symmetries can be written as

$$\theta_{FERP}(\xi_1)_{(\tau=0.1)} = \theta_{FERP}(\xi_2)_{\tau=0.1} = \theta_{FERP}(\xi_3)_{\tau=0.1},$$

$$\theta_{FERP}(\xi_1)_{(\tau=0.2)} = \theta_{FERP}(\xi_2)_{\tau=0.2} = \theta_{FERP}(\xi_3)_{\tau=0.2},$$

$$\theta_{FERP}(\xi_1)_{(\tau=0.3)} = \theta_{FERP}(\xi_2)_{\tau=0.3} = \theta_{FERP}(\xi_3)_{\tau=0.3},$$

$$\theta_{FERP}(\xi_1)_{(\tau=0.7)} = \theta_{FERP}(\xi_2)_{\tau=0.7} = \theta_{FERP}(\xi_3)_{\tau=0.7},$$

$$\theta_{FERP}(\xi_1)_{(\tau=0.8)} = \theta_{FERP}(\xi_2)_{\tau=0.8} = \theta_{FERP}(\xi_3)_{\tau=0.8},$$

$$\theta_{FERP}(\xi_1)_{(\tau=0.9)} = \theta_{FERP}(\xi_2)_{\tau=0.9} = \theta_{FERP}(\xi_3)_{\tau=0.9}.$$

The rejection of null hypothesis implies that bearish FERP, bullish FERP, and moderate FERP behavior has a differential impact on a particular quantile of the equity market indices.

4. Data and Descriptive Statistics

This research investigates how stock market returns (SMRs) in selected South Asian countries respond to multiple thresholds of forward exchange rate premiums (FERPs) and confirmed COVID-19 cases during the pandemic. Based on the interest rate parity (IRP) framework, forward premiums should exist between developed and developing economies due to differences in borrowing costs[71,72]. The relationship between forward and spot rates is expressed as $1 + i_d = \frac{\frac{S_d}{f}(1+i_f)}{\frac{F_d}{f}}$. Moreover, in this context, i_d and i_f denote the risk-free interest rates for domestic and foreign currencies, respectively, presented in terms of periodic interest rates. The spot exchange rate, $\frac{S_d}{f}$, represents the current exchange rate quoted as units of domestic currency per unit of foreign currency, while $\frac{F_d}{f}$ is the forward exchange rate, also expressed as units of domestic currency per unit of foreign currency. A forward premium or discount is identified by the difference between forward and spot rates (South Asian currencies/USD). Currencies from lower-interest-rate countries are typically traded at a premium compared to those with higher interest rates [73]. This study calculates FERPs for 3, 6, 9, and 12 months for individual South Asian economies using domestic interest rates from Trading Economics (https://tradingeconomics.com/) and spot rates from (https://www.investing.com/).

Equations (6.1)–(6.3) illustrate the estimation of bearish (lower), bullish (upper), and moderate (median) quantiles of the forward exchange rate premium (FERP). Similarly, Equations (6.4)–(6.6) present the lower, upper, and median quantiles of COVID-19 cases, serving as proxies for bearish, bullish, and moderate behavioral conditions associated with COVID-19 cases. The confirmed COVID-19 cases are also incorporated into the model and divided into multiple thresholds points by using time series data from 1 January 2020 to 30 April 2022. However, the starting time frame for asymmetrical model estimation is dependent upon the detection of the first COVID-19 cases in Pakistan, India, Bangladesh, and Sri Lanka. The stock market returns are calculated using the values of the logarithmic transformed return series of KSE-100 (Karachi stock indices), BSE-200 (Bombay stock indices), DSE-30 (Bangladesh stock indices), and S&P-SL-20 (Sri Lankan stock indices). For example, stock market returns are provided by the first logarithmic price difference (SMR) = $Ln(p_t) - Ln(p_{t-1})$, where p is price and t is time. This stock market return metric is in line with [74]. All the data series related to stock market indices are extracted from Bloomberg and data stream (https://www.lseg.com/en/data-analytics/products/datastream-macroeconomic-analysis), and the observations in relation to COVID-19 cases are incorporated from the WHO's COVID-19 portal (https://data.who.int/dashboards/covid19/cases?n=c).

Descriptive Statistics

Table 1 provides descriptive statistics for the logarithmically transformed FERPs and stock market indices of Pakistan, India, Bangladesh, and Sri Lanka. India's FERP exhibits greater excess kurtosis than other South Asian economies, indicating a leptokurtic distribution with extreme outliers and pronounced tails. This feature, coupled with positive skewness, suggests potential currency deflation linked to elevated forward exchange rate premiums. In contrast to Pakistan, the FERPs in India, Sri Lanka, and Bangladesh are positively skewed and leptokurtic, indicating higher risks for exporters and South Asian importers due to greater deviations from mean exchange rates. During COVID-19, the log-transformed stock indices for Pakistan, India, and Bangladesh show negative skewness, indicating lower returns and an increased likelihood of losses due to extended left tails in the distribution.

According to the results of the unit root tests like the augmented Dickey–Fuller (ADF) test by Dickey and Fuller [75], the Philips–Peron (PP) test by Phillips and Perron [76], and the Kwiatkowski–Philips–Schmidt–Shin (KPSS) test by Kwiatkowski et al. [77], Table 1 shows that the South Asian economies' FERPs estimated for the 3rd, 6th, 9th, and 12th months follow a similar pattern of integration, i.e., all are I (1) at first differenced data. At the 1% level of significance, the alternative hypothesis regarding the presence of stationarity cannot be ruled out. This is due to the ADF and PP test statistics being lower than the critical values at the 1% significance threshold. However, the greater KPSS test statistics imply the rejection of the null hypothesis of stationarity at the 1% significance level for FERPs of the 3rd, 6th, 9th, and 12th months and stock indices of the selected South Asian economies. Therefore, the ARDL model can be applied for the association between FERPs and SMRs. This is because the applicability of the linear ARDL model is irrespective of the order of the integration of the incorporated variables in the autoregressive framework.

Table 1. Descriptive statistics and unit root estimations of ADF [75], PP [76], and KPSS [77].

	Pakistan					**India**					**Bangladesh**					**Sri Lanka**				
	LNSI	**Ln (FERP3M)**	**Ln (FERP6M)**	**Ln (FERP9M)**	**Ln (FERP12M)**	**LNSI**	**Ln (FERP3M)**	**Ln (FERP6M)**	**Ln (FERP9M)**	**Ln (FERP12M)**	**LNSI**	**Ln (FERP3M)**	**Ln (FERP6M)**	**Ln (FERP9M)**	**Ln (FERP12M)**	**LNSI**	**Ln (FERP3M)**	**Ln (FERP6M)**	**Ln (FERP9M)**	**Ln (FERP12M)**
Mean	7.63	−8.95	−8.65	−7.849	−7.56	8.68	−8.97	−8.68	−7.87	−7.58	7.632494	−8.91	−8.63	−7.821	−7.53	7.973	−9.54	−9.27	−8.45	−8.16
Median	7.69	−8.95	−8.66	−7.85	−7.56	8.74	−8.97	−8.691	−7.88	−7.59	7.69	−8.92	−8.63	−7.82	−7.54	7.97	−9.55	−9.26	−8.45	−8.16
Maximum	7.93	−8.72	−8.43	−7.62	−7.33	8.99	−8.70	−8.42	−7.60	−7.32	7.93	−8.73	−8.44	−7.63	−7.35	8.44	−9.113	−8.82	−8.01	−7.73
Minimum	7.09	−9.14	−8.85	−8.043	−7.75	8.07	−9.081	−8.79	−7.98	−7.69	7.09	−9.002	−8.715	−7.907	−7.61	7.43	−9.81	−9.52	−8.71	−8.42
Std. Dev.	0.23	0.099	0.099	0.099	0.099	0.23	0.052	0.052	0.052	0.052	0.22	0.043	0.0433	0.043	0.043	0.219	0.088	0.088	0.089	0.089
Skewness	−0.62	0.020	0.020	0.021	0.022	−0.547	2.255	2.240	2.16	2.124	−0.63	1.993	1.989	1.972	1.956	0.113	1.31	1.30	1.27	1.26
Kurtosis	2.19	2.045	2.045	2.051	2.054	2.09	13.38	13.28	13.05	12.88	2.250	8.12	8.11	8.089	8.056	2.367	7.98	7.964	7.85	7.78
Jarque–Bera	36.72	15.20	15.16	14.99	14.89	46.84	2974.09	2919.60	2783.06	2686.41	34.95	676.02	673.85	665.36	655.73	9.516	668.01	662.51	633.09	616.06
Probability	0.000	0.0005	0.0005	0.0005	0.000	0.000	0.000	0.0000	0.000	0.000	0.0000	0.0000	0.0000	0.0000	0.000	0.008	0.0000	0.0000	0.0000	0.0000
Sum	3044.91	−3569.54	−3454.85	−3131.77	−3017.28	4846.6	−4997.89	−4837.97	−4386.9	−4227.17	2938.51	−3433.82	−3323.15	−3011.42	−2900.88	4026.71	−4821.55	−4676.4	−4267.63	−4122.78
Sum Sq. Dev.	19.99	3.97	3.96	3.95	3.945	30.108	1.506	1.515	1.534	1.550	19.03	0.72	0.723	0.728	0.72	24.38	3.95	3.96	3.99	4.009
Observations	399	399	399	399	399	558	557	557	557	557	385	385	385	385	385	505	505	505	505	505
ADF (1st diff)	−20.98 ***	−11.89 ***	−12.10 ***	−9.83 ***	−10.50 ***	−7.17 ***	−8.09 ***	−8.11 ***	−8.13 ***	−8.96 ***	−23.90 ***	−19.55 ***	−22.80 **	−22.90 ***	−25.90 ***	−27.90 ***	−18.75 ***	−18.90 ***	−18.92 ***	−20.10 ***
PP (1st diff)	−21.1 ***	−19.90 ***	−21.50 ***	−20.90 ***	−22.60 ***	−25.43 ***	−23.17 ***	−23.52 ***	−25.83 ***	−23.10 ***	−25.80 ***	−19.50 ***	−21.73 ***	−22.4 ***	−26.90 ***	−27.1 ***	−19.10 ***	−19.15 ***	−20.80 ***	−21.60 ***
KPSS (1st diff)	0.15	0.11	0.18	0.15	0.30	0.12	0.06	0.05	0.023	0.030	0.015	0.05	0.068	0.090	0.095	0.045	0.015	0.095	0.011	0.05

Note: This table presents the descriptive statistics of logarithmic transformed stock indices and forward exchange rate premium (FERP) for 3rd, 6th, 9th, and 12th months. The bottom of the table shows the unit root characteristics of the variables with first difference operator. The asterisk signs of ***, **, and * show the rejection of null of non-stationarity at 1%, 5%, and 10% levels of significance for the augmented Dickey–Fuller [75] and Philips Perron [76] unit root tests. However, the KPSS [77] null hypothesis is about the presence of stationarity in data.

5. Results with Practical Implications for Short-Run Speculators and Long-Run Shareholders

According to the results of the ARDL model (see Table 2), the longer-term association between the FERPs of the 3rd, 6th, 9th, and 12th months and the SMRs of the South Asian region cannot be determined significantly. This may be because of the non-identical and non-independent nature of the distribution of the data as shown by the BDS test of non-linearity in Table 3. Therefore, the application of a linear or symmetrical framework may provide spurious and biased estimates for data exhibiting non-linear characteristics (see Table 3). Moreover, similar to the BDS test by Brock et al. [78], the HWBZ test by Hui et al. [79] serves dual purposes: detecting non-linearity and aiding model development. A key next step is assessing if residuals show linear or non-linear dependence after regressing one time series on another using a chosen model. The HWBZ test results in Table A2 avoid the over-rejection issues common in many non-linearity tests like BDS. Additionally, the simulation analysis in Table A2 confirms the robustness and effectiveness of our test, indicating that non-linear analysis is better suited to explore the FERP-SMR relationship.

Figure A1 presents significant fluctuations in stock indices and the forward exchange rate premiums (FERPs) for Pakistan, India, Sri Lanka, and Bangladesh during the first and second quarters of 2020. Notably, Pakistan, Bangladesh, and Sri Lanka exhibited marked upward movements in both FERP and stock indices in the final quarters of 2021 and the initial quarter of 2022. In contrast, India's FERP followed a stable pattern of both upward and downward shifts from the third quarter of 2020 to the end of 2022. By late 2021, stock indices across these South Asian economies had reached their peak levels. However, a sharp decline occurred in the stock indices of Sri Lanka, Pakistan, India, and Bangladesh during the first quarter of 2022, accompanied by an overall depreciation in FERPs across these economies. Sri Lanka, India, and Bangladesh experienced particularly steep FERP declines during this period. This furthermore motivated us to explore the quantile domain (bullish, bearish, and moderate) impact of FERPs on the multiple quantiles of stock returns in the South Asian economies for different investment horizons (short and long term).

Cho et al. [50] also suggest that the linear estimation procedure for non-linear data may not uncover hidden co-integrations. Furthermore, the linear ARDL model's convergence toward the longer-term equilibrium at a specific adjustment speed is also absent for Pakistan and Bangladesh. The results of the linear ARDL model suffer from heteroscedasticity and model misspecification because of the non-constant variability of the residual's variance and non-constant variability in the predictand's variance observed against the set of regressors (see Table 2). This may be due to the estimation of the ARDL model in a linear fashion (see Ramsey reset test results and Breusch–Pagan tests for heteroscedasticity in Table 2). These problems can be solved by disintegrating the regressand into various quantiles and estimating the autoregressive framework with lags of the dependent and the independent variable on the quantile regression framework [50].

Table 2. Conventional ARDL results.

Variables	Pakistan				India				Bangladesh				Sri Lanka			
	FERP-3M	**FERP-6M**	**FERP-9M**	**FERP-12M**	**FERP-3M**	**FERP-6M**	**FERP-9M**	**FERP-12M**	**FERP-3M**	**FERP-6M**	**FERP-9M**	**FERP-12M**	**FERP-3M**	**FERP-6M**	**FERP-9M**	**FERP-12M**
α_0	−0.270 **	−0.2627 ***	−0.2414 ***	−0.2340 ***	0.0953	0.089468	0.09788	0.09757	−0.11182	−0.10589	−0.08773	−0.08208	0.162565	0.161059	0.157351	0.156171
α_1	0.0024	0.002501	0.00251	0.002525	−0.0143 ***	−0.01435 ***	−0.01431 ***	−0.01432 ***	−0.00796	−0.00795	−0.0079	−0.0079	−0.0138 **	−0.0138 ***	−0.01382 ***	−0.01381
β_1	−0.0269	−0.027	−0.0269	−0.02702	−0.00205	−0.00284	−0.00201	−0.00215	−0.01894	−0.01888	−0.01846	−0.01841	0.006179	0.006207	0.006384	0.006475
β_2	0.001668 **	0.001669 **	0.001675 ***	0.00167 ***	0.00078 **	0.000787 **	0.000788 ***	0.000788 ***	0.00072	0.00072	0.000722	0.00072	0.00126 ***	0.00126 ***	0.00126 ***	0.00126
γ_1	−0.1127 **	−0.1127 **	−0.1126 **	−0.1125 ***	−0.1128 ***	−0.1117 ***	−0.1130 **	−0.1125 ***					0.1350 ***	0.1350 ***	0.1350 ***	0.135059
γ_2	−0.1047 ***	−0.1049 ***	−0.105 ***	−0.1064 ***	0.030759	−0.1472 ***	−0.1432 **	−0.1408 ***	−0.3484 ***	−0.3475 ***	−0.3410 ***	−0.3412 ***	−0.04226	−0.04218	−0.04185	−0.04168
γ_3	0.009251	0.009	0.00106	0.001056	−0.0351 ***	−0.0340 ***	−0.0350 ***	−0.0349 ***	−0.00294 **	−0.00294 **	−0.0028 **	−0.0005 **	−0.0004 **	−0.0035 ***	−0.00046 **	−0.0035
ρ	0.0024	0.002	0.0025	0.0025	−0.01	−0.0143 ***	−0.01431 ***	−0.01432 ***	−0.007	−0.0079	−0.0079	−0.007	−0.013 **	−0.013 ***	−0.00138 **	−0.0138 **
DW	1.99	2.01	1.89	1.95	2.001	2.05	2.12	2.15	1.99	2.1	1.8	2.2	1.9	2.1	2.2	2.3
BP test	9.62 ***	11.625 ***	8.73 ***	10.21 ***	7.32 ***	8.62 ***	9.12 ***	9.10 ***	6.63 ***	6.87 ***	7.7 ***	8.9 ***	11.2 ***	12.3 ***	11.90 ***	12.50 ***
CUSUM	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable
RR test	2.63 ***	2.2 ***	3.15 ***	2.21 ***	2.4 ***	3.39 ***	2.1 ***	2.55 ***	2.2 ***	2.76 ***	2.75 ***	2.6 ***	2.1 ***	2.33 ***	2.5 ***	2.2 ***

Note: The levels of significance at 1%, 5%, and 10% are represented by the asterisk signs of ***, **, and *. DW, BB test, and RR test are the abbreviations of the Durbin–Watson test for autocorrelation, Breusch–Pagan test for heteroscedasticity, and Ramsey reset test for model specification, respectively. The null hypothesis for BP and RR tests implies the presence of homoscedasticity and the correct specification of the model, respectively.

Table 3. BDS test for non-linearity.

	Pakistan					India					Bangladesh					Sri Lanka				
	Absolute Returns	**FERP-3M**	**FERP-6M**	**FERP-9M**	**FERP-12M**	**Absolute Returns**	**FERP-3M**	**FERP-6M**	**FERP-9M**	**FERP-12M**	**Absolute Returns**	**FERP-3M**	**FERP-6M**	**FERP-9M**	**FERP-12M**	**Absolute Returns**	**FERP-3M**	**FERP-6M**	**FERP-9M**	**FERP-12M**
Dimension	**BDS Statistic**					**BDS Statistic**					**BDS Statistic**					**BDS Statistic**				
2	0.029 ***	0.193 ***	0.193 ***	0.192 ***	0.192 ***	0.032 ***	0.194 ***	0.197 ***	0.1945 ***	0.1938 ***	0.032 ***	0.1853 ***	0.185 ***	0.190 ***	0.1943 ***	0.0474 ***	0.189 ***	0.189 ***	0.189 ***	0.188 ***
3	0.046 ***	0.325 ***	0.325 ***	0.324 ***	0.324 ***	0.060 ***	0.329 ***	0.333 ***	0.329 ***	0.328 ***	0.049 ***	0.313 ***	0.314 ***	0.323 ***	0.329 ***	0.0881 ***	0.318 ***	0.318 ***	0.317 ***	0.317 ***
4	0.0613 ***	0.417 ***	0.417 ***	0.416 ***	0.414 ***	0.0716 ***	0.423 ***	0.426 ***	0.423 ***	0.422 ***	0.0656 ***	0.401 ***	0.402 ***	0.412 ***	0.421 ***	0.113 ***	0.405 ***	0.405 ***	0.405 ***	0.404 ***
5	0.0703 ***	0.47 ***	0.479 ***	0.478 ***	0.476 ***	0.0782 ***	0.488 ***	0.491 ***	0.4879 ***	0.486 ***	0.0762 ***	0.462 ***	0.463 ***	0.473 ***	0.485 ***	0.127 ***	0.464 ***	0.464 ***	0.464 ***	0.462 ***
6	0.072 ***	0.521 ***	0.5211 ***	0.519 ***	0.517 ***	0.079 ***	0.532 ***	0.535 ***	0.532 ***	0.53 ***	0.076 ***	0.506 ***	0.506 ***	0.517 ***	0.531 ***	0.136 ***	0.503 ***	0.504 ***	0.503 ***	0.501 ***

Note: BDS test estimates the presence of identical, independent, and linearly distributed data series. The null hypothesis implies that data are processing linear characteristics with identical and independent distribution.

5.1. QARDL Estimations and Weak Response of South Asian Stock Market (SM) Bullish and Bearish Returns to Forward Exchange Rate Premium (FERP) of 3rd, 6th, 9th, and 12th Months

Table A3 in the Appendix A section presents the results of the conventional QARDL framework and Wald test statistics results for the asymmetrical pass-through from the FERP and COVID-19 cases toward the quantiles of the SMRs of selected South Asian economies. According to the results, the model's adjustment speed (ϱ), indicating the rate at which the model converges toward long-term equilibrium, is statistically insignificant for Pakistan and only weakly significant for Bangladesh. Table A3a shows the weak predictive capacity of the conventional QARDL model in estimating Pakistani, Bangladeshi, and Indian stock market responses at all quantiles to the fluctuations in FERP of the 3rd, 6th, 9th, and 12th months. This is due to the weak or insignificant QARDL model's speed of adjustment in the case of Bangladesh and Pakistan and the insignificant longer-term relation between FERP and stock market returns of India and Pakistan. Third, Wald test statistics for the QARDL model are unable to detect longer-term asymmetrical pass-through from the FERP toward the stock market returns of India, Bangladesh, Sri Lanka, and Pakistan at various quantiles, as can be seen in Table A3b. Therefore, we have extended the conventional QARDL framework by Cho et al. [34], the MT-NARDL model byPal and Mitra [29–31], and the ARDL approach by Pesaran et al. [35] into the novel multiple threshold-based autoregressive model (MT-QARDL).

5.2. MT-QARDL Estimated Results

The estimation of the MT-QARDL approach is presented in Table 4a,b, and the Wald test statistics used to determine the departure from symmetrical distribution for the novel MT-QARDL framework are presented in Table A4. Table A4 shows the results of the "sign"- and "location"-based asymmetries, respectively. According to the results of the MT-QARDL framework (Table 4a,b), the speed of adjustment (ϱ) by which the model converges toward the long-run equilibrium is greater and more statistically significant when compared with "ϱ" values of the QARDL approach (Table A3a) for all selected economies. However, the ECT is more significant at upper (lower) quantiles of India and Sri Lanka (Pakistan and Bangladesh). This confirms that the estimation technique of the multiple thresholds-based QARDL model increases the adjustment speed of the model at which it corrects its disequilibrium.

Table 4. (**a**) MT-QARDL results. (**b**) MT-QARDL results (Cont'd).

(a)

		Pakistan				India				Bangdladesh				Sri Lanka			
		3M-FERP	**6M-FERP**	**9M-FERP**	**12M-FERP**	**3M-FERP**	**6M-FERP**	**9M-FERP**	**12M-FERP**	**3M-FERP**	**6M-FERP**	**9M-FERP**	**12M-FERP**	**3M-FERP**	**6M-FERP**	**9M-FERP**	**12M-FERP**
	Quantile	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
β	0.1	0.5324	0.6939	0.6807	0.6756	0.1225	0.1388	0.12343	0.1167	0.4783 ***	0.4782 ***	0.4780 ***	0.4781 ***	−0.1566	−0.1661	−0.1499	−0.1611
	0.2	1.1940	1.1556	1.1011	1.0819	0.2175	0.2175	0.21697	0.2139	0.3636 ***	0.3637 ***	0.3593 ***	0.3588 ***	−0.0122	−0.0106	−0.0146	−0.0158
	0.3	1.0972	1.0632	1.0207	0.9754	0.1277	0.1273	0.12914	0.1291	0.2604 ***	0.2603 ***	0.2564 ***	0.2601 ***	−0.0517	−0.0495	−0.0496	−0.0509
	0.7	1.942 ***	1.800 ***	1.663 ***	1.622 ***	0.3704 ***	0.3711 ***	0.3708 ***	0.3734 ***	0.11310	0.11276	0.11232	0.11175	0.3192 ***	0.3328 ***	0.33085 ***	0.3299 ***
	0.8	1.334 **	1.294 **	1.181 *	1.151 *	0.4597 ***	0.4602 ***	0.4602 ***	0.46044 ***	0.02881	0.02859	0.02867	0.02854	0.4035 ***	0.4033 ***	0.4034 ***	0.4027 ***
	0.9	1.0602	1.0785	0.9970	0.9802	0.7493 *	0.7400	0.7575 *	0.7631 *	0.11346	0.11146	0.11324	0.11164	0.4994 ***	0.5049 ***	0.5021 ***	0.5004 ***
ρ	0.1	−0.088 **	−0.092 **	−0.0928 **	−0.0927 **	−0.0144	−0.0163	−0.01454	−0.0138	−0.06933 ***	−0.06937 ***	−0.06936 ***	−0.0699 ***	0.0233	0.0219	0.0222	0.0239
	0.2	−0.0690 ***	−0.0687 ***	−0.0689 ***	−0.0689 ***	−0.0248	−0.0248	−0.02470	−0.0244	−0.05275 ***	−0.05275 ***	−0.05221 ***	−0.05214 ***	0.0072	0.0070	0.0074	0.0076
	0.3	−0.0389 **	−0.0386 **	−0.0396 **	−0.0390 **	−0.0145	−0.0145	−0.01470	−0.0147	−0.03701 ***	−0.03701 ***	−0.03649 ***	−0.03697 ***	0.0117	0.0114	0.0114	0.0116
	0.7	−0.0431 ***	−0.0421 ***	−0.0422 ***	−0.0451 ***	−0.04148 ***	−0.04149 ***	−0.0414 ***	−0.04174 ***	−0.01218	−0.01213	−0.01207	−0.01200	−0.03925 ***	−0.0410 ***	−0.04078 ***	−0.04073 ***
	0.8	−0.0323 *	−0.0322 *	−0.0318	−0.0318	−0.05141 ***	−0.05146 ***	−0.0514 ***	−0.05148 ***	−0.00046	−0.00043	−0.00045	−0.00043	−0.04905 ***	−0.04897 ***	−0.04899 ***	−0.04889 ***
	0.9	−0.0321	−0.0360	−0.0361	−0.0363	−0.08370 *	−0.0827	−0.08463 *	−0.08525 *	−0.00973	−0.00949	−0.00971	−0.00951	−0.05832 ***	−0.05900 ***	−0.05865 ***	−0.05848 ***
$\theta_{FERP}FERP_{t-1}(\xi_1)$	0.1	−0.0022	0.0122	0.0119	0.0117	0.006436 *	0.006764 *	0.007332 *	0.007557 *	0.001925	0.001988	0.002177	0.002274	0.004987	0.002915	0.005441	0.0058
	0.2	0.0783	0.0768	0.0776	0.0779	0.00536 ***	0.005534 ***	0.006098 ***	0.006304 ***	0.00022	0.00022	0.00018	0.00020	0.006128 ***	0.006353 ***	0.006844 ***	0.007069 ***
	0.3	0.0901	0.0894	0.0922	0.0904	0.0017	0.0018	0.00195	0.0020	0.00137	0.00142	0.00155	0.00162	0.005293 ***	0.005466 ***	0.005973 ***	0.006179 ***

	0.7	0.1782 ***	0.1687 ***	0.1685 ***	0.1668 ***	0.001392 *	0.001437 *	0.001584 *	0.001654 *	0.003549 ***	0.003661 ***	0.004029 ***	0.004167 ***	0.0008	0.0007	0.0008	0.0007
	0.8	0.1190 *	0.1184 *	0.1166 *	0.1170 *	0.001635 *	0.001691 *	0.001864 *	0.001935 **	0.00168	0.00174	0.00192	0.00199	0.0014	0.0015	0.0016	0.0017
	0.9	0.0877	0.0894	0.0882	0.0891	0.0025	0.0025	0.00288	0.0030	0.00141	0.00143	0.00159	0.00164	0.0037 **	0.003838 **	0.004185 **	0.00429 **
$\theta_{FERP}FERP_{t-1}(\xi_2)$	0.1	−0.0202	−0.0082	−0.0103	−0.0112	−0.0119	−0.0119	−0.01274	−0.0124	−0.00393	−0.00405	−0.00444	−0.00457	−0.01193 **	−0.01396 ***	−0.0133 **	−0.01378 **
	0.2	0.0636	0.0617	0.0605	0.0602	−0.02065 ***	−0.02089***	−0.02150 ***	−0.02174 ***	−0.005228 *	−0.005378 *	−0.005666 *	−0.00585 *	−0.009856 ***	−0.007222 **	−0.01099 ***	−0.01143 ***
	0.3	0.0899	0.0893	0.091737 *	0.0901	−0.02438 ***	−0.02453 ***	−0.02546 ***	−0.025745 ***	0.00202	0.00209	0.00238	0.00237	−0.009353 ***	−0.009613 ***	−0.01046 ***	−0.01082 ***
	0.7	0.1575 ***	0.1482 ***	0.1460 ***	0.1430 ***	0.0102	0.0094	0.0110	0.0112	0.00100	0.00102	0.00111	0.00115	−0.0008	−0.0010	−0.0010	−0.0011
	0.8	0.0912	0.0900	0.0858	0.0853	0.0079	0.0083	0.0073	0.0073	0.00149	0.00154	0.00166	0.00174	0.0031	0.0031	0.0034	0.0035
	0.9	0.0628	0.0630	0.0595	0.0593	0.0058	0.0052	0.0061	0.0057	0.00225	0.00235	0.00257	0.00265	0.01022 ***	0.01095 ***	0.01154 ***	0.011797 ***
$\theta_{FERP}FERP_{t-1}(\xi_3)$	0.1	0.0077	0.0228	0.0235	0.0238	0.0159	0.0172	0.0182	0.0184	0.02763 ***	0.02854 ***	0.03142 ***	0.03267 ***	0.0023	−0.00310	0.0025	0.0026
	0.2	0.0876	0.0862	0.0878	0.0885	0.0094	0.0098	0.0107	0.0110	0.02126 ***	0.02196 ***	0.02416 ***	0.02510 ***	0.0050	0.0053	0.0054	0.0055
	0.3	0.0947	0.0944	0.0976	0.0958	0.0024	0.0029	0.0027	0.0028	0.01583 ***	0.01636 ***	0.01791 ***	0.01872 ***	0.0006	0.0007	0.0008	0.0008
	0.7	0.1660 ***	0.1563 ***	0.1551 ***	0.1536 ***	0.007855 *	0.008125 *	0.008944 *	0.009427 *	0.00169	0.00175	0.00190	0.00203	0.0038	0.0040	0.0043	0.0046
	0.8	0.1108 *	0.1100 *	0.1074 *	0.1074 *	0.008898 **	0.00913 **	0.01030 **	0.01070 **	−0.00202	−0.00208	−0.00234	−0.00238	0.0037	0.0039	0.0042	0.0044
	0.9	0.0804	0.0823	0.0805	0.0811	0.0085	0.00902	0.0098	0.0100	−0.00832	−0.00850	−0.00947	−0.00975	0.0012	0.0013	0.0014	0.0014
$\theta_{covid_{19cases}}(\beta_1)$	0.1	0.0152 ***	0.0150 ***	0.0150 ***	0.01508 ***	0.003287 **	0.003314 **	0.003285 **	0.003274 **	0.007411 ***	0.00741 ***	0.007413 ***	0.007403 ***	0.004186 ***	0.004052 ***	0.004075 ***	0.004139 ***
	0.2	0.00315 *	0.00316 *	0.00316 *	0.00315 *	0.00231 ***	0.002315 ***	0.002313 ***	0.002309 ***	0.003696 ***	0.003696 ***	0.003675 ***	0.003672 ***	0.002609 **	0.002608 **	0.00259 **	0.002588 **
	0.3	0.0006	0.0007	0.0006	0.0006	0.0006	0.0006	0.0006	0.0006	0.004193 ***	0.004192 ***	0.004197 ***	0.004187 ***	0.002613 **	0.002592 **	0.002574 **	0.002569 **
	0.7	−0.0010	−0.0008	−0.0009	−0.0008	0.0000	0.0000	0.0000	0.0000	0.003058 *	0.003054 *	0.003042 *	0.003033 *	0.0002	0.0000	0.0000	0.0000
	0.8	−0.0016	−0.0016	−0.0017	−0.0017	−0.0001	−0.0001	−0.0001	−0.0001	−0.00003	−0.00003	−0.00004	−0.00004	0.0006	0.0006	0.0006	0.0006

	0.9	−0.0032	−0.0032	−0.0031	−0.0031	−0.000518 *	−0.00053 *	−0.000525 *	−0.000518 *	−0.00286	−0.00286	−0.00287	−0.00287	0.001905 **	0.001944 **	0.001923 **	0.001911 **
$\theta_{covid_{19cases}}(\beta_2)$	0.1	−0.0035	−0.0055	−0.0052	−0.0051	−0.0064	−0.0062	−0.0060	−0.0056	0.00187	0.00188	0.00192	0.00194	−0.02335 ***	−0.02243 ***	−0.02286 ***	−0.02315 ***
	0.2	−0.0120	−0.0119	−0.0123	−0.0122	−0.01080 ***	−0.010584 ***	−0.009883 ***	−0.009632 ***	−0.00057	−0.00054	−0.00029	−0.00028	−0.02110 ***	−0.01733 ***	−0.02086 ***	−0.02092 ***
	0.3	−0.0001	0.0000	−0.0004	−0.0002	−0.01261 ***	−0.01229 ***	−0.011562 ***	−0.01126 ***	0.004915 **	0.004911 **	0.004963 **	0.004893 **	−0.01931 ***	−0.01928 ***	−0.01919 ***	−0.01917 ***
	0.7	−0.0255 ***	−0.02436 ***	−0.0241 ***	−0.0243 ***	0.0056	0.0050	0.0053	0.0052	−0.00098	−0.00099	−0.00101	−0.00101	0.0003	0.0004	0.0005	0.0005
	0.8	−0.0325 ***	−0.03226 ***	−0.0317 ***	−0.0314 ***	0.0046	0.0047	0.0038	0.0037	−0.00019	−0.00020	−0.00024	−0.00023	0.0057	0.0057	0.0056	0.0056
	0.9	−0.02951 **	−0.030053 **	−0.02944 **	−0.02956 **	0.0036	0.0032	0.0034	0.0031	−0.00077	−0.00070	−0.00073	−0.00075	0.01310 ***	0.01363 ***	0.01310 ***	0.01295 ***
$\theta_{covid_{19cases}}(\beta_3)$	0.1	0.0274 **	0.02775 *	0.02766 *	0.02762 *	0.0082	0.0086	0.0082	0.0080	0.03842 ***	0.03842 ***	0.03836 ***	0.03839 ***	−0.0038	−0.0085	−0.0036	−0.0040
	0.2	0.0152 **	0.01493 **	0.01480 **	0.01471 **	0.0047	0.0047	0.0046	0.0046	0.02991 ***	0.02991 ***	0.02984 ***	0.02984 ***	−0.0012	−0.0011	−0.0015	−0.0016
	0.3	0.0060	0.0062	0.0060	0.0058	0.0012	0.0014	0.0012	0.0012	0.02155 ***	0.02154 ***	0.02137 ***	0.02152 ***	−0.0065	−0.0063	−0.0063	−0.0064
	0.7	−0.0161 ***	−0.01574 ***	−0.01541 ***	−0.01448 ***	0.004097 *	0.004103 *	0.004095 *	0.004158 *	0.00067	0.00069	0.00066	0.00071	0.0060	0.0064	0.0062	0.0065
	0.8	−0.0113 **	−0.01132 **	−0.01130 **	−0.01131 **	0.004665 **	0.004633 **	0.004742 **	0.004745 **	−0.00443	−0.00443	−0.00447	−0.00443	0.0052	0.0052	0.0052	0.0052
	0.9	−0.0104	−0.0098	−0.0095	−0.0096	0.0043	0.00441	0.0043	0.0042	−0.01291	−0.01277	−0.01288	−0.01279	−0.0014	−0.0014	−0.0014	−0.0014

(b)

		Pakistan				**India**				**Bangladesh**				**Sri Lanka**			
		3M-FERP	**6M-FERP**	**9M-FERP**	**12M-FERP**	**3M-FERP**	**6M-FERP**	**9M-FERP**	**12M-FERP**	**3M-FERP**	**6M-FERP**	**9M-FERP**	**12M-FERP**	**3M-FERP**	**6M-FERP**	**9M-FERP**	**12M-FERP**
	Quantile	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
δ	0.1	0.0260	0.0333	0.0331	0.0331	0.0236	0.01443	0.0228	0.0259	0.17361 *	0.17360 *	0.1731 *	0.17356 *	0.3518 ***	0.3347 ***	0.34576 ***	0.3518 ***
	0.2	0.0545	0.0543	0.0512	0.0538	0.0819	0.08235	0.0817	0.0808	0.0729	0.07301	0.06674	0.06614	0.2865 ***	0.2854 ***	0.28845 ***	0.2883 ***
	0.3	0.0105	0.0104	0.0109	0.0106	0.0986	0.09872	0.0987	0.0988	0.0254	0.02540	0.03510	0.02544	0.2440 ***	0.2452 ***	0.24591 ***	0.2454 ***
	0.7	−0.0389	−0.0387	−0.0391	−0.0556	0.0041	0.00426	0.0042	0.0051	−0.0120	−0.01263	−0.01327	−0.01343	0.0444	0.0467	0.0491	0.0493
	0.8	−0.1165	−0.1175	−0.1246	−0.1246	0.0061	0.00513	0.0152	0.0161	−0.0083	−0.00791	−0.00797	−0.00790	−0.0220	−0.0215	−0.0219	−0.0213

	0.9	−0.1234	−0.1212	−0.1221	−0.1223	−0.0510	−0.04378	−0.0515	−0.0568	−0.0165	−0.02002	−0.01653	−0.01962	−0.0066	0.0045	−0.0007	−0.0030
$\varphi\Delta FERP_{t-1}(\xi_1)$	0.1	0.2470	0.2542	0.2540	0.2539	−0.0551	−0.05715	−0.0615	−0.0629	0.0021	0.00219	0.00246	0.00253	0.0051	0.0021	0.0056	0.0058
	0.2	0.3095 ***	0.3097 ***	0.3098 ***	0.3096 ***	0.0415	0.04253	0.0475	0.0500	0.0079	0.00815	0.00935	0.00974	−0.0005	−0.0003	−0.0007	−0.0008
	0.3	0.2804 **	0.2805 *	0.2804	0.2805	−0.0100	−0.01015	−0.0115	−0.0119	0.01055 **	0.01091 **	0.01154 **	0.01249 **	−0.0015	−0.0017	−0.0019	−0.0019
	0.7	0.2069 **	0.1956 **	0.1669	0.1667	−0.0036	−0.00370	−0.0041	−0.0039	0.0062	0.00647	0.00716	0.00744	−0.0051	−0.0058	−0.0063	−0.0066
	0.8	0.1524	0.1474	0.1306	0.1282	0.0033	0.00232	0.0095	0.0097	−0.0027	−0.00283	−0.00313	−0.00325	−0.007596 *	−0.007819 *	−0.008596 *	−0.00886 *
	0.9	0.0434	0.0400	0.0190	0.0123	0.0099	0.01809	0.0086	0.0027	−0.0132	−0.01336	−0.01501	−0.01534	−0.01016 ***	−0.01071 ***	−0.01156 ***	−0.0119 ***
$\varphi\Delta FERP_{t-1}(\xi_2)$	0.1	0.1696	0.1687	0.1605	0.1571	0.0188	0.01851	0.0186	0.0180	−0.0009	−0.00105	−0.00151	−0.00178	0.0168	0.0501	0.0138	0.0221
	0.2	0.2282 ***	0.2256 ***	0.2193 ***	0.21518 ***	0.0045	0.00438	0.0035	0.0032	−0.0607	−0.06284	−0.06761	−0.07026	−0.0380	−0.0569	−0.0393	−0.0386
	0.3	0.0800	0.0738	0.0528	0.0445	−0.0156	−0.0156	−0.0168	−0.0171	−0.0442	−0.04571	−0.05079	−0.05235	0.0063	0.0061	0.0072	0.0061
	0.7	0.1949 ***	0.1929 ***	0.1884 ***	0.1897 ***	−0.1173 ***	−0.1152 ***	−0.11733 ***	−0.1162 ***	0.0000	0.00014	0.00029	0.00019	0.1072	0.0732	0.0817	0.0841
	0.8	0.2160 ***	0.2142 ***	0.2067 ***	0.2047 ***	−0.1340 ***	−0.13207 ***	−0.13262 ***	−0.1315 ***	−0.09323 *	−0.09362 *	−0.09442 *	−0.09493 *	0.0459	0.0476	0.0517	0.0541
	0.9	0.1439 **	0.1438 **	0.13544 **	0.1354 **	−0.1438 ***	−0.1417 ***	−0.14318 ***	−0.1421 ***	−0.0449	−0.06358	−0.07265 *	−0.07355 *	0.1679	0.1844	0.1909	0.1971
$\varphi\Delta FERP_{t-1}(\xi_3)$	0.1	0.5122 ***	0.5333 ***	0.5621 ***	0.5738 ***	0.0580	0.0603	0.0658	0.0651	0.3380 ***	0.3492 ***	0.38524 ***	0.3999 ***	0.0154	−0.1160	0.0104	0.0168
	0.2	0.5472 ***	0.559 ***	0.5881 ***	0.5972 ***	0.1437	0.1466	0.1638	0.1710	0.2316 ***	0.2393 ***	0.2651 ***	0.2751 ***	0.0805	0.0846	0.0852	0.0869
	0.3	0.4854 ***	0.4919 ***	0.5120 **	0.5228 **	0.0212	0.0243	0.0238	0.0255	0.1535 *	0.15866 *	0.1766 *	0.18163 *	−0.0146	−0.0129	−0.0142	−0.0149
	0.7	0.2811 **	0.2470 **	0.2173 *	0.2144	−0.0081	−0.0078	−0.0092	−0.0065	0.0446	0.04568	0.04188	0.05144	−0.0049	−0.0029	−0.0069	−0.0006
	0.8	0.1894	0.1823	0.1724	0.1715	0.0566	0.0554	0.0815	0.0852	0.1219	0.12580	0.13997	0.14386	0.0330	0.0336	0.0372	0.0376
	0.9	−0.0334	−0.0222	−0.0487	−0.0570	−0.0294	−0.0302	−0.0351	−0.0373	0.1307	0.13317	0.14729	0.15302	−0.0503	−0.0582	−0.0607	−0.0614
$\omega\Delta Covid_{19}cases_{t-1}($	0.1	0.0125 ***	0.01256 ***	0.0125 ***	0.0125 ***	−0.0384	−0.0386	−0.0378	−0.0371	−0.0081	−0.00811	−0.00805	−0.00808	−0.0059	−0.0076	−0.0059	−0.0061
	0.2	−0.0320 **	−0.0320 **	−0.0323 **	−0.0321 **	0.0136	0.0135	0.0137	0.0140	0.0037	0.00371	0.00416	0.00420	−0.0166	−0.0163	−0.0167	−0.0167
	0.3	0.0005	0.0005	0.0005	0.0005	−0.0076	−0.0076	−0.0076	−0.0076	0.0070	0.00698	0.00637	0.00699	−0.0153	−0.0156	−0.0157	−0.0156
	0.7	−0.0024	−0.0026	−0.0026	−0.0028	−0.0009	−0.0010	−0.0009	−0.0009	0.0024	0.00241	0.00246	0.00247	−0.0102	−0.0112	−0.0111	−0.0111

	0.8	−0.0026	−0.0025	−0.0014	−0.0014	−0.0001	−0.0005	0.0021	0.0020	−0.0068	−0.00685	−0.00685	−0.00685	−0.01452 *	−0.01453 *	−0.01453 *	−0.01450 *
	0.9	0.0961 ***	0.09519 ***	0.0950 ***	0.0950 ***	0.0086	0.0129	0.0073	0.0043	−0.0182	−0.01790	−0.01822	−0.01794	−0.02196 ***	−0.02261 ***	−0.02227 ***	−0.02217 ***
$\omega \Delta Covid_{19}cases_{t-1}($	0.1	0.0189	0.0162	0.0174	0.0178	0.0165	0.0159	0.0149	0.0140	0.0848	0.08465	0.08425	0.08410	0.0652	0.0336	0.0545	0.0674
	0.2	−0.0419	−0.0408	−0.0373	−0.0377	0.0133	0.0130	0.0117	0.0112	−0.0067	−0.00686	−0.00518	−0.00524	0.0221	−0.0054	0.0235	0.0255
	0.3	−0.1679 ***	−0.1674 ***	−0.1664 ***	−0.1656 ***	0.0046	0.0046	0.0040	0.0039	−0.0146	−0.01456	−0.01457	−0.01453	0.0257	0.0264	0.0269	0.0251
	0.7	0.0283	0.0313	0.0540	0.0535	−0.06651 ***	−0.06297 ***	−0.05879 ***	−0.05627 ***	0.0110	0.01105	0.00935	0.01092	0.1525	0.1019	0.1018	0.1046
	0.8	0.1087	0.1091	0.1127	0.1101	−0.07421 ***	−0.07105 ***	−0.064285 ***	−0.06151 ***	−0.0749	−0.07201	−0.06301	−0.06039	0.0810	0.0812	0.0809	0.0812
	0.9	0.2133	0.2173	0.2186	0.2208	−0.07843 ***	−0.07456 ***	−0.068771 ***	−0.06563 ***	−0.0180	−0.03719	−0.03951	−0.03770	0.1967	0.2081	0.1961	0.1965
$\omega \Delta Covid_{19}cases_{t-1}($	0.1	0.3710 ***	0.3774 ***	0.3781 ***	0.37838 ***	0.0216	0.0215	0.0215	0.0203	0.4256 ***	0.4256 ***	0.4255 ***	0.4255 ***	0.0379	−0.2173	0.0252	0.0361
	0.2	0.2883 ***	0.2945 ***	0.2977 ***	0.2967 ***	0.0698	0.0688	0.0699	0.0703	0.2889 ***	0.2889 ***	0.2902 ***	0.2901 ***	0.1675	0.1706	0.1577	0.1555
	0.3	0.2812 ***	0.2806 ***	0.2790 ***	0.2817 ***	0.0097	0.0107	0.0096	0.0099	0.1896 *	0.1896 *	0.1917 *	0.1895 *	−0.0211	−0.0171	−0.0172	−0.0175
	0.7	0.1159	0.0816	0.0738	0.0672	−0.0080	−0.0077	−0.0080	−0.0067	0.06009	0.05956	0.04939	0.05853	−0.0155	−0.0116	−0.0180	−0.0070
	0.8	0.0584	0.0548	0.0591	0.0591	0.0252	0.0237	0.0329	0.0331	0.17076	0.17054	0.17198	0.17029	0.0616	0.0608	0.0614	0.0599
	0.9	−0.0037	0.0178	0.0187	0.0196	−0.0191	−0.01911	−0.01986	−0.02014	0.19138	0.18871	0.18923	0.18931	−0.1029	−0.1155	−0.1100	−0.1076

Note: The asterisk signs of *, **, and *** are the representation of levels of significance at 10%, 5%, and 1%, respectively.

5.2.1. The Impact of Bearish, Bullish, and Median Quantiles of the Forward Exchange Rate Premium (FERP) on the Lower Quantiles of the Stock Market Returns (SMRs) in the Short and Long Term

In the long run, the 3rd-, 6th-, 9th-, and 12th-month FERP's bullish ($\theta_{FERP}(\xi_2$) in Table 4a,b), bearish ($\theta_{FERP}(\xi_1$) in Table 4a,b), and normal behavior ($\theta_{FERP}(\xi_3$) in Table 4a,b) is unable to influence the SMRs of Pakistan at lower quantiles. For portfolio managers and firms, the minimal influence of FERP on Pakistan's stock returns during bearish phases indicates its inadequacy as a hedge against stock price declines. Regulators and policymakers should observe that FERP lacks significant impact on equity returns in downturns, suggesting that exchange rate policies may have limited utility in promoting equity market stability under such conditions. Investors are advised to consider that FERP does not contribute effectively to portfolio diversification in bearish markets, encouraging a reassessment of diversification strategies toward assets or indicators more strongly correlated with stock returns during declines. Conversely, the FERP behavior in India and Sri Lanka, assessed across all distinct periods, has different implications, exerting varied influences on the stock returns in these two markets.

For instance, the bearish (ξ_1 in Table 4a,b) behavior of the FERP of India and Sri Lanka calculated for the 3rd, 6th, 9th, and 12th months positively influenced the stock market returns at lower quantiles, but the bullish ($\theta_{FERP}(\xi_3$) in Table 4a,b) behavior of the FERP influenced the stock market inversely or negatively. This implies asymmetry and shows that the bearish FERP changes maximize the stock market returns, but bullish FERP behavior yields a negative impact on the stock market returns at lower quantiles. This means that lower (higher) premium charged on long-term FERP agreements prove to be much more favorable (adverse) for SMRs of India, Bangladesh, and Sri Lanka at lower quantiles ($\tau = 0.1, 0.2, 0.3$) and during COVID-19. In periods of bearish FERP, Indian and Sri Lankan investors might consider increasing equity exposure, particularly at lower quantiles, which may support stock market returns. Strategic approaches may involve acquiring undervalued stocks or raising investments in high-dividend-yield equities during bearish FERP phases. Conversely, in bullish FERP periods, prudence is recommended, as these phases generally suppress stock market returns. Investors in India, Bangladesh, and Sri Lanka may consider hedging positions or lowering equity exposure to mitigate potential losses. Monitoring FERP trends and their stock market impacts can provide valuable insights for economic policy development.

One potential positive effect of the forward exchange rate premium (FERP) on stock market returns could be the enhanced profitability of the export-driven sectors in the economies of India and Sri Lanka. This outcome is linked to the appreciation of the U.S. dollar in global markets, leading to the depreciation of local currencies and consequently increasing premiums on forward contracts [80,64] However, over the long term, the deflation of local currencies may also have a converse effect on stock market returns due to the appreciation in producer prices, potentially causing greater losses for the importing sectors of these economies. These losses may also contribute to the downside reaction of the stock market because of the loss of sales to the import-oriented sectors of the Indian and Sri Lankan economies [68]. Therefore, bullish FERP behavior increases the local currency deflation at an accelerating rate, and SMRs may experience a downward shift due to the greater losses to the firms engaged in importing raw materials for Sri Lanka and India. This also reflects that stock market investors, exporters, and importers should consider the fluctuations in FERP with respect to its bullish and bearish behavior to yield longer-term benefits during the different equity market conditions. However, traditional quantile regressions are unable to examine the differential short- and long-run impact of multiple thresholds of FERP on the stock market bullish or bearish behavior.

Interestingly, the normal behavior ($\theta_{FERP}(\xi_3$) in Table 4a,b) of the FERP calculated for the 3rd-, 6th-, 9th-, and 12th-month periods for Pakistan, Sri Lanka, and India cannot explain the variability of stock market returns at lower quantiles. However, in the case of

Bangladesh, there is a positive influence of the FERP on the SMRs of Bangladesh. One of the premier justifications is the dependence of the Bangladeshi economy on both imports and exports. Therefore, the rise in premiums of the forward ER agreements at an accelerating rate (FERP bullish behavior) decreases the SMRs at lower quantiles, but during normal FERP behavior, Bangladesh's SMRs appreciate because of the deflating local currency and appreciating profitability of the local exporters. This justifies the decomposition reasoning of the FERP into various thresholds $(\theta_{FERP}(\xi_1), \theta_{FERP}(\xi_2), and$ $(\theta_{FERP}(\xi_3\ )$ in Table 4a,b) and the utilization of the multiple threshold-based QARDL frameworks. The differential response of SMRs at the different quantiles to the multiple thresholds of the FERP is again reflected in the short-term results.

In the short run, the bearish $(\varphi\Delta FERP_{t-1}(\xi_1)$ in Table 4a,b), bullish $(\varphi\Delta FERP_{t-1}(\xi_2)$ in Table 4a,b), and normal $(\varphi\Delta FERP_{t-1}(\xi_3)$ in Table 4a,b) FERP behavior calculated for the 3rd, 6th, 9th, and 12th months for Indian and Sri Lankan economies cannot influence the SMRs at lower quantiles ($\tau = 0.1, 0.2, 0.3$). However, the bearish $(\varphi\Delta FERP_{t-1}(\xi_1)$ in Table 4a,b) and normal $(\varphi\Delta FERP_{t-1}(\xi_3)$ in Table 4a,b) behavior of Bangladesh's FERP calculated for the 3rd-, 6th-, 9th-, and 12th-month periods positively influence the stock market returns of Bangladesh at lower quantiles, whereas the bullish FERP $(\varphi\Delta FERP_{t-1}(\xi_2)$ in Table 4a,b) cannot influence the Bangladeshi equity market variability at lower quantiles ($\tau = 0.1, 0.2, 0.3$).

These findings diverge from those of Kumar et al. [47] and Salisu et al. [42] for three key reasons: First, these studies primarily examine the differential effects of exchange rate shocks on average equity values. Second, they utilize spot-based currency rates instead of FERP. Third, both analyses are conducted outside the COVID-19 context and are limited to examining a single economy.

Table 4a,b illustrates the differentiated reactions of stock market returns (SMRs) across various quantile levels, including both extremes, when influenced by bearish, bullish, or moderate FERP quantiles, highlighting location-based asymmetries (as depicted in Table A4). The findings indicate that the impacts of bearish, bullish, and moderate FERP quantiles on SMRs of South Asian economies are distinct, especially at lower (bearish) quantiles of equity returns. Consequently, the MT-QARDL approach effectively captures "sign"-based asymmetries (see Table A5). For example, Table 4a,b shows that bearish FERP movements lead to increased SMRs for India and Sri Lanka at lower quantiles, while bullish FERP has a negative impact on SMRs of India, Bangladesh, and Sri Lanka at these same quantiles. This demonstrates "sign"-based asymmetries, stemming from the contrasting effects of bearish and bullish FERP on the lower quantiles of SMRs (see Table A5). Additionally, Table 4a,b reveals that bearish FERP positively affects SMRs for only India and Sri Lanka at lower quantiles, with a positive significant impact at higher quantiles of all the South Asian economies' stock returns. This indicates "location"-based asymmetries (see Table A4) due to the differential impact of bearish FERP on higher vs. lower quantiles of SMRs. Similarly, bearish FERP exerts a depreciative effect on SMRs for India, Bangladesh, and Sri Lanka at lower quantiles, while its influence at higher quantiles is either positive (Sri Lanka) or insignificant (India and Bangladesh). These findings justify the presence of long-term "location"-based asymmetries (please see Table A4).

5.2.2. The Impact of Bearish, Bullish, and Median Quantiles of the Forward Exchange Rate Premium (FERP) on the Higher Quantiles of the Stock Market Returns (SMRs) in the Short and Long Term

This section explains the response of the bullish stock market returns (SMRs) to the FERP-related bullish $(\theta_{FERP}(\xi_2)$ in Table 4a,b), bearish $(\theta_{FERP}(\xi_1)$ in Table 4a,b), and normal behavioral states $(\theta_{FERP}(\xi_3)$ in Table 4a,b). According to the results of the MT-QARDL framework, the bullish $(\theta_{FERP}(\xi_2)$ in Table 4a,b), bearish $(\theta_{FERP}(\xi_1)$ in Table 4a,b), and normal behavior $(\theta_{FERP}(\xi_1)$ in Table 4a,b) of the FERP calculated for four distinct periods (3rd, 6th, 9th, and 12th months) positively influence the higher-order quantiles of Pakistani stock market returns ($\tau = 0.7, 0.8, 0.9$) in the long term. Moreover, both the bullish and bearish FERP fluctuations positively affect the SMRs of Pakistan and Sri Lankan equity returns at higher quantiles in the long term. Therefore, Pakistani and Sri Lankan investors are likely to realize higher returns during the bullish behavior (higher quantiles) of the stock market. This analysis suggests that adopting more assertive investment strategies, such as increasing equity exposure or leveraging positions, could prove beneficial in maximizing returns during bullish fluctuations in FERP. However, in bearish equity market phases (τ = 0.1, 0.2, 0.3), FERP's effect on Pakistani stock returns becomes negligible. Given that FERP does not significantly impact equity market returns during market downturns, investors are encouraged to diversify their portfolios to manage risk effectively. Investment strategies centered on FERP may not provide the anticipated protection in these conditions, prompting investors to consider defensive tactics, such as reallocating to more stable or defensive sectors, to preserve portfolio value. Pakistani and Sri Lankan stock investors, in particular, should acknowledge FERP's influence during extreme equity market conditions and adapt their strategies with regard to FERP fluctuations and equity market behavioral conditions.

One of the justifications for the appreciation in the SMRs at higher quantiles due to the bullish states of the FERP of Pakistan and Sri Lanka is generally due to the greater profitability of the export-oriented business due to local currency deflation (see [1]. Another possibility may be due to Pakistan's government initiative to increase exporting activities to attract foreign exchange reserves. Due to the ongoing depletion of foreign exchange reserves, the growth in local currency deflation may offer local exporters the best investment opportunity and the potential to earn foreign exchange. This may encourage local exporters to expand their business and operational activities. Therefore, local currency depreciation makes Pakistan's exportable products more attractive to international buyers, and this is again reflected by an upward movement in stock returns.

Table 4a,b illustrates that in the long term, bearish fluctuations in the forward exchange rate premium ($\theta_{FERP}(\xi_1)$ in Table 4a,b) lead to notable increases in stock market returns (SMRs) across all South Asian economies at higher quantiles, particularly during bullish equity market conditions. In contrast, at lower quantiles (bearish equity market conditions), only the SMRs of Pakistan and Sri Lanka exhibit a positive response to bullish FERP shifts ($\theta_{FERP}(\xi_2)$ in Table 4a,b). Thus, South Asian firms engaged in international trade and investment could benefit from hedging strategies that account for both bearish and bullish FERP conditions. Anticipating stock market performance during these periods could aid in designing more robust hedging tactics to manage currency and market risks. Investors in South Asia, particularly during bearish FERP periods, should remain vigilant, as these phases are often linked to considerable positive impacts on SMRs at higher quantiles, suggesting a stronger potential for stock price growth. Conversely, bullish FERP states show minimal long-term influence on the bearish stock price movements in India and Bangladesh, indicating that investor strategies may not need significant adjustments in response to bullish FERP trends. Portfolio managers are advised to keep a close watch on FERP. While bearish FERP periods may present opportunities for higher returns, they also entail heightened volatility risks that require careful management. Therefore, bearish FERP (bullish FERP) fluctuations cause an appreciative impact of the higher quantiles of stock returns of all South Asian economies (only Pakistan and Sri Lanka). Moreover, moderate FERP fluctuations (($\theta_{FERP}(\xi_3)$ in Table 4a,b) positively affect the stock returns of Pakistan and India at higher quantiles.

The favorable effect of the FERP on stock price returns may stem from the appeal of local monetary policies as a channel that draws foreign exchange reserves, potentially encouraging positive investor responses to shifts in international currency dynamics[68]. The stock market's varied reactions across quantiles to different FERP thresholds support the adoption of a threshold-based QARDL framework. This MT-QARDL approach enables the examination of both "location" and "sign" asymmetries, as demonstrated in Table A4. For example, bearish FERP fluctuations lead to greater positive impacts on higher quantiles of stock market returns (SMRs) in all South Asian economies, while at lower quantiles, SMRs of Pakistan and Bangladesh show limited responsiveness to bearish FERP shifts, highlighting "location"-based asymmetries. Similarly, moderate FERP changes ($\theta_{FERP}(\xi_3)$ in Table 4a,b) positively influence SMRs of Pakistan and India at higher quantiles, though they have minimal effects at lower quantiles. Moreover, in addition to "location"-based asymmetries, the MT-QARDL approach also identifies "sign"-based asymmetries, revealing differences in responses to bearish versus bullish FERP thresholds. For instance, while bearish FERP increases SMRs in all South Asian economies at higher quantiles, bullish FERP positively affects only Pakistan and Sri Lanka while adversely impacting SMRs in Bangladesh and India at higher quantiles of stock market returns. Similarly, the moderate FERP positively affects the SMRs of Pakistan and India at higher quantiles, whereas the bullish FERP positively affect only the SMRs of Pakistan and Sri Lanka. This provides evidence that the MT-QARDL approach effectively reveals "sign"-based asymmetries, as presented in Table A5.

In the short run, the lower premium charged on forward exchange rate agreements ($\varphi \Delta FERP_{t-1}(\xi_1)$ in Table 4a,b) negatively influences the SMRs of Sri Lanka during the equity market bullish conditions, whereas higher FERP values ($\varphi \Delta FERP_{t-1}(\xi_2)$ in Table 4a,b) yield an insignificant impact. Similarly, a higher premium charged on forward exchange rate agreements negatively influences higher quantiles of SMRs of India and Bangladesh, whereas bearish FERP values cannot explain the SMR variability for India and Bangladesh at higher financial market conditions of these economies. This shows that higher (lower) premium charges on short-run forward exchange rate agreements render a negative influence on the SMRs of Bangladesh and India (Sri Lanka).

5.2.3. Behavioral Response of the Stock Market to the Bullish, Bearish, and Normal Fluctuations in COVID-19 Cases

Conferring to Table 4a,b, the bearish fluctuations in COVID-19 cases ($\theta_{covid_{19cases}}(\beta_1)$ in Table 4a,b) cannot influence the stock market returns at lower quantiles and in the long run. However, only Indian and Sri Lankan stock market returns at lower quantiles depreciate due to the bullish fluctuations in COVID-19 cases ($\theta_{covid_{19cases}}(\beta_2)$ in Table 4a,b), whereas Pakistan and Bangladesh bearish stock market returns attain long-term resilience against higher COVID-19 cases. Similarly, under normal fluctuations in COVID-19-related cases ($\theta_{covid_{19cases}}(\beta_3)$ in Table 4a,b), all economies' stock market returns at lower quantiles remain resilient in the long term. In the wake of the health crisis, investors and fund managers are advised to reassess their portfolios to minimize exposure to Indian and Sri Lankan equities. This reassessment may involve diversifying into alternative markets or asset classes that are less impacted by the health crisis regime. Additionally, employing hedging strategies that focus on the lower quantiles of stock returns, particularly during bearish market conditions, can mitigate downside risks associated with the health crisis period. Policymakers in India and Sri Lanka may also need to implement economic support measures during COVID-19 surges to stabilize their stock markets. Such measures could encompass fiscal stimulus, monetary easing, or targeted support for sectors most affected by the pandemic.

Previous studies noted the adverse effects of COVID-19 cases without breaking down these shocks into partial sums [5,81]. We show, however, that COVID-19's bullish, bearish, and normal fluctuations impact stock market return differently and asymmetrically at lower quantiles. While past research focused on symmetrical associations [82], some studies highlight the resilience of stock indices against COVID-19 fluctuations due to factors like high employment or mass vaccination [25] and corporate social responsibility [44]. In periods of strong market performance, only lower quantiles of COVID-19 cases negatively affect India's returns, while higher quantiles impact Pakistan's returns in the long term. Investors and analysts in India and Pakistan should monitor COVID-19 case distributions across quantiles for potential trends in stock performance, as adverse effects may emerge when cases cluster within certain quantiles. Conversely, Bangladesh's bullish returns remain resilient against COVID-19 fluctuations over the long term.

This suggests that government administrative agencies in Pakistan (India) should manage the higher (lower) COVID-19 fluctuations during periods of strong stock market performance. In the short term, with a bullish equity market, only bullish COVID-19 cases ($\omega \Delta Covid_{19}cases_{t-1}(\beta_2)$ in Table 4a,b) in India and bearish cases ($\omega \Delta Covid_{19}cases_{t-1}(\beta_1)$ in Table 4a,b) in Sri Lanka reduce equity returns, while in Pakistan, both bearish and bullish COVID-19 cases negatively impact market returns during periods of low equity returns. This indicates that the connection between equity markets and COVID-19 is dependent on market conditions and the direction of COVID-19 shocks (positive, moderate, or negative), contrasting with prior studies that assumed a linear relationship [82].

5.2.4. Robustness Analysis: A Multivariate Non-Causality Analysis

Moreover, for further robustness regarding the non-linear association between FERP and SMRs of South Asian economies, we also apply the multivariate non-linear causality test by Bai et al. [83] to examine non-linear spillover effects from 3rd-, 6th-, 9th-, and 12th-month forward exchange rate premiums (FERP) on South Asian stock returns. Table A6 confirms non-linear Granger causality from FERP toward stock returns in South Asian economies.

6. Conclusions with General Policy Guidelines and Future Research Directions

The COVID-19 pandemic triggered a liquidity crisis in stock markets and spurred currency depreciation, influenced by volatile oil prices and rising inflation. Fluctuations in foreign exchange rates impact global trade, income, and production, leading businesses to rely on forward exchange contracts to hedge against currency risk. Importantly, the effects of the multiple quantiles of the forward exchange rate premiums (FERPs) and COVID-19 cases on the multiple quantiles on South Asian stock market returns (SMRs) remain underexplored. Most existing research focuses on shock transmission through spot exchange rates, COVID-19, and financial markets, frequently overlooking the quantile-specific asymmetrical effects of FERP and COVID-19 cases on South Asian equity returns. This research gap largely arises from the dominance of traditional econometric models, which often assume a linear relationship between exchange rates and SMRs, potentially obscuring non-linear or asymmetric responses of SMRs to varying degrees of FERP, whether bullish, bearish, or moderate. To address this gap, we combine the quantile regression model by Koenker and Hallock [32] with the Multiple Threshold-based Non-linear Autoregressive Distributed Lag (MT-NARDL) model by Pal and Mitra [29–31] to create a novel Multiple Threshold-based Quantile Autoregressive Distributed Lag (MT-QARDL) model. Distinct from prior studies, this MT-QARDL model effectively captures both "sign"- and "location"-based asymmetries in the asymmetric FERP-SMR relationship.

Overall findings suggested that long-term bearish FERP (lower quantiles of FERP) increases the SMRs of only India and Sri Lanka at lower quantiles, whereas bearish FERP causes an appreciative impact on the SMRs of all South Asian economies at higher quantiles. This shows the presence of long-term "location"-based asymmetries due to the differential response of SMRs at varied quantile levels (higher vs. lower) to the bearish FERP fluctuations. Moreover, bullish FERP fluctuations decrease the SMRs of India, Bangladesh, and Sri Lanka at lower quantiles, whereas at higher quantiles of SMRs, the bullish FERP fluctuations insignificantly affect the Indian and Bangladesh's SMRs and positively affect the SMRs of Sri Lanka. Therefore, South Asian financial institutions and policymakers might adopt forecasting models that account for quantile-specific variations to anticipate stock market responses to shifts in FERP. By recognizing the distinct effects across different quantiles, economic policies can be refined to more effectively control inflationary and deflationary trends, adjust interest rates, and implement fiscal strategies that bolster market stability during periods of FERP volatility.

South Asian policymakers, especially in India and Sri Lanka, should monitor long-term bearish FERP trends, as these can boost stock returns at lower quantiles. Regulatory bodies might stabilize FERP to help markets leverage this benefit in bearish conditions. At higher quantiles of equity markets, since bearish FERP is broadly favorable across South Asia, intervention could be minimal, though governments may bolster financial buffers against excessive FERP volatility. Given location-specific asymmetries, these countries should adjust policies to support markets differently during bearish versus bullish FERP phases. Investment incentives and liquidity support could be more effective during bearish FERP, while managing currency expectations and volatility controls would help mitigate the negative effects of bullish FERP on stock returns. Additionally, India, Bangladesh, and Sri Lanka should consider hedging tools to protect portfolios from bullish FERP's adverse impact on SMRs in volatile periods. Therefore, capitalizing on bearish FERP conditions at lower quantiles in India and Sri Lanka while strategically rebalancing portfolios during bullish FERP periods in Bangladesh, India, and Sri Lanka could enhance returns and mitigate risk.

Moreover, insights into quantile interactions can improve market sentiment analysis. Analysts may view high FERP levels as signs of potential market distress, particularly when linked to lower quantile SMRs. This understanding can shape market predictions and trading decisions, allowing for more informed, quantile-specific recommendations. Beyond the "location"-based asymmetries discussed, the MT-QARDL approach also examines "sign"-based asymmetries in both the long- and short-term contexts. For instance, bullish FERP yields a positive effect on stock market returns (SMRs) for Pakistan and Sri Lanka at higher quantiles. Meanwhile, moderate FERP fluctuations lead to an appreciation in SMRs for Pakistan and India at higher quantiles. In contrast, bearish FERP shocks generate an appreciation in SMRs across all South Asian economies at higher quantiles. These findings underscore the presence of "sign"-based asymmetries, as SMRs respond differently to bearish, bullish, and moderate FERP conditions. Regulatory bodies should develop and enforce comprehensive risk management frameworks that require financial institutions to implement quantile-specific risk assessments, thereby promoting stability amid fluctuating FERP conditions. By utilizing quantile-specific forecasting models, policymakers can anticipate and address FERP variations that could affect stock market returns (SMRs), allowing for proactive, data-informed policy modifications aimed at stabilizing the markets ahead of time.

The MT-QARDL model can be further developed by incorporating the concepts of good and bad volatility in stock returns. Additionally, Tabash et al.[84] emphasize a significant gap in the literature regarding the transmission of extreme volatility shocks—both positive and negative—across global stock markets. Consequently, examining the effects of various quantiles of forward exchange rate premiums and COVID-19 cases on the good and bad volatility of stock markets in South Asian economies may assist both short-term speculators and long-term investors in adapting their strategies in response to anticipated volatility. This understanding can facilitate more informed decision-making, potentially improving returns and reducing risks.

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Appendix A

Table A1. The comparison of the proposed model (MT-QARDL) with the existing literature.

Authors	Econometric Model	The Purpose of the Study	Is the Employed Model Possess Asymmetrical Characteristics?	Is the Study Conducted for the Context of South Asian Economies?	Is the Employed Model Effectively Identify Potential Asymmetries?	Is the Employed Model Capable of Estimating 'Location-Based' Asymmetries?	Is the Employed Model Capable of Estimating 'Sign-Based' Asymmetries?	Does the Model Have the Capability to Estimate for the 'Short' and 'Long-Term' Investment Periods?
(Chen and Sun, [85]	Quantile domain Granger causality approach	The asymmetrical interactions between spot-based forex and financial markets	Yes	Yes	Yes	Yes	No	No
(Tabash et al. [4]	Panel-based Non-linear Autoregressive Distributive Lag model with pooled mean group approach	The asymmetrical causation from spot values of the exchange rates toward stock returns	Yes	Yes	Yes	No	Yes	Yes
(Tian et al. [86]	The GARCH-based copula quantile regression approach	The tail dependency between exchange rates and stock returns	Yes	Yes	Yes	Yes	No	No
Suleman et al. [3]	Panel-based Non-linear Autoregressive Distributive Lag model with pooled mean group approach	Asymmetrical impact of stock returns to the inflation and deflation in spot-based currency values	Yes	No	Yes	No	Yes	Yes
(Chen et al. [63]	The time-varying parameter factor augmented VAR and non-linear Granger causality approach	The non-linear interactions between stocks and spot-based exchange rates	Yes	Yes	Yes	No	No	No
(Hashmi et al. [41]	Quantile Autoregressive Distributive Lag model (QARDL)	The asymmetrical response of stock returns at different quantiles to the fluctuations in spot exchange rate	Yes	Yes	Yes	Yes	No	Yes
Salisu et al. [87]	Threshold augmented vector global auto-regression (GVAR)	The impact of COVID-19 on the stock and spot exchange rates	Yes	Yes	Yes	No	No	No

Salisu et al. [42]	The panel domain Non-linear Autoregressive Distributive Lag model	The response of U.S. firms' stock returns to the positive and negative shocks in spot values of the exchange rates	Yes	No	Yes	No	Yes	Yes
Zhu et al. [43]	The threshold rolling window quantile regression approach	The response of stock returns of BRICS to the fluctuations in spot exchange rate	Yes	Yes	Yes	Yes	No	No
Ding et al. [44]	Ordinary least square regression model	The stock and exchange rate interactions	No	No	No	No	No	No
Huang et al. [45]	Time-varying Parameter Vector Auto-regression	The response of stock returns to the fluctuations in spot exchange rate	No	No	No	No	No	No
Khan et al. [46]	Autoregressive Distributive Lag model (ARDL) with graphical simulations	The linear response of stock returns to the fluctuations in spot currency values	No	No	No	No	No	Yes
Kumar et al. [47]	The Non-Linear Autoregressive Distributive Lag model approach (NARDL)	The response of Indian stock returns to the positive and negative fluctuations in spot exchange rates	Yes	Yes	Yes	No	Yes	Yes
Salisu et al. [48]	Panel-based Autoregressive Distributive Lag model	The response of stock returns to the positive and negative fluctuations in exchange rates under different interest rate regimes	No	Yes	No	No	No	Yes
Xie et al. [40]	Symmetric and asymmetric panel domain Granger causation approach	The dynamic interaction between stock and exchange rate	Yes	Yes	Yes	No	No	No
Ansriansyah and Messins [37]	Granger causality approach	The dynamic interaction between stock and exchange rate	No	Yes	No	No	No	No
Current article (contribution with respect to novel method)	Multiple Threshold-based Quantile-based Autoregressive Distributive Lag model approach	The response of stock returns at different quantiles to the bearish, bullish, and moderate fluctuations in forward exchange rate premiums	Yes	No	Yes	Yes	Yes	Yes

Note: This table reports the authors' contribution with the respect to the introduction of the novel Multiple Threshold-based Quantile Autoregressive Distributive Lag (MT-QARDL) approach to explore the impact of multiple quantiles of forward exchange rate premiums on the multiple quantiles of stock returns in the short- and long-term periods.

Table A2. HWBZ test of non-linearity.

	Pakistan					**India**					
	Absolute Returns	FERP-3M	FERP-9M	FERP-12M		Absolute Returns	FERP-3M	FERP-6M	FERP-9M	FERP-12M	
Dimension	HWBZ test					HWBZ test					
$\eta = 1$	0.593	0.572	0.593	0.639		0.553	0.584	0.623	0.652	0.573	
$\eta = 1.5$	0.61	0.582	0.599	0.6083		0.57	0.573	0.599	0.66	0.58	
	Bangladesh						Sri Lanka				
	Absolute Returns	FERP-3M	FERP-6M	FERP-9M	FERP-12M		Absolute Returns	FERP-3M	FERP-6M	FERP-9M	FERP-12M
	HWBZ test						HWBZ test				
$\eta = 1$		0.573	0.58	0.592	0.61			0.67	0.593	0.688	0.581
$\eta = 1.5$		0.55	0.5899	0.602	0.599			0.66	0.608	0.69	0.59

Note: In the BDS test, the parameters δ and k are identical to those used by [78], with δ defined as $0.5\sqrt{\mathrm{Var}(Y_t)}$ and k set to 2 and 3. In the HWBZ test, the residual sequence $\{Y_t\}$ is first standardized, and the parameter η is chosen to be 1 and 1.5.

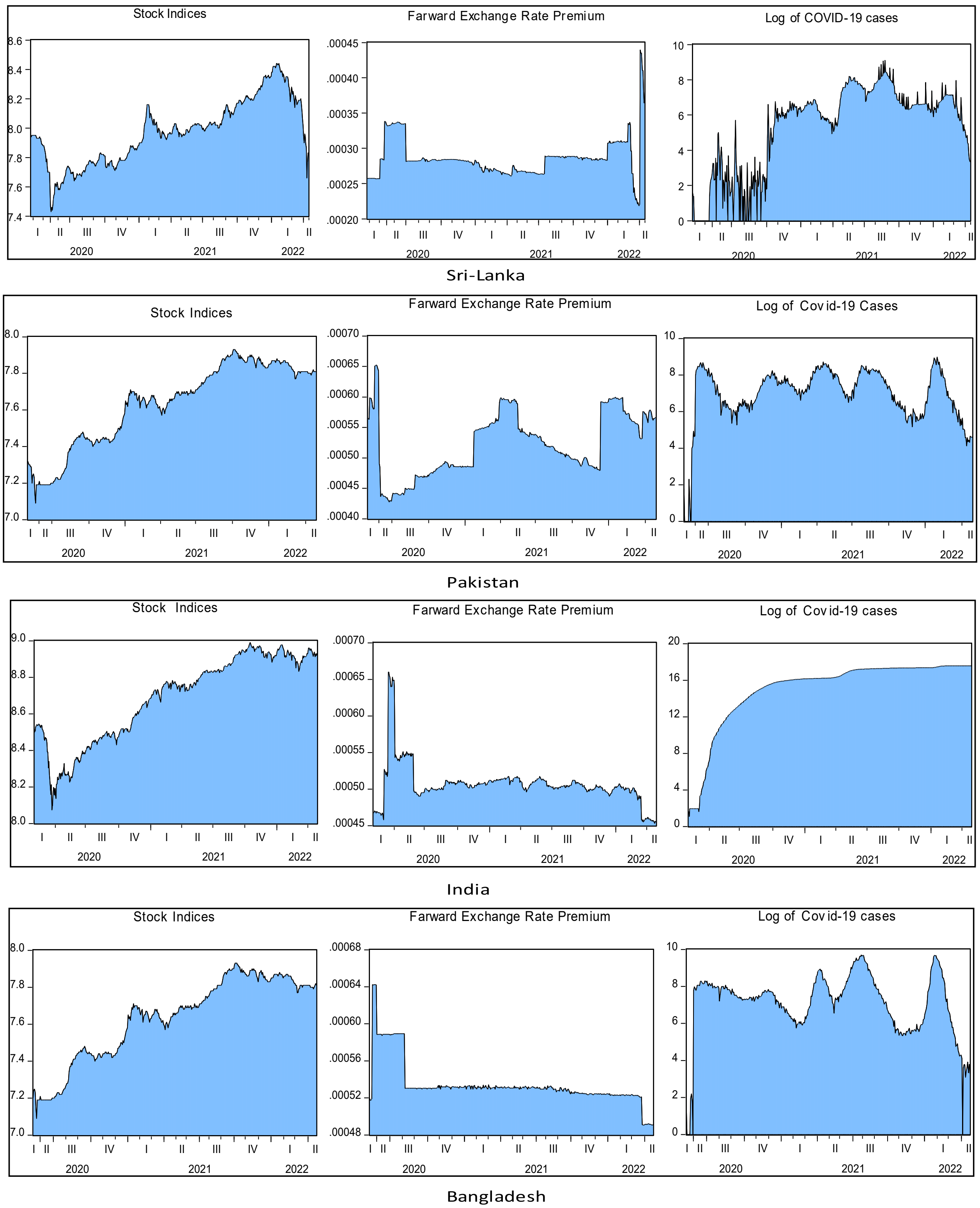

Figure A1. The graphical representation of log of stock market indices, forward exchange rate premium, and logarithmic transformed COVID-19 cases of the South Asian economies.

Table A3. (**a**): Traditional QARDL frameworks. (**b**): Departure from symmetries by using Wald test statistics.

		(a)															
		Pakistan				**India**				**Bangladesh**				**Sri Lanka**			
		FERP-3M	**FERP-6M**	**FERP-9M**	**FERP-12M**	**FERP-3M**	**FERP-6M**	**FERP-9M**	**FERP-12M**	**FERP-3M**	**FERP-6M**	**FERP-9M**	**FERP-12M**	**FERP-3M**	**FERP-6M**	**FERP-9M**	**FERP-12M**
		Coef.	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**
β	0.1	−0.4250	−0.4135	−0.3690	−0.3578	0.0460	−0.0246	0.0546	−0.0233	−0.3751	−0.3520	−0.2949	−0.2663	−0.4969 ***	−0.4782 ***	−0.3844 ***	−0.3712 ***
	0.2	−0.2376	−0.2308	−0.2125	−0.2065	−0.1181	−0.0747	−0.0598	−0.0632	0.6141 **	0.5930 **	0.5331 **	0.5111 **	−0.3199 *	−0.3065 *	−0.26020	-0.24567
	0.3	−0.0436	−0.0428	−0.0413	−0.0423	−0.0740	−0.0686	−0.0538	−0.0476	−0.1650	−0.1580	−0.1324	−0.1312	−0.07481	−0.06874	−0.05057	-0.04386
	0.7	−0.0582	−0.0561	−0.0503	−0.0482	0.3000	0.2899	0.2740	0.2715	−0.2701	−0.2603	−0.1991	−0.1809	0.4144 ***	0.4092 ***	0.3807 ***	0.3688 ***
	0.8	0.0099	0.0100	0.0102	0.0103	0.2881	0.2763	0.2576	0.2514	−0.0072	−0.0065	−0.0022	−0.0039	0.4828 ***	0.4730 ***	0.4392 ***	0.4249 ***
	0.9	0.0809	0.0823	0.0860	0.0874	0.4071	0.4085 *	0.3634	0.3531	−0.8694 **	−0.8356 **	−0.7372 **	−0.6930 **	0.7959 ***	0.7660 ***	0.7010 ***	0.6799 ***
ρ	0.1	0.0034	0.0034	0.0029	0.0029	−0.0208	−0.0191	−0.0208	−0.0185	−0.0116	−0.0116	−0.0124	−0.0121	−0.01209	−0.01187	−0.00953	-0.00952
	0.2	−0.0012	−0.0011	−0.0011	−0.0010	−0.01566 **	−0.01516 ***	−0.01548 ***	−0.01563 ***	0.0003	0.0003	0.0009	−0.0001	−0.01237	−0.012616 *	−0.0128 *	-0.01321 *
	0.3	0.0006	0.0006	0.0007	0.0008	−0.01175 ***	−0.01191 ***	−0.01177 ***	−0.01176 ***	−0.008814 *	−0.008812 *	−0.008669 *	−0.008803 *	−0.01445 **	−0.01448 **	−0.01446 **	−0.01450 **
	0.7	−0.0008	−0.0008	−0.0008	−0.0008	−0.01090 ***	−0.00989 **	−0.01089 ***	−0.01057 ***	−0.0049	−0.0049	−0.0058	−0.0060	−0.00797	−0.00793	−0.00785	-0.00788
	0.8	−0.0004	−0.0004	−0.0004	−0.0004	−0.006047 *	−0.0057	−0.00599 *	−0.0060	−0.0005	−0.0005	−0.0004	−0.0005	−0.009091 **	−0.008965 **	−0.008964 **	-0.008829 *
	0.9	−0.01427 **	−0.01428 **	−0.01427 **	−0.01427 **	−0.0061	−0.0061	−0.0060	−0.0061	−0.01987 **	−0.01987 **	−0.01964 **	−0.0191 **	−0.00109	−0.00115	−0.00094	-0.00083
θ_{FERP}	0.1	−0.0400	−0.0400	−0.0390	−0.0390	−0.0067	−0.0134	−0.0065	−0.0147	−0.0484	−0.0473	−0.0457	−0.0434	−0.05974 ***	−0.0594 ***	−0.05198 ***	−0.05217 ***
	0.2	−0.02498 *	−0.02502 *	−0.02518 *	−0.02527 *	−0.0243	−0.0195	−0.0199	−0.0213	0.07100 **	0.07087 **	0.07110 **	0.06990 **	−0.04236 **	−0.04243 **	−0.04125 **	−0.04122 **
	0.3	−0.0036	−0.0036	−0.0037	−0.0038	−0.0178	−0.0179	−0.0177	−0.0176	−0.0242	−0.0242	−0.0234	−0.0241	−0.01864	−0.01856	−0.01820	-0.01805
	0.7	−0.0073	−0.0073	−0.0073	−0.0073	0.0231	0.0234	0.0230	0.0239	−0.0349	−0.0349	−0.0315	−0.0304	0.03637 **	0.03697 **	0.03720 **	0.03701 **
	0.8	−0.0003	−0.0003	−0.0003	−0.0003	0.0250	0.0248	0.0247	0.0248	−0.0024	−0.0023	−0.0020	−0.0023	0.04217 ***	0.04254 ***	0.04261 ***	0.0424 ***
	0.9	−0.0045	−0.0045	−0.0045	−0.0045	0.0372	0.03875 *	0.0369	0.0369	−0.1172 **	−0.1172 **	−0.11664 **	−0.11474 **	0.08086 ***	0.08007 ***	0.08019 ***	0.08047 ***
$\theta_{covid_{19cases}}$	0.1	0.00411 *	0.004114 *	0.004023 *	0.004023 *	0.0239	0.0231	0.02388	0.02265	0.002626 ***	0.002627 ***	0.002589 ***	0.002619 ***	0.00040	0.00040	0.00012	0.00013
	0.2	0.0020	0.0020	0.0021	0.0021	0.01162 *	0.01170 **	0.01189 **	0.01202 **	0.001163 **	0.001158 **	0.001089 **	0.00112 **	0.00037	0.00038	0.00046	0.00049
	0.3	0.000799 *	0.000805 *	0.000846 **	0.000872 **	0.005296 *	0.005335 *	0.005325 *	0.005357 *	0.001847 **	0.001847 **	0.001734 **	0.001843 **	0.000938 **	0.000942 **	0.000957 **	0.000967 **
	0.7	0.001109 *	0.00111 *	0.00111 *	0.001111 *	0.003473 **	0.0024	0.003403 **	0.003288 **	0.0007	0.0007	0.0008	0.000851 *	0.000999 ***	0.000993 ***	0.000974 ***	0.000966 ***
	0.8	0.00004	0.00003	0.00004	0.00004	−0.0003	−0.0004	−0.0004	−0.0004	0.0000	0.0000	0.0000	0.0000	0.000727 **	0.000743 **	0.000726 **	0.000725 **
	0.9	0.0005	0.0005	0.0005	0.0005	−0.0022	−0.0019	−0.0023	−0.0024	−0.0012	−0.0012	−0.0013	−0.0014	0.00078	0.00075	0.00065	0.00060
δ	0.1	−0.0701	−0.0701	−0.0665	−0.0665	0.0882	0.0520	0.0885	0.0504	0.0156	0.0156	0.0218	0.0163	0.4785 ***	0.4804 ***	0.4914 ***	0.4934 ***
	0.2	0.0053	0.0051	0.0039	0.0031	0.0634	0.0773	0.0718	0.0662	−0.0419	−0.0418	−0.0527	−0.0408	0.3689 ***	0.3693 ***	0.3621 ***	0.3615 ***
	0.3	0.0063	0.0057	0.0025	0.0007	0.1022 **	0.10226 **	0.1022 **	0.10230 **	−0.0128	−0.0128	−0.0039	−0.0132	0.3591 ***	0.3593 ***	0.3592 ***	0.3581 ***
	0.7	−0.0659	−0.0659	−0.0658	−0.0658	−0.0535	−0.0450	−0.0533	−0.0522	−0.0093	−0.0092	−0.0115	−0.0101	0.04572	0.04160	0.03704	0.03466
	0.8	−0.0023	−0.0023	−0.0023	−0.0023	−0.0631	−0.0581	−0.0636	−0.0634	−0.0029	−0.0030	−0.0029	−0.0030	0.00113	0.00070	0.00031	0.00186
	0.9	−0.1709 ***	−0.1708 ***	−0.1707 ***	−0.1706 ***	−0.0866	−0.0868	−0.0871	−0.0849	−0.0924	−0.0924	−0.0980	−0.1011	−0.07470	−0.07115	−0.06676	-0.06338

φ	0.1	−0.0462	−0.0462	−0.0460	−0.0460	0.0455	0.0396	0.0445	0.0344	−0.3068 ***	−0.30571 ***	−0.3018 ***	−0.2989 ***	−0.01497	−0.01466	−0.01148	−0.01134
	0.2	−0.051539 *	−0.05154 *	−0.0516	−0.0516	−0.0494	−0.11042 *	−0.1126	−0.1122	−0.3524 ***	−0.35105 ***	−0.3429 ***	−0.3399 ***	−0.0320 ***	−0.03205 ***	−0.03269 ***	−0.03278 ***
	0.3	−0.0850 ***	−0.0858 ***	−0.08529 ***	−0.08507 ***	−0.0047	−0.0049	−0.0045	−0.0045	−0.37794 ***	−0.37653 ***	−0.3708 ***	−0.3657 ***	−0.03206 **	−0.03201 **	−0.03187 **	−0.03192 **
	0.7	−0.0181	−0.0181	−0.0181	−0.0181	0.1470 **	0.1209	0.1446 **	0.1442 **	−0.2073	−0.2071	−0.1922	−0.2519	−0.05581	−0.05368	−0.05162	−0.05046
	0.8	−0.0352	−0.0352	−0.0352	−0.0352	−0.0102	−0.0105	−0.0106	−0.0103	−0.0950	−0.0950	−0.0954	−0.0950	−0.06687 ***	−0.06577 ***	−0.06344 ***	−0.06134
	0.9	−0.1349 ***	−0.1348 ***	−0.1348 ***	−0.1348 ***	0.0434	0.0427	0.0431	0.0437	−0.0932	−0.0932	−0.0929	−0.1229	−0.07808 ***	−0.07810 ***	−0.07750 ***	−0.07711 ***
ω	0.1	−0.0051	−0.0051	−0.0053	−0.0053	−0.1685	−0.1595	−0.1686	−0.1572	−0.0033	−0.0033	−0.0034	−0.0030	0.00266	0.00267	0.00237	0.00239
	0.2	−0.0048	−0.0048	−0.0048	−0.0049	−0.07398 *	−0.07608 ***	−0.07668 ***	−0.07642 ***	−0.00204 ***	−0.00202 ***	−0.0019 ***	−0.00189 ***	0.002708 **	0.002704 **	0.002668 **	0.002658 **
	0.3	−0.0019	−0.0019	−0.0019	−0.0020	−0.03952 *	−0.03968 *	−0.039437 *	−0.03948 *	−0.0013	−0.0013	−0.0012	−0.0012	0.00077	0.00078	0.00080	0.00081
	0.7	0.0020	0.0020	0.0020	0.0020	−0.00911 *	−0.0053	−0.00911 *	−0.009274 *	−0.0004	−0.0004	−0.0003	−0.0010	−0.001775 *	−0.001769 *	−0.001761 *	−0.001746 *
	0.8	0.0001	0.0001	0.0001	0.0001	0.01315 **	0.01311 **	0.0132 **	0.01324 **	0.0003	0.0003	0.0002	0.0003	−0.00066	−0.00059	−0.00061	−0.00059
	0.9	0.0016	0.0016	0.0016	0.0016	0.0299	0.0281	0.0300	0.0299	0.0013	0.0013	0.0013	0.0009	−0.002106 *	−0.002004 *	−0.00178	−0.00171

(b)

		Pakistan				**India**				**Bangladesh**				**Sri Lanka**			
		FERP-3M	**FERP-6M**	**FERP-9M**	**FERP-12M**	**FERP-3M**	**FERP-6M**	**FERP-9M**	**FERP-12M**	**FERP-3M**	**FERP-6M**	**FERP-9M**	**FERP-12M**	**FERP-3M**	**FERP-6M**	**FERP-9M**	**FERP-12M**
		Restr.Value	**Restr.Value**	**Restr.Value**	**Restr.Value**	**Restr.Value**	**Restr.Value**	**Restr.Value**	**Restr.Value**	**Restr.Value**	**Restr.Value**	**Restr.Value**	**Restr.Value**	**Restr.Value**	**Restr.Value**	**Restr.Value**	**Restr.Value**
0.1, 0.9	β	−0.3440	−0.3312	−0.2830	−0.2704	0.3305	0.2960	0.2892	0.2065	−1.2432	−1.1864	−1.0321	−0.9581	0.2990	0.2878	0.3166	0.3088
	ρ	−0.0109	−0.0109	−0.0114	−0.0114	−0.0055	−0.0045	−0.0054	−0.0036	−0.03147 ***	−0.03146 ***	−0.03206 ***	−0.03120 ***	−0.0132	−0.0130	−0.0105	−0.0104
	θ_{FERP}	−0.0445	−0.0445	−0.0435	−0.0435	0.0358	0.0339	0.0356	0.0278	−0.1654	−0.1644	−0.1624	−0.1579	0.0211	0.0207	0.0282	0.0283
	$\theta_{covid_{19cases}}$	0.004614 **	0.004615 **	0.004527 **	0.004528 **	0.0138	0.0133	0.0137	0.0124	0.0014	0.0014	0.0013	0.0013	0.0012	0.0011	0.0008	0.0007
	δ	−0.2410 *	−0.2409 *	−0.2372 *	−0.2371 *	0.0174	−0.0186	0.0172	−0.0329	−0.0764	−0.0765	−0.0761	−0.0843	0.403839 **	0.409285 **	0.424734 **	0.430117 **
	φ	−0.1811 **	−0.1811 **	−0.1808 **	−0.1808 **	−0.1800	−0.1778	−0.1812	−0.1886	−0.0205	−0.0194	−0.0133	0.0279	−0.0931	−0.0928	−0.0890	−0.0884
	ω	−0.0035	−0.0035	−0.0036	−0.0036	−0.1227	−0.1173	−0.1227	−0.1134	−0.0022	−0.0021	−0.0021	−0.0022	0.0006	0.0007	0.0006	0.0007
0.2, 0.8	β	−0.2277	−0.2209	−0.2023	−0.1962	0.0474	0.1136	0.0689	0.0649	0.6083 **	0.5877 **	0.5309 **	0.5085 **	0.1629	0.1666	0.1790	0.1793
	ρ	−0.0015	−0.0015	−0.0014	−0.0014	−0.0003	−0.0003	0.0000	−0.0007	−0.0002	−0.0002	0.0005	−0.0006	−0.021463 **	−0.021581 **	−0.021852 **	−0.022047 **
	θ_{FERP}	−0.0253	−0.0253	−0.0255	−0.0256	0.0060	0.0139	0.0100	0.0091	0.06885 *	0.06872 *	0.06915 *	0.06778 *	−0.0002	0.0001	0.0014	0.0013
	$\theta_{covid_{19cases}}$	0.0021	0.0021	0.0021	0.0021	0.0035	0.0035	0.0037	0.0038	0.001197 *	0.001192 *	0.00112 *	0.00115 *	0.001098 *	0.001125 *	0.001181 **	0.001213 **
	δ	0.0031	0.0028	0.0016	0.0008	0.0160	0.0354	0.0238	0.0044	−0.0445	−0.0444	−0.0556	−0.0434	0.370105 ***	0.370037 ***	0.362431 ***	0.363442 ***
	φ	−0.0867	−0.0867	−0.0867	−0.0868	−0.3284	−0.3810 ***	−0.3920 ***	−0.3891 ***	−0.0680	−0.0666	−0.0568	0.0148	−0.0990	−0.0978	−0.0961	−0.0941
	ω	−0.0047	−0.0047	−0.0047	−0.0048	−0.0449	−0.04877 *	−0.04751 *	−0.04928 *	−0.0019	−0.0019	−0.0017	−0.0018	0.0020	0.0021	0.0021	0.0021
0.3, 0.7	β	−0.1018	−0.0989	−0.0916	−0.0905	0.1034	0.1334	0.0914	0.1006	−0.4338	−0.4170	−0.3315	−0.3108	0.3396	0.3405	0.3302	0.325025 *
	ρ	−0.0002	−0.0002	−0.0001	−0.0001	−0.0012	−0.0012	−0.0012	−0.0014	−0.01366 **	−0.01365 **	−0.01451 **	−0.01479 **	−0.022424 ***	−0.022383 ***	−0.022311 ***	−0.022391 ***
	θ_{FERP}	−0.0109	−0.0109	−0.0110	−0.0111	0.0105	0.0141	0.0105	0.0118	−0.0589	−0.0589	−0.0549	−0.0543	0.0177	0.0184	0.0190	0.0190
	$\theta_{covid_{19cases}}$	0.001908 ***	0.001915 ***	0.001957 ***	0.001983 ***	0.0010	−0.0001	0.0009	0.0008	0.002529 ***	0.002528 ***	0.002543 ***	0.002697 ***	0.001937 ***	0.001934 ***	0.001931 ***	0.001932 ***
	δ	−0.0596	−0.0602	−0.0633	−0.0651	0.0645	0.0735	0.0647	0.0517	−0.0217	−0.0217	−0.0154	−0.0229	0.404841 ***	0.400952 ***	0.396339 ***	0.39285 ***
	φ	−0.1040 *	−0.1039 *	−0.1034 *	−0.1032 *	−0.1265	−0.1441	−0.1287	−0.1270	−0.2057	−0.2042	−0.1816	−0.1680	−0.0879	−0.0857	−0.0835	−0.0824

ω	0.00010	0.00008	0.00005	0.00002	−0.0327	−0.0308	−0.0326	−0.03485 *	−0.0018	−0.0017	−0.0015	−0.0023	−0.0010	−0.0010	−0.0010	−0.0009

Note: This table explains the departure from symmetrical distribution by comparing the coefficients at 0.1 and 0.9, 0.2 and 0.8, and 0.3 and 0.7 quantiles. The asymmetrical Newey and Powel (1987) test, i.e., $(\frac{\beta_{0.1} + \beta(1 - 0.9)}{2} = \beta(1/2))$, analyzes whether the coefficient value at the set of two distinct quantiles equals their median value. The asterisk signs of *, **, and *** represent the departure from the symmetrical distribution because of the rejection of the null hypothesis of symmetry at the 10%, 5%, and 1% significance levels, respectively.

Table A4. Departure from symmetries by using Newey and Powel (1987) test (locational asymmetries).

		Pakistan				India				Bangladesh				Sri Lanka			
		3M-FERP	6M-FERP	9M-FERP	12M-FERP	3M-FERP	6M-FERP	9M-FERP	12M-FERP	3M-FERP	6M-FERP	9M-FERP	12M-FERP	3M-FERP	6M-FERP	9M-FERP	12M-FERP
	Quantiles	**Restr. Value**	**Restr. Value**	**Restr. Value**	**Restr. VALUE**	**Restr. Value**	**Restr. Value**	**Restr. Value**	**Restr. Value**	**Restr. Value**	**Restr. Value**	**Restr. Value**	**Restr. Value**	**Restr. Value**	**Restr. Value**	**Restr. Value**	**Restr. Value**
β	0.1, 0.9	1.436	1.628	1.572	1.579	0.0063 ***	0.2959	0.2935	0.2957	0.5917 ***	0.5897 ***	0.5912 ***	0.5898 ***	0.1353	0.1026	0.1241	0.1315
ρ	0.1, 0.9	−0.1143 **	−0.1230 **	−0.1236 **	−0.123 **	−0.1558	−0.0332	−0.0329	−0.0332	−0.07910 ***	−0.07886 ***	−0.07907 ***	−0.0788 ***	−0.0186	−0.0170	−0.0174	−0.0182
$\theta_{FERP}FERP_{t-1}(\xi_1)$	0.1, 0.9	0.073	0.090	0.091	0.096	−0.0021 ***	0.0055	0.0060	0.0063	0.0033	0.0034	0.0038	0.0039	0.0006	−0.0015	0.0005	0.0006
$\theta_{FERP}FERP_{t-1}(\xi_2)$	0.1, 0.9	0.032	0.045	0.043	0.044	−0.0023	0.0164	0.0184	0.0226	−0.0017	−0.0017	−0.0019	−0.0019	0.0004	−0.0019	−0.0002	0.0004
$\theta_{FERP}FERP_{t-1}(\xi_3)$	0.1, 0.9	0.076	0.094	0.096	0.100	−0.0114	0.0115	0.0114	0.0113	0.01930 **	0.02004 **	0.02195 **	0.0229 **	−0.0058	−0.0116	−0.0072	−0.0074
$\theta_{covid_{19cases}}(\beta_1)$	0.1, 0.9	0.0117 ***	0.0116 ***	0.0116 ***	0.0114 ***	−0.0016 ***	0.0020	0.0020	0.0020	0.0045	0.0046	0.0045	0.0045	0.00675 ***	0.006642 ***	0.006656 ***	0.006744 ***
$\theta_{covid_{19cases}}(\beta_2)$	0.1, 0.9	−0.031	−0.034	−0.033	−0.034	−0.0014	0.0082	0.0083	0.0099	0.0011	0.0012	0.0012	0.0012	0.0015	0.0013	0.0009	0.0015
$\theta_{covid_{19cases}}(\beta_3)$	0.1, 0.9	0.017	0.018	0.018	0.018	−0.0032	0.0054	0.0049	0.0046	0.02551 **	0.02565 **	0.02548 **	0.02560 **	−0.0071	−0.0121	−0.0077	−0.0079
δ	0.1, 0.9	−0.094	−0.084	−0.086	−0.086	0.1170	−0.1123	−0.1230	−0.1270	0.1571	0.1536	0.1566	0.1539	0.2527	0.2389	0.2500	0.2565
$\varphi\Delta FERP_{t-1}(\xi_1)$	0.1, 0.9	−0.044	−0.036	−0.032	−0.036	0.1053	−0.0275	−0.0469	−0.0546	−0.0155	−0.0158	−0.0177	−0.0181	−0.0125	−0.0160	−0.0142	−0.0148
$\varphi\Delta FERP_{t-1}(\xi_2)$	0.1, 0.9	−0.004	−0.001	0.001	0.002	−0.0148	−0.0116	−0.0129	−0.0176	−0.0435	−0.0623	−0.0716	−0.0727	0.3004	0.3507	0.3364	0.3579
$\varphi\Delta FERP_{t-1}(\xi_3)$	0.1, 0.9	0.127	0.164	0.200	0.208	0.1997	0.3184	0.2723	0.2701	0.4710	0.4847 *	0.5350 *	0.5556 *	−0.0363	−0.1747	−0.0583	−0.0542
$\omega\Delta Covid_{19}cases_{t-1}(\beta_1)$	0.1, 0.9	0.1091 ***	0.1081 ***	0.1080 ***	0.1079 ***	0.0516	−0.0332	−0.0379	−0.0403	−0.0263	−0.0260	−0.0263	−0.0260	−0.0261	−0.0278	−0.0260	−0.0262
$\omega\Delta Covid_{19}cases_{t-1}(\beta_2)$	0.1, 0.9	0.243	0.242	0.240	0.244	−0.0066	−0.0141	−0.0142	−0.0176	0.0667	0.0475	0.0447	0.0464	0.4050	0.3828	0.3927	0.4071
$\omega\Delta Covid_{19}cases_{t-1}(\beta_3)$	0.1, 0.9	0.341	0.370	0.384	0.387	0.1071	0.1547	0.1193	0.1141	0.6171	0.6144	0.6147 *	0.6149 *	−0.0703	−0.3357	−0.1005	−0.0899
β	0.2, 0.8	2.3726 **	2.3062 **	2.1775 **	2.1560 **	0.0039 **	0.0949	0.0897	0.0903	0.3924 **	0.3922 **	0.3880 **	0.3874 **	0.1838	0.1566	0.1608	0.1790
ρ	0.2, 0.8	−0.0954 ***	−0.0950 ***	−0.0953 ***	−0.0953 ***	−0.1064	−0.0105	−0.0099	−0.0100	−0.0532 **	−0.05318 **	−0.05266 **	−0.05256 **	−0.0254	−0.0218	−0.0225	−0.0249
$\theta_{FERP}FERP_{t-1}(\xi_1)$	0.2, 0.8	0.1843 *	0.1835 *	0.18576 *	0.1897 *	−0.0013	0.003426 *	0.003781 *	0.003922 *	0.0019	0.0020	0.0021	0.0022	−0.0005	−0.0004	−0.0006	−0.0007
$\theta_{FERP}FERP_{t-1}(\xi_2)$	0.2, 0.8	0.144	0.142	0.140	0.142	−0.0009	0.0106	0.0109	0.0149	−0.0037	−0.0038	−0.0040	−0.0041	−0.0047	−0.0030	−0.0059	−0.0056

$\theta_{FERP}FERP_{t-1}(\xi_3)$	0.2, 0.8	0.1863 *	0.1848 *	0.1869 *	0.19079 *	−0.0047	0.0041	0.0045	0.0047	0.01924 ***	0.01988 ***	0.02182 ***	0.02273 ***	−0.0005	−0.0006	−0.0015	−0.0015
$\theta_{covid_{19}cases}(\beta_1)$	0.2, 0.8	0.001	0.001	0.001	0.001	−0.00116 *	0.001473 *	0.001481 *	0.001477 *	0.0037	0.0037	0.0036	0.0036	0.003833 **	0.003849 **	0.003822 **	0.003853 **
$\theta_{covid_{19}cases}(\beta_2)$	0.2, 0.8	−0.0427 ***	−0.0423 **	−0.0425 ***	−0.0427 ***	−0.0006	0.0053	0.0049	0.0065	−0.0008	−0.0007	−0.0005	−0.0005	−0.0037	−0.0016	−0.0045	−0.0037
$\theta_{covid_{19}cases}(\beta_3)$	0.2, 0.8	0.004	0.004	0.003	0.003	−0.0014	0.0017	0.0017	0.0017	0.02548 ***	0.02547 ***	0.02536 ***	0.02541 ***	0.0022	0.0018	0.0009	0.0011
δ	0.2, 0.8	−0.059	−0.059	−0.071	−0.067	0.0779	0.0045	0.0027	0.0008	0.0646	0.0651	0.0588	0.0582	0.1720	0.1635	0.1715	0.1747
$\varphi\Delta FERP_{t-1}(\xi_1)$	0.2, 0.8	0.127	0.127	0.135	0.136	0.1095	0.0564	0.0631	0.0652	0.0007	0.0007	0.0011	0.0012	−0.0155	−0.0155	−0.0176	−0.0183
$\varphi\Delta FERP_{t-1}(\xi_2)$	0.2, 0.8	0.127	0.126	0.132	0.130	−0.0049	−0.0161	−0.0174	−0.0219	−0.1516 *	−0.1541 *	−0.1594 *	−0.1625 *	0.1236	0.1070	0.1442	0.1541
$\varphi\Delta FERP_{t-1}(\xi_3)$	0.2, 0.8	0.385	0.396	0.447	0.460	0.2051	0.490264 **	0.486899 *	0.4985	0.3558 ***	0.36745 ***	0.4076 ***	0.4216 ***	0.1121	0.1177	0.1145	0.1149
$\omega\Delta Covid_{19}cases_{t-1}(\beta_1)$	0.2, 0.8	−0.034	−0.034	−0.033	−0.033	0.0532	0.0054	0.0083	0.0085	−0.0031	−0.0031	−0.0027	−0.0026	−0.0293	−0.0284	−0.0290	−0.0292
$\omega\Delta Covid_{19}cases_{t-1}(\beta_2)$	0.2, 0.8	0.077	0.077	0.079	0.078	−0.0022	−0.0134	−0.0129	−0.0162	−0.0816	−0.0789	−0.0682	−0.0656	0.2463	0.2169	0.2466	0.2499
$\omega\Delta Covid_{19}cases_{t-1}(\beta_3)$	0.2, 0.8	0.320	0.324	0.344	0.345	0.1081	0.244894 **	0.22041 *	0.2174	0.4597 ***	0.4594 ***	0.4621 ***	0.46045 ***	0.2238	0.2285	0.2035	0.1970
β	0.3, 0.7	2.8838 ***	2.7196 ***	2.5787 ***	2.5211 ***	0.0037 **	−0.0845	−0.0874	−0.0815	0.3735 ***	0.3731 ***	0.3687 ***	0.37186 ***	0.0600	0.0471	0.0533	0.0712
ρ	0.3, 0.7	−0.0760 ***	−0.0749 ***	−0.0765 ***	−0.0788 ***	−0.1289	0.0097	0.0101	0.0094	−0.04919 ***	−0.0491 ***	−0.04857 ***	−0.04899 ***	−0.0112	−0.0096	−0.0104	−0.0128
$\theta_{FERP}FERP_{t-1}(\xi_1)$	0.3, 0.7	0.2558 ***	0.2464 ***	0.2522 ***	0.2519 ***	−0.0008	−0.0006	−0.0006	−0.0006	0.00492 ***	0.005077 ***	0.005574 ***	0.005786 ***	−0.0020	−0.0021	−0.0023	−0.0025
$\theta_{FERP}FERP_{t-1}(\xi_2)$	0.3, 0.7	0.2368 ***	0.2277 ***	0.2312 ***	0.2295 ***	0.0048	0.0080	0.0106	0.0148	0.0030	0.0031	0.0035	0.0035	−0.008123 *	−0.009526 **	−0.009849 **	−0.00957 *
$\theta_{FERP}FERP_{t-1}(\xi_3)$	0.3, 0.7	0.2486 ***	0.2393 ***	0.2444 ***	0.2442 ***	−0.0046	−0.0037	−0.0049	−0.0048	0.01752 ***	0.01811 ***	0.01981 ***	0.02074 ***	−0.0049	−0.0050	−0.0061	−0.0060
$\theta_{covid_{19}cases}(\beta_1)$	0.3, 0.7	−0.0006	−0.0005	−0.001	−0.001	−0.00083 *	−0.0002	−0.0002	−0.0002	0.007251 ***	0.007247 ***	0.007239 ***	0.00722 ***	0.003459 ***	0.003245 **	0.00324 **	0.003273 **
$\theta_{covid_{19}cases}(\beta_2)$	0.3, 0.7	−0.0238 **	−0.0226 *	−0.02316 *	−0.0235 *	0.0023	0.0039	0.0047	0.0064	0.003936 *	0.003918 *	0.003957 *	0.003886 *	−0.0073	−0.008747 *	−0.0080	−0.0070
$\theta_{covid_{19}cases}(\beta_3)$	0.3, 0.7	−0.01007 *	−0.009	−0.010	−0.009	−0.0014	−0.0021	−0.0024	−0.0023	0.02222 ***	0.02223 ***	0.02203 ***	0.02223 ***	−0.0023	−0.0022	−0.0029	−0.0024
δ	0.3, 0.7	−0.025	−0.024	−0.026	−0.041	0.0221	0.0200	0.0087	0.0079	0.0134	0.0128	0.0218	0.0120	0.1958 *	0.1915 *	0.1998 **	0.2023 **
$\varphi\Delta FERP_{t-1}(\xi_1)$	0.3, 0.7	0.153	0.146	0.142	0.145	0.116 ***	−0.0023	−0.0095	−0.0102	0.01231 *	0.01275 *	0.0136	0.01463 *	−0.0140	−0.0148	−0.0164	−0.0171
$\varphi\Delta FERP_{t-1}(\xi_2)$	0.3, 0.7	−0.042	−0.047	−0.053	−0.056	−0.0107	−0.0193	−0.0225	−0.0269	−0.0420	−0.0433	−0.0479	−0.0495	0.2292	0.1956	0.2207	0.2289
$\varphi\Delta FERP_{t-1}(\xi_3)$	0.3, 0.7	0.415	0.392	0.416	0.428	0.271 **	0.3048	0.2562	0.2613	0.2004	0.2067	0.2211	0.2357	−0.0208	−0.0164	−0.0289	−0.0251
$\omega\Delta Covid_{19}cases_{t-1}(\beta_1)$	0.3, 0.7	−0.001	−0.002	−0.002	−0.002	0.053 **	−0.0160	−0.0160	−0.0160	0.0093	0.0094	0.0088	0.0095	−0.0237	−0.0244	−0.0246	−0.0247
$\omega\Delta Covid_{19}cases_{t-1}(\beta_2)$	0.3, 0.7	−0.129	−0.127	−0.109	−0.107	−0.0081	−0.0138	−0.0151	−0.0183	−0.0036	−0.0035	−0.0052	−0.0036	0.3213	0.2693	0.2709	0.2730
$\omega\Delta Covid_{19}cases_{t-1}(\beta_3)$	0.3, 0.7	0.371	0.337	0.340	0.338	0.142 **	0.1554	0.1193	0.1172	0.2497	0.2492	0.2411	0.2481	−0.0419	−0.0317	−0.0508	−0.0429

Note: This table explains the departure from symmetrical distribution for MT-QARDL by comparing the coefficients at the 0.1 and 0.9, 0.2 and 0.8, and 0.3 and 0.7 quantiles. The asymmetric Newey and Powel (1987) test, i.e., $(\frac{\beta_{0.1} + \beta(1-0.9)}{2} = \beta(1/2))$, analyzes whether the coefficient value at the set of two distinct quantiles equals their median value. The asterisk signs of *, **, and *** represent the departure from the symmetrical distribution because of the rejection of the null hypothesis of symmetry at the 10%, 5%, and 1% significance levels, respectively. This test determines the location-based asymmetries for the MT-QARDL approach.

Table A5. Sign-based asymmetries.

	Pakistan					**India**					**Bangladesh**					**Sri Lanka**				
	3M-FERP	**6M-FERP**	**9M-FERP**	**12M-FERP**	**COVID-19**	**3M-FERP**	**6M-FERP**	**9M-FERP**	**12M-FERP**	**COVID-19**	**3M-FERP**	**6M-FERP**	**9M-FERP**	**12M-FERP**	**COVID-19**	**3M-FERP**	**6M-FERP**	**9M-FERP**	**12M-FERP**	**COVID-19**
Long-Run Sign-Based Asymmetries																				
	$\xi_1 = \xi_2 = \xi_3$				$o_1 = o_2 = o_3$	$\xi_1 = \xi_2 = \xi_3$				$o_1 = o_2 = o_3$	$\xi_1 = \xi_2 = \xi_3$				$o_1 = o_2 = o_3$	$\xi_1 = \xi_2 = \xi_3$				
r = 0.1	0.983	0.99	1.21	1.27	2.10 **	1.76	1.83 *	1.86 *	1.88 *	5.98 ***	2.68 **	3.847 ***	2.94 **	2.74 **	8.29 ***	3.12 ***	2.99 ***	3.847 ***	3.63 ***	8.746 ***
r = 0.2	1.07	1.2	1.09	0.99	2.99 ***	6.836 ***	8.19 ***	7.827 ***	6.10 ***	4.10 ***	5.17 ***	5.297 ***	7.10 ***	11.23 ***	4.82 ***	8.286 ***	11.13 ***	10.50 ***	10.012 ***	5.87 ***
r = 0.3	0.67	0.1	0.86	0.99	1.6	4.76 ***	4.99 ***	8.19 ***	8.27 ***	2.90 ***	3.88 ***	4.062 ***	4.25 ***	4.88 ***	1.99 **	2.187 **	3.32 ***	8.726 ***	11.22 ***	1.87 *
r = 0.7	1.81 *	1.69	1.37	1.79 *	3.87 ***	2.01 **	1.9 **	2.53 ***	2.91 ***	1.19	3.87 ***	4.10 ***	2.10 **	3.2 ***	5.09 ***	0.19	0.1	1.53	1.244	0.71
r = 0.8	1.91 **	2.01 **	2.87 ***	1.90 **	5.28 ***	3.12 ***	4.87 ***	2.37 ***	3.001 ***	6.12 ***	1.28	1.75	0.87	0.22	1.1	0.65	1.72	1.66	1.01	1.002
r = 0.9	1.62	0.58	0.22	1.7	3.45 ***	3.72 ***	5.10 ***	5.22 ***	6.09 ***	2.10 **	0.99	1.61	1.71	1.62	1.5	2.04 ***	2.6 **	1.99 **	2.01 **	1.90 **
Short-run Sign-based asymmetries																				
	Pakistan					India					Bangladesh					Sri Lanka				
	3M-FERP	6M-FERP	9M-FERP	12M-FERP	COVID-19	3M-FERP	6M-FERP	9M-FERP	12M-FERP	COVID-19	3M-FERP	6M-FERP	9M-FERP	12M-FERP	COVID-19	3M-FERP	6M-FERP	9M-FERP	12M-FERP	COVID-19
	$\xi_1 = \xi_2 = \xi_3$				$o_1 = o_2 = o_3$	$\xi_1 = \xi_2 = \xi_3$				$o_1 = o_2 = o_3$	$\xi_1 = \xi_2 = \xi_3$				$o_1 = o_2 = o_3$	$\xi_1 = \xi_2 = \xi_3$				$o_1 = o_2 = o_3$
r = 0.1	2.77 ***	3.23 ***	3.78 ***	4.10 ***	3.87 ***	0.22	1.09	0.81	1.65	0.19	4.89 ***	6.04 ***	9.82 ***	11.92 ***	3.99 ***	1.48	1.2	0.514	0.77	1.55
r = 0.2	1.78 *	1.67	1.89 *	1.09	4.92 ***	1.63	1.34	1.62	1.66	0.55	5.21 ***	7.91 ***	3.12 ***	6.38 ***	5.50 ***	1.66	0.99	0.87	0.76	1.61
r = 0.3	1.91 **	1.79 *	1.81 *	1.01	7.10 ***	0.192	0.918	1.052	1.33	1.69	7.10 ***	11.2 ***	10.5 ***	8.01 ***	3.17 ***	1.027	1.61	1.23	1.44	1.4
r = 0.7	1.22	0.87	0.99	0.1	1.2	6.92 ***	6.5 ***	6.89 ***	9.10 ***	4.78 ***	0.33	1.01	1.6	1.69	0.9	1.66	0.667	0.77	0.81	1.39
r = 0.8	1.99 **	2.55 **	2.41 **	3.8 ***	1.01	8.52 ***	8.11 ***	9.22 ***	11.1 ***	5.99 ***	1.22	1.35	0.99	1.01	1.01	1.88 **	2.3 **	2.76 ***	3.6 ***	5.10 ***

r = 0.9	4.87 ***	4.31 ***	4.72 ***	4.5 ***	2.2 **	8.34 ***	5.10 ***	3.76 ***	4.22 ***	6.10 ***	1.77	1.24	1.33	1.48	1.57	3.87 ***	4.10 ***	5.87 ***	7.10 ***	7.2 ***

Note: This table reports the sign-based asymmetries. The rejection of the null hypothesis implies that bearish, bullish, and moderate fluctuations in the forward exchange rate premium and COVID-19 cases have a non-linear impact on the individual stock market quantile (τ = 0.1 *or* 0.2 *or* 0.3 *or* 0.7 *or* 0.8 *or* 0.9). The asterisk signs of *, **, and *** represent the departure from the symmetrical distribution because of the rejection of the null hypothesis of symmetry at the 10%, 5%, and 1% significance levels, respectively.

Table A6. [83] non-linear causality analysis.

	Pakistan							**India**					
	e = 1			e = 1.5				e = 1			e = 1.5		
	l = 1	l = 2	l = 3	l = 1	l = 2	l = 3		l = 1	l = 2	l = 3	l = 1	l = 2	l = 3
FERP-3rd month to SMRs	0.0993 *	0.736	0.019 **	0.0192 **	0.0027 ***	0.0019 ***	FERP-3rd month to SMRs	0.00683 ***	0.001 ***	0.002 **	0.001 ***	0.00692 ***	0.0032 ***
FERP-6th month to SMRs	0.067 *	0.054 *	0.0021 ***	0.032 **	0.0099 ***	0.0082 ***	FERP-6th month to SMRs	0.055 *	0.0837 *	0.015 **	0.049 **	0.0019 ***	0.001 ***
FERP-9th month to SMRs	0.071 *	0.22	0.003 ***	0.0152 **	0.0029 ***	0.0069 ***	FERP-9th month to SMRs	0.012 **	0.099 *	0.0066 ***	0.01 **	0.002 ***	0.0083 ***
FERP-12th month to SMRs	0.058 *	0.001 ***	0.0092 ***	0.011 **	0.029 **	0.002 ***	FERP-12th month to SMRs	0.034 **	0.1	0.0882 *	0.038 **	0.00778 ***	0.00192 ***
	Bangladesh							Sri Lanka					
	e = 1			e = 1.5				e = 1			e = 1.5		
	l = 1	l = 2	l = 3	l = 1	l = 2	l = 3		l = 1	l = 2	l = 3	l = 1	l = 2	l = 3
FERP-3rd month to SMRs	0.0538 *	0.0488 **	0.009 ***	0.0016 **	0.082 *	0.0166 **	FERP-3rd month to SMRs	0.0186 **	0.0073 ***	0.00192 ***	0.00382 **	0.0067 ***	0.0012 ***
FERP-6th month to SMRs	0.0273 **	0.0281 **	0.049 **	0.0079 ***	0.0019 ***	0.047 **	FERP-6th month to SMRs	0.023 **	0.017 **	0.0088 ***	0.012 **	0.00182 ***	0.0019 ***
FERP-9th month to SMRs	0.079 *	0.036 **	0.001 ***	0.0012 ***	0.0001 ***	0.00155 ***	FERP-9th month to SMRs	0.837	0.09 *	0.012 **	0.01 **	0.00610 ***	0.0011 ***
FERP-12th month to SMRs	0.010 **	0.008 ***	0.031 **	0.00554 ***	0.00285 ***	0.0072 ***	FERP-12th month to SMRs	0.0192 **	0.087 *	0.0069 ***	0.02 **	0.0049 ***	0.002 ***

Note: The asterisk signs of ***, **, and * show the rejection of the null hypothesis of "No non-linear causality" at 1%, 5%, and 10% levels of significance.

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