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Linkage between US Financial Uncertainty and Stock Markets of SAARC Countries

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Abstract

The primary purpose of the study is to investigate the volatility spillover from financial uncertainty (FU) of the United States (US) to the stock markets of SAARC member countries including India, Sri-Lanka, Pakistan, and Bangladesh. The empirical literature overlooked SAARC countries and the FU index. Based on the estimation method, the data of FU is available for three different forecast horizons including 1-month, 3-months, and 12-months. For empirical analysis, monthly data is used from February 2013 to September 2019. EGARCH model is employed to investigate the volatility spillover effects. The findings of the study show that the spillover effect of FU varies with the forecast horizon. The FU with a higher forecast horizon has a significant spillover effect on more countries. The spillover effect of US financial uncertainty is negative in most of the SAARC countries. Bangladesh stock market is influenced by FU with all three forecast horizons whereas the volatility of the Pakistan stock market is not influenced by FU with any forecast horizon. The findings are consistent with the concept of "limited trade openness" in the financial markets of emerging economies. The emerging economies avoid financial market openness to minimize the risk of spillover of other countries.

Keywords: Financial Uncertainty, SAARC, EGARCH, Stock Returns, Spillover

JEL Classification Code: C32, G01, G11, G15, O57

1. Introduction

The economic certainty of a country is greatly associated with the performance of stock markets. Investors are very sensitive to the internal and external risks associated with the stock returns. Generally, investors seek minimum risk and maximum returns. The findings of Merton (1973) and Campbell (1993, 1996) provided a base for the argument that economic uncertainty adversely affects the investment volume in a country. Because with the increase in economic uncertainty, investors reduce their investment to enhance savings that may help to respond to future depression in the economy (Du & Minh, 2018). Liu and Zhang (2008), Chen (2010), Bekaert et al. (2015), and Bekaert and Engstrom (2017) described economic uncertainty as the future outlook for the economy is unpredictable. When people talk of economic uncertainty, they usually imply there is a high likelihood of negative economic events. Volatility is an investment term that describes when a market or security experiences periods of unpredictable, and sometimes sharp, price movements. People often think about volatility only when prices fall, however, volatility can also refer to sudden price rises too. Therefore, the recent literature considers uncertainty as a source of market volatility and hence explore a verity of the dimension of uncertainty and their association with stock market returns.

In the recent decade, financial market integration gains higher importance. Financial integration is a phenomenon in which financial markets in neighboring, regional, and/or

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global economies are closely linked together. It attracts the focus of researchers and practitioners (Barberis et al., 2005). A market contagion is the spread of an economic crisis from one market or region to another and can occur at both a domestic or international level. That is, a high correlation among the returns/volatilities of different financial markets is generally referred to as market contagion (Forbes & Rigobon, 2002). Empirical studies such as Hamao et al. (1990), Bekaert and Harvey (2005), Boubaker et al. (2016), Su et al. (2019), and Karamat et al. (2020) provided evidence of an association between the returns and volatilities across financial markets The market of the United States (US) is one of the largest markets that influence the markets of non-US markets (Su et al., 2019). However, the literature mostly focused on the contagion effect from the US market on the stock return of developed countries.

Uncertainty is one of the major factors of asset pricing and influences investors' preferences (Drechsler, 2013). Literature quantifies the economic uncertainty in several ways. For example, economic policy uncertainty (EPU) developed by Baker et al. (2016); the macroeconomic uncertainty index (MUI) used by Bali et al. (2014); the financial and macro uncertainty (FU & MU) developed by Jurado et al. (2015) and Ludvigson et al. (2015); the news-based implied volatility (NVIX) of Manela and Moreira (2017); and the global uncertainty (GU) used by Ozturk and Sheng (2018). Further, the US economy uncertainty news act as a channel for market contagion and influence the stock markets of other countries (Su et al. 2019). But it is still plausible that the financial uncertainty of the US plays a critical role in the stock market volatility of other countries.

Considering the above discussion, the current study aims to investigate volatility spillover from the US financial uncertainty (FU) to the stock market returns of emerging economies. More specifically, the study considers the SAARC member countries and uses the new measure of FU. Both SAARC and FU are overlooked in the literature. Further, the FU is a direct measure of financial uncertainty and utilizes the common variance of 147 financial time series items to calculate the index. Moreover, financial uncertainty and stock market volatility are time-varying variables. Therefore, their association needs to be continuously examined.

As the level of FU varies with forecast horizon, therefore, the current study uses three different forecast horizons of FU including 1-month (FU01), 3-months (FU03), and 12-months (FU12). Based on the objective of the study, we employed the EGARCH model for the investigation of volatility spillover from the FU of the US to the stock returns of SAARC member countries. The FU with different forecast horizons shows different results. The volatility spillover from US financial uncertainty with one month forecast horizon (FU01) is significant only for the stock market return of Bangladesh. Similarly, the volatility of FU with a 3-month forecast horizon significantly influences the stock market volatility of stock market returns of Sri-Lanka and Bangladesh. However, the volatility of FU with a 12-month forecast horizon (FU12) significantly influences the volatility of stock market returns of India, Sri-Lanka, and Bangladesh.

The study contributes literature in different ways. First, the study focuses on emerging economies that are not adequately explored in previous studies, particularly, the market contagion of the US economy on the stock markets of SAARC member countries. Second, the study uses the FU index of economic uncertainty which is a new and appropriate index for measuring financial uncertainty, and not tested in the contexts of the SAARC countries. Third, economic uncertainty is the time-varying variable that needs to be updated continuously. Therefore, the study provides an updated version of the volatility spillover effect of US FU on the stock market returns.

The remaining paper is distributed as: the second section is a literature review that discusses the relevant literature. The third section is the methodology that explains data and econometric models used for analysis. The fourth section is the results and discussion that describes and interprets the results of empirical models. The last section is the conclusion that provides the concluding remarks of the study.

2. Literature Review

A rich amount of empirical studies investigated the relationship of economic uncertainty with stock market returns. The studies used different measures and methodologies to quantify economic uncertainty. A few of the major indices to measure the economic uncertainty are discussed in the below section.

The economic policy uncertainty (EPU) that was developed by Baker et al. (2016) developed a new index of economic policy uncertainty (EPU) based on newspaper coverage frequency. Several types of evidence—including human readings of 12,000 newspaper articles—indicated that the index proxies for movements in policy-related economic uncertainty. Their U.S. index spikes near tight presidential elections, Gulf Wars I and II, the 9/11 attacks, the failure of Lehman Brothers, the 2011 debt ceiling dispute, and other major battles over fiscal policy. Using firm-level data, they found that policy uncertainty is associated with greater stock price volatility and reduced investment and employment in policy-sensitive sectors like defense, health care, finance, and infrastructure construction. At the macro level, innovations in policy uncertainty foreshadow declines in investment, output, and employment in the US and, in a panel vector autoregressive setting, for 12 major economies.

Similarly, Bali et al. (2014) estimated hedge fund and mutual fund exposure to newly proposed measures of macroeconomic risk that are interpreted as measures of economic uncertainty. They found that the resulting uncertainty betas explain a significant proportion of the cross-sectional dispersion in hedge fund returns. However, the same is not true for mutual funds, for which there is no significant relationship. After controlling for a large set of fund characteristics and risk factors, the positive relation between uncertainty betas and future hedge fund returns remains economically and statistically significant. Hence, they argued that macroeconomic risk is a powerful determinant of cross-sectional differences in hedge fund returns.

Jurado et al. (2015) exploited a data-rich environment to provide direct econometric estimates of time-varying macroeconomic uncertainty. Their estimates displayed significant independent variations from popular uncertainty proxies, suggesting that much of the variation in the proxies are not driven by uncertainty. Quantitatively important uncertainty episodes appear far more infrequently than indicated by popular uncertainty proxies, but when they do occur, they are larger, more persistent, and are more correlated with real activity. Their estimates provided a benchmark to evaluate theories for which uncertainty shocks play a role in business cycles

Manela and Moreira (2017) constructed a text-based measure of uncertainty starting in 1890 using front-page articles of the *Wall Street Journal*. News implied volatility (NVIX) peaks during stock market crashes, times of policy-related uncertainty, world wars, and financial crises. In US postwar data, periods, when NVIX is high, are followed by periods of above-average stock returns, even after controlling for contemporaneous and forward-looking measures of stock market volatility. News coverage related to wars and government policy explains most of the time variation in risk premia that the measure identified. Over the longer 1890–2009 sample that includes the Great Depression and two world wars, high NVIX predicts high future returns in normal times and rises just before transitions into economic disasters. The evidence is consistent with recent theories emphasizing time variation in rare disaster risk as a source of aggregate asset price fluctuations.

Asgharian et al. (2015) showed that the long-run stock and bond volatility and the long-run stock-bond correlation depend on macroeconomic uncertainty. We use the mixed data sampling (MIDAS) econometric approach. The findings are in accordance with the flight-to-quality phenomenon when macroeconomic uncertainty is high.

The economic uncertainty is measured through the macroeconomic uncertainty index (MUI) developed by Bali et al. (2015). Macroeconomic uncertainty also influences the returns of stock options. Aramonte (2014) and Mustika et al. (2016) analyzed the options returns of the US market and found that macroeconomic uncertainty is a priced factor. Liu and Zhang (2015) investigated the predictability of economic policy uncertainty (EPU) to stock market volatility. Their in-sample evidence suggested that higher EPU leads to significant increases in market volatility. Out-of-sample findings showed that incorporating EPU as an additional predictive variable into the existing volatility prediction models significantly improves the forecasting ability of these models. The improvement is robust to the model specifications. Similarly, Arouri et al. (2016) also used EPU for economic uncertainty and found a negative impact of EPU on stock returns of the US stock index. Phan et al. (2018) argued that EPU can predict excess returns. However, the predictability is sensitive to country and sector. Moreover, the predictability is asymmetric by nature. Luo and Zhang (2020) argued that EPU has a significant influence on stock crash risk. The relationship is stronger for small, young, high volatile, and growth stocks.

Su et al. (2017) investigated the role of uncertainty measured by news-based implied volatility (NVIX) in anticipating US long-term market volatilities from a GARCH-MIDAS model. They found that NVIX performed well in predicting long-term aggregate market volatilities. A subsample analysis provides that the predictive power of news-based implied volatility is decreasing. Mo et al. (2019) further extend the argument and found that the relationship between NVIX and stock market volatility is strong only in the long-term. Many other studies also found a significant association between NVIX and stock market returns (Fang et al., 2018; Su et al., 2018, 2019). They measured the economic uncertainty by NVIX and found a significant association of NVIX with the stock market returns and volatility.

Beber and Brandt (2009) established an empirical link between the ex-ante uncertainty about macroeconomic fundamentals and the ex-post resolution of this uncertainty in financial markets. They measured macroeconomic uncertainty using prices of economic derivatives and relate this measure to changes in implied volatilities of stock and bond options when the economic data is released. Higher macroeconomic uncertainty is associated with a greater reduction in implied volatilities following the news release. It is also associated with increased volume and decreased open interest in options markets after the release, consistent with market participants using financial options to hedge or speculate on macroeconomic news. Adjasi (2009) obtained the economic uncertainty by taking the volatility of macroeconomic factors including CPI, exchange rate, interest rates, money supply, oil & gold prices, and cocoa price. They found a significant association of macroeconomic uncertainty with the stock market volatility.

Chinzara (2011) also quantified the economic uncertainty by taking the volatility of macroeconomic factors and found a significant association of the uncertainty with stock market volatility of South Africa. Demir and Ersan (2018)_ ENREF_11 examined the effects of EPU on stock prices of listed tourism companies in Turkey for the time period of 2002–2013. They showed that EPU in Europe and Turkey has significant negative effects on tourism index returns. The finding reflects that stock returns of the Turkish tourism companies apparently depend on domestic and international economic uncertainty. Among the included macroeconomic variables, consumer confidence index is the only factor which has an impact on stock returns.

Li et al. (2016) investigated the causal relationship between EPU and stock market returns in the context of India and China. They conclude that the causal relationship between the said variables is weak in both the countries and sensitive to structural changes in the analysis method. Guo et al. (2018) explored the dependence pattern between EPU and stock market returns in G7 and BRIC countries and found a negative association of the stock returns with EPU where the relationships are asymmetric in most countries. Chiang (2019) examined the EPU connection with stock returns in Asian stock markets and found a significant association between market risk and EPU. Kannadhasan and Das (2019) focused on Asian markets and found a significant impact of EPU on the stock returns of the emerging markets. Further, they argued that EPU influences the stock markets more than the geopolitical risk.

The global market integration is continuously increasing and grabbing the attention of researchers and practitioners (Barberis et al., 2005; Pukthuanthong & Roll, 2009). The US has the largest stock markets and has a higher market share in the global economy. It is observed that the fluctuation in the US market also spread to the economies of other countries (Donadelli, 2015; Su et al., 2019). For example, in the case of the financial crisis of 2008, the downfall shifted to the other economies. Therefore, many empirical studies investigated the volatility spillover of US uncertainty to the other economies. Hamao et al. (1990) examined the interdependence and price volatility among New-York, Tokyo, and London stock markets. They found a significant volatility spillover from the New-York stock market to the London and Tokyo stock market. Bekaert and Harvey (2003) examined the contagion effect among three different regions including Europe, Latin America, and South-East Asia. They documented mixed results and also explained the shared volatility in terms of different global, regional, and local factors. Boubaker et al. (2016) examined the contagion effect of the US economy on both developed and emerging economies. Similarly, Su et al. (2019) investigated the spillover effect of US economic uncertainty on the stock markets of non-US countries and found that the different proxies of economic uncertainty show different nature spillover effects on the stock returns of non-US countries.

The spillover effect of US financial and economic uncertainty is not limited to stock markets, but it also influences the currency markets of both developing and developed countries. The findings of Han et al. (2019) utilized a quantile-on-quantile (QQ) approach to uncover the complex and unstable relationships between uncertainty and the currency performance of developed and developing countries. Strong empirical evidence demonstrated that the state-dependent spillover effect of US uncertainty exerts shocks on exchange rates. They shed new light on the asymmetric characteristic of "flight to quality." When US uncertainty is at a high level, safe-haven currencies are favored, while the weak currencies depreciate. However, with a low quantile of uncertainty, the developed currencies remain relatively stable, while emerging currencies are confronted by greater depreciation. Moreover, unexpected uncertainty spillover from the US to different currency markets plays an important role under low uncertainty, heightening the variations in exchange rates, and causing the currency values to deviate.

McIver and Kang (2020) documented that the spillover effect between the US and non-US markets become more dominant after the recent financial crisis. At the same time, US uncertainty also influences cash flows and consumer prices. Bhattarai et al. (2019) found a significant spillover from US uncertainty on the fifteen emerging markets and argued that the fluctuations in US uncertainty adversely affect the capital flows, consumer prices, exchange rates, outputs, and stock markets performance of the emerging economies. Trung (2019) also validated the same argument and documented that the US uncertainty is a risk for the emerging economies, and significantly decline their exports, capital inflows, consumptions, and investments.

In summary of the above literature, it is noted that previous studies mostly focused on developed economies. Before the discovery of economic uncertainty indices, the volatility of macroeconomic factors was used to measure the economic uncertainty. Most of the studies are using EPU as a proxy of economic uncertainty. Only a few studies consider the other indices of economic uncertainty like NVIX, MUI, and FU; however, they were tested mostly in developed markets. Therefore, the current study examines the volatility spillover from the US FU to the stock market of emerging economies. The study uses the FU index because this index mainly focuses on financial factors and uses the common variance of 147 financial items. Further, the study concentrates on emerging markets of SAARC member countries.

3. Methodology

3.1. Data

The study uses monthly data for the period from February 2013 to September 2019. We include only four major SAARC countries including India, Pakistan, Sri-Lanka, and

Bangladesh because these countries account for a major market share of the SAARC group of countries and have higher trading relations with the US (Sharma & Bodla, 2011). The market data of the SAARC countries was obtained from Investing.com whereas the data of the US uncertainty index (FU) was extracted from the database developed by Sydney Ludvigson. The data estimation is made on different forecast horizons to account for different forecast errors. Therefore, the data of FU is available in three different series. We use all three data distributions of FU to capture more insights. All the variables are used in growth form.

3.2. Unit Root Test

The existence of unit root in a data series means that the series is not stationary. According to Brooks (2019), a series will be stationary if it has a constant mean, constant variance, and constant auto-covariance. In statistics, a unit root test tests whether a time series variable is non-stationary and possesses a unit root. The null hypothesis is generally defined as the presence of a unit root and the alternative hypothesis is either stationarity or trend stationarity on the test used. The behavior and treatment techniques of stationary and non-stationary data are different. Therefore, it is important to use the unit root test for checking the behavior of the variables. We use two different unit root tests to obtain fair and robust results, including the augmented dickey fuller test (ADF) and Phillip Perron unit root test (PP). Both the tests examine the null hypothesis that the data series has a unit root (series is non-stationary). ADF *tests* the null hypothesis that a unit root is present in a time series sample. The alternative hypothesis is different depending on which version of the *test* is used but is usually stationarity or trend-stationarity. The Phillips–Perron test is a unit root test That is, it is used in time series analysis to test the null hypothesis that a time series is integrated of order 1 The results of both the tests for each country are summarized in Table 1.

The table shows that the stock market returns of each country are non-stationary at the level. However, it becomes stationary at first difference. The results of both tests provide the same information.

Table 1: Unit Root Test

Market	ADF		PP	
	Level	1st Difference	Level	1st Difference
Pakistan	–2.12	–9.11*	–2.12	–9.12*
India	–0.85	–9.03*	–0.75	–9.11*
Sri Lanka	–1.98	–8.83*	–1.99	–8.83*
Bangladesh	–1.86	–8.96*	–1.79	–9.02*

3.3. Econometric Model

The study uses Exponential Generalized Autoregressive Conditional Heteroscedastic (EGARCH) model to investigate the volatility spillover effect of the US FU index on the stock market returns of major SAARC member countries including India, Pakistan, Sri-Lanka, and Bangladesh. The basic EGARCH model was developed by Nelson (1991) that allows for asymmetry and leverage the effect of positive and negative shocks. Simply, the EGARCH model is an extension of the GARCH model. The algebraic presentation of the GARCH model is shown in Brooks (2019) as follow:

$$y_t = \mu + \delta y_{t-1} + \epsilon_t, \quad \epsilon_t \sim N(0, \delta_t^2) \tag{1}$$

$$\delta_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \gamma \delta_{t-1}^2 \tag{2}$$

Where, equation (1) and (2) represent the mean equation and variance equation, respectively. However, the implication of the GARCH model becomes limited and fails to capture the complete leptokurtosis in the data when the conditional variance does not follow the normal distribution (Alexander & Lazar, 2006). Further, the standard GARCH model assumes the symmetric effect of good and bad news (positive and negative shocks) but in practice, mostly the negative shocks produce higher volatility than good news which is called the leverage effect (Brooks, 2019; Nelson, 1991). Therefore, to surmount the limitation of the GARCH model, the EGARCH model is developed that allows for the leverage effect.

The EGARCH model is one of the effective models to investigate the spillover effects (Bhar, 2001; Bhar & Nikolova, 2009). The algebraic expression of the EGARCH is given below:

$$\text{ret}_t = \alpha_0 + \alpha_1 \text{ret}_{t-1} + \alpha_2 \text{FU}_{t-1} + u_t \tag{3}$$

$$\begin{aligned} \ln\left(\delta^2_{t(\text{ret})}\right) &= \beta_0 + \beta_1 \ln\left(\delta^2_{t-1(\text{ret})}\right) + \beta_2 \frac{u_{t-1}}{\sqrt{\delta^2_{t-1}}} \\ &\quad + \bar{\varphi}\left[\frac{|u_{t-1}|}{\sqrt{\delta^2_{t-1}}} - \sqrt{\frac{2}{\pi}}\right] + \rho \text{Vol}_{(FU)} \end{aligned} \tag{4}$$

Equation (1) shows the mean equation and equation (2) represents the variance equation of the EGARCH model. In the mean equation, 'ret_t' is the stock market returns of time 't' and 'ret_{t-1}' is the lag term of the stock market returns. FU shows the financial uncertainty of the US and u_t is the error term of the equation. α_0, α_1, and α_2 are the coefficient of the respected variables. Similarly, in the variance equation,

$\ln\left(\delta^2_{t(ret)}\right)$ is the natural log of the variance of the stock market returns. β_0 is a constant term of the equation. β_1 is the coefficient of the ARCH term that measures the size effect of shocks. Size effect refers to whether the small and large shocks affect future volatility in the same way? Similarly, β_2 measures the leverage effect. If the sign of β_2 is negative and statistically significant then it shows the existence of leverage effect. The leverage effect means the negative shocks generate higher volatility than positive shocks in the past values, or we can say a negative relationship between asset value and volatility. In contrast, if the β_2 is not significantly different from zero then it shows the symmetric effect of the volatility. φ is the coefficient of the GARCH term that measures the persistency of the past volatility. Similarly, the ρ shows the volatility spillover effect of FU. The EGARCH model is used separately for each country and each FU distribution. More specifically, we have four countries (India, Pakistan, Sri-Lanka, and Bangladesh) and three forecast horizons of financial uncertainty including 1,3, and 12 months (FU01, FU03, and FU12), hence 12 (i.e. 4 × 3) different EGARCH models are used.

4. Results and Discussion

4.1. Descriptive Statistics

Descriptive statistics provide a quick picture of data distribution. The descriptive statistics of the variables are shown in Table 2. The mean values of the stock market return of Pakistan, India, Sri-Lanka, and Bangladesh are 0.71, 0.90, 0.02, and 0.27, respectively. It shows that the Indian stock market has the highest returns whereas the Sri-Lankan stock market has the lowest returns during the sample period. However, the standard deviation of the Sri-Lankan stock market is lower than other stock markets which suggests that the market is less volatile, and the market prices are more stable as compared to the prices of other stock markets. Further, the values of skewness and kurtoses show that the returns are nearly normally distributed. The Jarque-Bera test also accepts the hypothesis of normal distribution at a 5% level of significance for all the countries.

The average value of FU one month forecast horizon (FU01), three months forecast (FU03), and twelve months forecast horizon (FU12) are 0.81, 0.87, and 0.96, respectively. However, the standard deviation of the 12-month forecast horizon is lower than other forecast horizons. It means the higher time horizon FU shows higher volatility. The values of skewness and kurtosis show that all three distributions are nearly normally distributed. However, the Jarque-Bera test rejects the hypothesis of normal distribution. The trend lines of FU distributions are also shown in figure 1. The figure shows that from 2013 to 2018 the mean values of FU01, FU03, and FU12 are different from each other. However, after 2018 all the mean values of FU distributions come closer to each other.

The table comprises two panels. Panel A shows the descriptive statistics for the monthly stock market returns of Pakistan. Panel B shows the descriptive statistics for the US financial uncertainty (FU) with three different forecast horizons. FU01, FU03, and FU12 show the FU with a forecast horizon of 1-month, 3-months, and 12-months, respectively.

4.2. EGARCH Estimations Results

The EGARCH model provides the volatility spillover from US FU to the stock market returns of major SAARC countries including India, Pakistan, Sri-Lanka, and Bangladesh. The model is used separately for all the countries. Similarly, the model is used separately for the three different forecast horizons of FU including 1, 3, and 12 months (FU01, FU03, and FU12).

Table 2: Descriptive Statistics of Stock Returns and U.S. Financial Uncertainty Index

	Pakistan	India	Sri–Lanka	Bangladesh	FU01	FU03	FU12
Mean	0.71	0.9	0.02	0.27	0.81	0.87	0.96
Median	1.14	0.92	–0.2	0.36	0.77	0.84	0.95
Maximum	13.94	9.68	9.96	12.5	1.15	1.13	1.04
Minimum	–11.02	–7.81	–8.38	–11.27	0.66	0.74	0.91
Std.Dev	5.32	3.77	3.38	4.71	0.11	0.09	0.03
Skewness	0.01	–0.07	0.53	0.29	1.25	1.18	1.01
Kurtosis	2.63	2.63	3.75	3.33	3.63	3.48	3.12
Jarque–Bera	0.44 (–0.8)	0.52 (–0.76)	5.59(–0.06)	1.49(–0.47)	22.27(0.00)	19.61(0.00)	13.68(0.00)

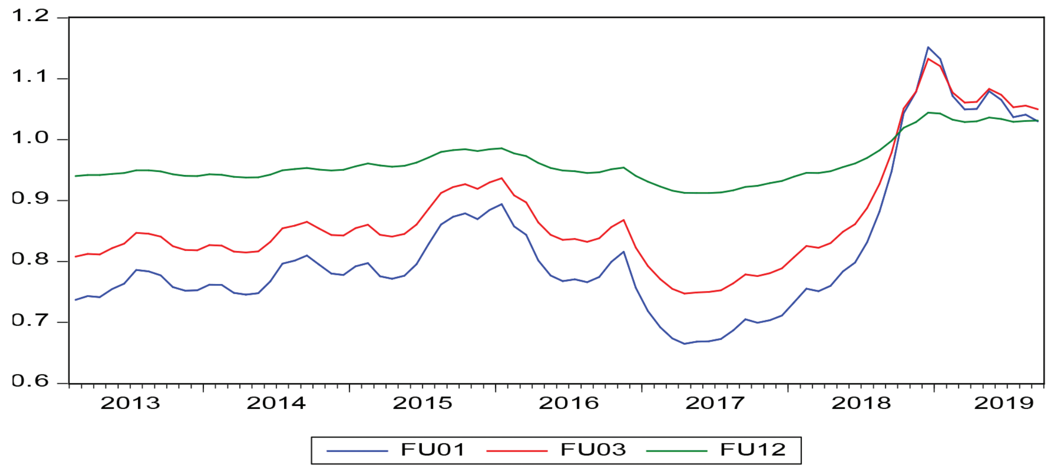

Figure 1: Trend Lines of Financial Uncertainty

Table 3: EGARCH estimation using U.S. Financial Uncertainty with a forecast horizon of One Month

	India	Sri–Lanka	Pakistan	Bangladesh
α_0	5.70** (0.04)	3.09 (0.20)	10.21* 0.05	3.6 0.23
α_1	–0.12 (0.15)	–0.04 (0.64)	0.12 0.25	–0.08 0.3
α_2	–5.64* (0.09)	–4.07 (0.18)	–12.06* 0.07	–4.44 0.22
β_0	1.99 (0.11)	0.22 (0.44)	1.49* 0.08	0.69*** 0.00
β_1	–0.6 (0.11)	–0.39*** (0.00)	–0.3 0.12	–0.31** 0.04
β_2	–0.28 (0.20)	0.03 (0.68)	–0.31** 0.04	–0.15 0.11
φ	0.50** (0.06)	0.92*** (0.00)	0.69*** 0.00	0.95*** 0.00
P	–0.31 (0.64)	0.31 (0.43)	–0.38 0.56	–0.38** 0.02
LL	–206.38	–192.12	–231.26	–217.61
SCI	5.81	5.44	6.45	6.1

The values in parenthesis are p-value for each of the coefficients. "LL shows the log-likelihood and SS shows the Schwarz info criteria SIC" *, **, *** represents the significance at 10%, 5%, and 1%, respectively.

The results of the EGARCH model that investigate the volatility spillover effect of FU 1-month forecast horizon (FU01) on the stock market returns of each country are shown in Table 3. The results show that the coefficient ρ is statistically significant only for the stock market of Bangladesh. It suggests that only the stock market of Bangladesh is significantly influenced by the volatility of US FU with one month forecast horizon (FU01). The sign of the coefficient is negative which shows that higher volatility in the FU of the US reduces the volatility of stock market returns of Bangladesh. Similarly, the coefficient β_2 is negative and significant only in the context of Pakistan which indicates that the leverage effect exists only in the stock market returns of Pakistan. In other words, bad news generates more volatility in future returns as compared to the good news. The coefficient α_2 is negative and significant in the context of India and Pakistan that describes that a general increase in the US financial uncertainty (FU01) negatively influences the stock market returns of India and Pakistan.

Table 4 summarizes the results of the EGARCH model that examine the volatility spillover effect of US financial uncertainty of 3-months forecast horizon (FU03) on the stock market returns of the major SAARC member countries. The results show the volatility spillover coefficient ρ is negative and significant for the stock market returns of Bangladesh. It shows that higher volatility of financial uncertainty declines the stock returns volatility of the Bangladesh market. Similarly, the volatility of financial uncertainty negatively influences the stock market returns volatility of Pakistan and India, but the coefficient is not statistically significant. In contrast, the Sri-Lankan stock market returns volatility increase with the increase in FU03. The coefficient of GARCH term φ is statically significant, indicating the persistence of past volatility. The leverage effect only exists in the stock market returns of Pakistan. Similarly, the ARCH term is negative and significant in the case of Sri-Lanka and Bangladesh which shows that the size of shocks has a negative impact on the stock market returns. The coefficient of mean values of FU03 (α_2) is significant at a 10% level of significance only for India and Pakistan.

The results for the volatility spillover effect from US FU with the forecasting horizon of 12-months to the stock market returns of each country are summarized in Table 5. The results of FU with the time horizon of 12-months (FU12) are different from the FU with time horizons of 1-month and 3-months. The volatility spillover effect of FU12 on the stock market returns of the major SAARC countries is more dominant. The volatility of FU12 significantly transmits into the stock market returns of all the countries except Pakistan. The increase in volatility of FU12 declines the volatility of stock returns of India and Bangladesh. However, the volatility of stock market returns of the Sri-Lanka increases with the rise in the volatility of FU12. The coefficient of the GARCH term is also significant in the case of all the countries that describes that the past volatility of the stock returns significantly explains the current volatility. Similarly, the leverage effect is present in the stock returns of all the countries except Sri-Lanka. On the other hand, the results show that the stock market returns of India, Sri-Lanka, and Bangladesh are sensitive to the size of shocks in the past returns. The mean values of FU12 have a negative significant impact on the stock returns of all the countries except Sri-Lanka.

Table 4: EGARCH Estimation Using U.S. Financial Uncertainty Index with a Forecast Horizon of Three Months

	India	Sri–Lanka	Pakistan	Bangladesh
α_0	7.41* (0.05)	3.28 (0.29)	12.67* (0.07)	3.64 (0.35)
α_1	–0.13 (0.13)	–0.05 (0.59)	0.14 (0.19)	–0.08 (0.27)
α_2	–7.23* (0.08)	–4.07 (0.25)	–14.11* (0.09)	–4.16 (0.35)
β_0	2.03 (0.13)	–0.08 (0.40)	1.66 (0.10)	0.81*** (0.00)
β_1	–0.60 (0.10)	–0.35** (0.01)	–0.30 (0.13)	–0.34*** (0.00)
β_2	–0.27 (0.21)	0.00 (0.91)	–0.32** (0.04)	–0.14 (0.16)
φ	0.51** (0.05)	0.94*** (0.00)	0.68*** (0.00)	0.94*** (0.00)
P	–0.35 (0.66)	0.57*** (0.00)	–0.52 (0.52)	–0.44*** (0.00)
LL	–206.33	–191.88	–231.20	–217.20
SCI	5.81	5.43	6.45	6.09

The values in parenthesis are p-value for each of the coefficients. "LL shows the log-likelihood and SS shows the Schwarz info criteria SIC" *, **, *** represents the significance at 10%, 5%, and 1%, respectively.

Overall, the results show that the volatility of US FU has a significant influence on the volatility of stock market returns of major SAARC countries. The higher volatility in US FU declines the market volatility of most SAARC countries. In the analysis, the forecast horizon is also an important factor. The uncertainty of the higher forecast horizon is also higher. We use three different forecast horizons including 1-month, 3-months, and 12-months. The spillover effects of the three forecast horizons are different. The volatility of FU12 influences the volatility of more SAARC countries as compared to FU01 and FU03. In contrast to the other countries, the volatility of the Sri-Lankan stock market increases with an increase in the volatility of financial uncertainty. The results are consistent with the findings of Donadelli (2015), Dakhlaoui and Aloui (2016), and Su et al. (2019) who argued that the economic and FU of the US market influences the stock market of other countries. The negative volatility association is consistent with the argument that emerging countries avoid the openness of the financial market. Therefore, the regulatory authorities of emerging countries impose multiple restrictions on the trading activities in their stock markets (Su et al. 2019).

Table 5: EGARCH Estimation with U.S. Financial Uncertainty Index with a Forecast Horizon of Twelve Months

	India	Sri-Lanka	Pakistan	Bangladesh
α_0	22.08*** (0.00)	13.49 (0.13)	40.81** (0.04)	21.91*** (0.00)
α_1	–0.14*** (0.00)	–0.06 (0.57)	0.12 (0.23)	–0.13 (0.16)
α_2	–21.43*** (0.00)	–14.30 (0.12)	–42.16** (0.04)	–22.77*** (0.00)
β_0	2.14*** (0.00)	–1.75*** (0.00)	3.01 (0.25)	2.00*** (0.00)
β_1	–0.99*** (0.00)	–0.31*** (0.00)	–0.29 (0.17)	–0.28*** (0.00)
β_2	–0.12** (0.01)	0.02 (0.74)	–0.37** (0.03)	–0.18** (0.06)
φ	0.67*** (0.00)	0.94*** (0.00)	0.66*** (0.00)	0.96*** (0.00)
P	–0.55*** (0.00)	2.20*** (0.00)	–1.80 (0.48)	–1.75*** (0.00)
LL	–202.96	–192.43	–231.04	–216.94
SCI	5.72	5.44	6.45	6.08

The values in parenthesis are p-value for each of the coefficients. "LL shows the log-likelihood and SS shows the Schwarz info criteria SIC" *, **, *** represents the significance at 10%, 5%, and 1%, respectively

5. Conclusion

The current study examines the volatility spillover effect from the FU of the US to the stock market of major SAARC countries including India, Pakistan, Sri-Lanka, and Bangladesh. The financial uncertainty index (FU) is used for US FU that was developed by Jurado et al. (2015) and Ludvigson et al. (2015). Three different forecast horizons of FU are used for empirical analysis including 1-month (FU01), 3-months (FU03), and 12-months (FU12). The results of the EGARCH model showed that the spillover effect from US FU to the market returns of the SAARC countries is different in the case of each forecast horizon. The higher forecast horizon shows higher financial uncertainty and influences the volatility of more countries as compared to fewer forecast horizons. There is a negative spillover effect of US FU on the stock market returns of SAARC member countries except for Sri-Lanka in which the spillover effect is positive. The volatility of the Pakistan stock market is not influenced by the volatility of US FU. As the SAARC group comprises emerging countries, the negative or insignificant volatility association in emerging economies is generally attributed to the restrictions on financial market openness that are imposed to provide a shield against risk spillover of other countries. The findings are helpful for international investors and for the local investors of the SAARC member countries to make their investment portfolios. Similarly, the results may also help the regulatory authorities in formulating different stock market and corporate policies.

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