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REGIME-DEPENDENT EFFECTS ON STOCK MARKET RETURN DYNAMICS: EVIDENCE FROM SAARC COUNTRIES

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ABSTRACT

This study empirically examines the link between stock market returns and exchange rate fluctuations using monthly data ranging from 1993 to 2016 for selected SAARC countries (Bangladesh, India, Pakistan, and Sri Lanka). In the presence of other macroeconomic factors, dynamic links in the financial markets are investigated using Hamilton's Markov switching approach. The multivariate analysis reveals that stock market returns develop in accordance with two different regimes: during a crisis and when there is no crisis. The study discovered evidence of switching suggesting that stock markets have persistent volatility in bullish trends and are influenced more by currency returns during both calm and turbulent periods. However, stock markets with persistent volatility in bearish trends are influenced more by other macroeconomic factors, in both periods. This implies that movements in the stock market are regime-dependent and transition probabilities between regimes can be affected by certain macroeconomic factors.

Contribution/Originality: This study contributes to the existing literature by examining whether there is a switching behavior in South Asian stock markets and whether regime-switching behavior is influenced by a number of factors that directly or indirectly affect internal and external economic, financial, and political elements during times of crisis and stability.

1. INTRODUCTION

Dramatic changes in the behavior of many financial time series mainly correlate with such incidents as financial shocks, crises, wars, or variations in governmental monetary policy. Stock market performance is directly or indirectly affected by local and international crises, due to the impact on currency markets and other macroeconomic factors. Similarly, unforeseen variations in inflation forecasts, contractionary monetary policies, and an increase in oil prices, exert a downward stress on financial market valuations, leading to uncertainty in economies' cash flows and further reactions in the financial markets. Therefore, imbalances in the economy result in volatile exchange rates and capital markets.

This study aims to empirically demonstrate the dynamic relationship between changes in currency exchange rates and stock market returns in selected SAARC countries.[1] This interrelationship is important for economic

[1] Only the emerging SAARC (South Asian Association for Regional Cooperation) countries were selected: Bangladesh, India, Pakistan, and Sri Lanka.

policies and decisions on international capital budgeting, particularly when negative shocks affecting one market are rapidly transmitted to the other markets. Following the Financial Crisis of 2008, the issue has become more critical: the stock market is currently very sensitive, with frequent upturns and downturns, disruptions, hedging, and crashes. Many aspects of this relationship have been observed several times, using numerous empirical techniques; however, recently, more effective statistical techniques have been employed to describe market fluctuations across different regimes: the Markov switching models.

In a significant work, Hamilton (1989) proposed Markov switching techniques for non-stationary time-series modeling, wherein parameters are observed as the product of the distinct-state Markov process. This methodology leads to a range of thought-provoking questions, including: Is it possible to differentiate regimes in stock market volatility when under the influence of other elements? In what way do the regimes differ? How often, and when, do regime switches occur? Are regime switches predictable? Other than regime switches, is stock market volatility foreseeable? Responses to these questions offer some evidence on stock market returns. There are a growing number of studies indicating that the regime-switching process represents stock market returns (e.g., Hamilton, 1989; Schwert, 1989; Turner *et al.*, 1989; Hamilton and Susmel, 1994; Schaller and Norden, 1997; Ang and Bekaert, 1999). There are also a small number of studies on the relationship between stock market returns and exchange rate fluctuations (e.g., Holmes and Nabil, 2002; Chkili and Nguyen, 2014).

The latter research hypothesized that currency returns have regime-dependent effects on stock market return dynamics in each selected SAARC country during calm and turbulent times. The interrelationship was observed within the environment of control macroeconomic variables, with simulation results demonstrating the existence of nonlinearities and asymmetries in the stock market. Furthermore, the behavior of financial markets depended on discrete volatility regimes, which was consistent with the past experience of bear being more volatile than bull markets. Likewise, it was inferred that if exchange rates were defined by the regime-dependent process, then greater exchange rate fluctuations and resulting higher risk premiums would increase the likelihood of regime switching faced by shareholders and investors.

This study conducts a joint evaluation of nonlinear reliance on regime switching, and the intensity and significance of stock market return performance as a result of currency movements, inflation, interest rates, industrial production growth, and oil prices. It also seeks further corroboration for capital market outcomes in the mainly South Asian currency crisis, Global Financial Crisis, and various other local crises within each country during a specified period. The occurrence of such crises entirely justifies the choice of regime-switching models, as stock and foreign exchange markets in the SAARC countries are interlinked in a regime-shift environment, which will be explored in this paper. The paper is structured as follows: Section 2 presents an empirical review of the literature; Section 3 explains the Markov switching models employed; Section 4 presents and discusses the results; and Section 5 summarizes and comments on the main conclusions.

2. EMPIRICAL LITERATURE REVIEW

Renowned analyses by Hamilton (1989) and Hamilton and Susmel (1994) are now attracting greater attention from researchers of Markov chain processes and Markov switching models. The proper application of the state-transition or regime-shifting features of Markov switching better explains economic and financial fluxes during both calm and turbulent, or more complex multiphase, periods. This technique enables complex observations and produces outcomes sensitive to the specific setting. Similar to other financial models, Markov switching clearly demonstrates the mechanics of the economic process rather than calculating simple statistics for an instant result. The framework for Markov switching helps to develop multiple regime-shifting models for capital returns, as evidenced in a series of experiential reviews (e.g., Turner *et al.*, 1989; Cecchetti *et al.*, 1990; Rydén *et al.*, 1998; Timmermann, 2000), which argued that these analyses better explained single regime shifts when describing asset price movements.

Initially, determining whether this model is statistically significant was undertaken successfully by Hansen (1992, 1993) and Garcia (1998), who conducted extensive evaluations and revealed regime switching in various directions for equity returns. The Blanchard–Watson model of stochastic bubbles (Blanchard and Watson, 1982) also demonstrated that returns could be drawn from either sustaining or declining bubbles for each specific period. In addition, Cecchetti *et al.*'s (1990) study used the Lucas asset-pricing model and found the economy's endowment shifted with high and low economic growth, which in turn accounted for several features of stock market returns, such as leptokurtosis and mean reversion. Similarly, Hamilton and Susmel (1994), using a Markov switching model (MS), discovered that frequent deviations in the model in terms of volatility provided a better statistical fit with the data than autoregressive conditional heteroskedasticity (ARCH) models without switching. Furthermore, Schaller and Norden (1997) applied a multivariate specification test for state-dependent switching: investigating whether stock market returns had marginal predictive power of the price/dividend ratio, they observed that the past ratio had strong asymmetry in the response of returns and strong proof of predictability. They also noted that the transition probability amongst different regimes was contingent on economic variables.

The MS model has been widely employed to evaluate stock markets' performances. Moore and Wang (2007) and Wang and Theobald (2008) applied the MS-AR (autoregressive) model to explore the occurrence of regime shifts and found strong corroboration for more than one regime existing in each stock market. Meanwhile, Ismail and Isa (2008) discovered not only regime shifts in the Malaysian stock market but also that the MS model was suitable for illustrating the timing of regime shifts and initiation of switches by several economic and financial crises during the period. A similar technique was applied by Chkili and Nguyen (2011) to examine the volatility behavior of developed and less-developed Mediterranean stock markets over a turbulent period and produced strong evidence of regime shifts; however, the developed ones were less affected by international market crises. Likewise, Qiao *et al.* (2011) adopted a multivariate MS-VAR (vector autoregressive) model (Krolzig, 1997) and regime-dependent impulse response analysis technique (Ehrmann *et al.*, 2003) to investigate the dynamic link among three different capital markets, finding two regimes and correlations among bear markets: the responses of each market to shocks proved resilient and more unrelenting during a bear market period.

With the growth of emerging countries and greater openness in the world economy, the associations between exchange rate volatility and stock market returns in emerging markets have been reviewed. Despite a sizeable amount of literature examining this relationship, the number using MS models are extremely limited. One such study that employed the Markov regim- switching model was Holmes and Nabil (2002), who revealed that Asian stock markets are regime-dependent when affected by currency devaluations: the Asian exchange rate crisis led to significant widespread volatility, indicated by the frequency of regime switches. In addition, Flavin *et al.* (2008) noticed that shocks in the East Asian region, instigated by either currency or stock market, spread to and manipulated other markets in turbulent environments. Chkili *et al.* (2011) also observed a regime-dependent relationship in both calm and turbulent periods and that stock market volatility responded asymmetrically to shocks in the currency market, while Chkili and Nguyen (2014), using the MS-VAR model and bidirectional tests, discovered stock markets had a unidirectional impact on exchange rates in Brazil, Russia, India, and China, but not South Africa (BRICS countries).

Recent empirical research studies have scrutinized the connection between economic and financial variables. Sarafrazi *et al.* (2015) accounted for the high volatility in the capital market and high pressure in the financial market by examining the relationship between real and fiscal factors in the United States following a regime shift: they noted that the effects and their fluctuations were significantly larger in a highly volatile regime. Meanwhile, investigating whether transition probabilities are constant and exogenous, Semmler and Chen (2014) applied multi-regime VAR analysis to identify the macro-finance link for the consequences of the shocks from financial trauma in a large number of economies: they studied two regimes of financial stress, finding that shocks in a high fiscal stress regime creates substantial and persistent influences on the real side of the economy, although shocks in low-stress regimes quickly diminish leaving lasting effects. Andreopoulos (2009) estimated a nonlinear model for the real oil price, real interest rate, and unemployment in the US economy, and the results revealed that during economic expansion, real interest rates affect unemployment while real oil prices affects it asymmetrically only in a recession; however, they observed that the real oil price rather than the real interest rate was significant for unemployment in the long term.

Considering the discrete impact of other economic factors on the dynamic relationship between stock market returns and inflation rates, Hondroyiannis and Papapetrou (2006) observed that real stock market returns were unrelated to expected and unexpected inflation while stock market movements were regime-dependent and unpredictable. More recently, Balcilar *et al.* (2015) analyzed the relationship between US crude oil and stock market prices and found highly volatile regimes appear more often in a recession. Similarly, Yıldırım *et al.* (2018) studied the dynamic relationship between global crude oil prices and stock prices in BRICS countries using the MS-VAR model and discovered positive stock market returns in response to oil price shocks in highly volatile regimes; thus, an increase in oil prices may be identified by demand-side shock.

Overall, the relevant literature displays mixed views. Empirical literature applying the MS model to determine the statistical link between exchange rate fluctuations and stock market returns, other than the presence of control macroeconomic variables, has not, however, studied the SAARC countries. Consequently, this study examines the potential regime shifts in stock market returns for four SAARC countries: Bangladesh, India, Pakistan, and Sri Lanka. It will add to the literature by investigating regime-switching behavior in the selected stock markets' volatility for the period 1993–2016. Using the Markov switching process proposed by Hamilton (1989) enables not only a distinction to be made between regime shifts during volatile processes in calm and turbulent periods but also observation of the intense market stresses during bear and bull market trends. In addition, from the sample data, this study supports the assessment that regime shifts are affected by fluctuations in the stock markets of all the emerging economies.

3. MARKOV SWITCHING MODEL (MSM)

According to earlier studies, received knowledge suggests that macroeconometric time-series models deal with structural change and/or regime shift (Granger, 1996). Research from Hansen (2001) or Perron (2006) certainly assert that econometric applications should consider regime shifts. Nonlinear time series comprise a category of MSM models that develop from nonlinear dynamic processes, such as upturns or crashes in time series, high-moment structures, uneven market rotations, and time-varying constraints.

An empirical examination, taking into account macroeconomic factors, of the impact of foreign exchange returns on equity market returns traditionally adopts the simple model in Equation 1, in which stock market returns are regressed against their own lagged values and γ_t:[2]

$$SR_t = f(SR_{t-1}, \gamma_t) \tag{1}$$

$$SR_t = \alpha_0 + \alpha_1 SR_{t-1} + \alpha_2 \gamma_t + \varepsilon_t \tag{2}$$

The regression model expressed in Equation 2 assumes that the exposure coefficient α is steady in time with a linear information structure, as well as reflecting the fact that all variables are dependent on similar shocks. The

[2] γ explains exchange rate fluctuations and other control macroeconomic variables in a calculation.

two regression parameters should be assessed for every regime switch, however, if the independent variables exhibit variations in financial composition at a specific time.

The time-series behaviors of economic and financial variables, demonstrated by several experiential analyses, may reveal diverse patterns over time; therefore, numerous models are usually used to describe these patterns instead of a single model for the conditional mean of a variable. The MSM combines two or more dynamic models through a Markovian switching mechanism, which was initially studied by the Goldfeld and Quandt (1973); then, Hamilton (1989) comprehensively examined this technique and its estimation methodology (Hamilton and Susmel, 1994; Kim and Nelson, 1999). In this analysis, a two-state Markov switching regime methodology was applied to elucidate that the relationship alternates between two states, due to discrete switches, owing to changes in the imperceptible Markov chain state variable s_t. This parameter takes the value of either 0 or 1, indicating the periods when there is or is not a crisis, bear or bull markets, or low or high returns.

In the absence of foreign exchange fluctuations and risk for other variables when stock market returns are supposed to follow a stationary stochastic process, this relationship can be described by two distributions with different means and variances, as in Equation 3:

$$SR_t = \alpha_0(1 - s_t) + \alpha_1 s_t + [\sigma_0(1 - s_t) + \sigma_1 s_t]\varepsilon_t \tag{3}$$

where $\varepsilon_t \sim i.i.d.N(0, \sigma_\varepsilon^2)$ is a standard Gaussian variable with variance σ_0.

This approach likewise allows for stochastic regime-dependent trends and long-term mean reversion in stock market returns resulting from foreign exchange risks, inflation instability, interest rate fluctuations, the speed of industrial production growth, and fluctuations in international crude oil prices. Each state can be distinguished by the magnitude and significance of the regression coefficients, as seen in Equation 4:

$$\begin{aligned} SR_t = {} & \alpha_0(1 - s_t) + \beta_0 s_t + \alpha_1(1 - s_t)SR_{t-1} + \beta_1 s_t SR_{t-1} + \alpha_2(1 - s_t)ER_t + \beta_2 s_t ER_t + \alpha_3(1 - s_t)IR_t^* + \beta_3 s_t IR_t^* \\ & + \alpha_4(1 - s_t)DR_t^* + \beta_4 s_t DR_t^* + \alpha_5(1 - s_t)IPG_t + \beta_5 s_t IPG_t + \alpha_6(1 - s_t)COP_t^* + \beta_6 s_t COP_t^* \\ & + [\sigma_0(1 - s_t) + \sigma_1 s_t]\varepsilon_t \end{aligned} \tag{4}$$

where $\varepsilon_t \sim i.i.d.N(0, \sigma_\varepsilon^2)$ is a standard Gaussian variable with variance σ_0, the * symbol indicates the difference for non-stationary variables (i.e., $y_t^* = \Delta y_t$), and s_t is a binary state variable adopting an irreducible ergodic two-state Markov process—markets experiencing a state of crisis or depression are given as $s_t = 0$, with $s_t = 1$ given to those in a state of calm or expansion. This is explained through *ex ante* transition probabilities P_{ij} between the two states, as shown in Equation 5 and Equation 6:

$$P_{ij} = P[s_t = i \,|\, s_{t-1} = j] \text{ with } \textstyle\sum_{j=1}^{2} P_{ij} = 1 \text{ for all } i, j \in \{0,1\} \tag{5}$$

The transition probability matrix τ being:

$$\tau = \begin{bmatrix} P_{00} & P_{01} \\ P_{10} & P_{11} \end{bmatrix} \tag{6}$$

where

$$\begin{cases} P_{00} = P(s_t = 0 \mid s_{t-1} = 0) = q \\ P_{01} = 1 - P_{00} = P(s_t = 0 \mid s_{t-1} = 1) = 1 - q \\ P_{10} = 1 - P_{11} = P(s_t = 1 \mid s_{t-1} = 0) = 1 - p \\ P_{11} = P(s_t = 1 \mid s_{t-1} = 1) = p \end{cases}$$

The probability for state 0(1) persisting from one period to the next is $q\,(p)$. For probabilities P_{00} and P_{11}, the return process remains in the same regime of 0 and 1, respectively. The dynamics of switching between the two states depends upon the conditional transition probabilities, which can also be identified as nonlinear functions of the independent variables. The values $P_{00} = \omega_0 + \vartheta_0 \gamma_t$ and $P_{11} = \omega_1 + \vartheta_1 \gamma_t$ represent the respective probabilities that whichever regime, 0 or 1, prevails in the current period will occur in the next. If ϑ_0(or ϑ_1) equals zero, then P_{00}(or P_{11}) has static significance and the average duration of regime 0 (or 1) can be computed as $(1 - P_{00})^{-1}$ (or $(1 - P_{11})^{-1}$). If ϑ_0(or ϑ_1) does not equal zero, then P_{00}(or P_{11}) is stochastic and dependent on foreign exchange returns and other relevant control factors. In this case, the transition probabilities of switching from depression to expansion, expansion to depression are P_{01} and P_{10}, respectively, as derived from the aforementioned restrictions.

The revolving point in this empirical analysis is exhibited in Equation 4. Conventional wisdom maintains that a small depreciation in domestic currency, inflation rates, discount rates, industrial production growth, and oil prices may benefit the national stock market, whereas a greater devaluation may not. When it is not assumed that significant depreciation results in harmful consequences in one regime, or creates a similar effect in the other, experiential substantiation can be provided for the regime-dependent theory. However, with the MSM, it is difficult to discern the state variables.

4. DATA AND EXPERIENTIAL EXPLANATION

The research data in this study comprises stock market returns (SR_t), and exchange rate fluctuations (ER_t), calculated as a difference in logarithmic monthly averages,[3] $(ln\,(p_t) - ln(p_{t-1})$, where *In* and p are index value and exchange rate, respectively. The exchange rates reflect the currencies of each of the selected countries in relation to the US dollar: Bangladeshi Taka BDT/USD, Indian Rupee INR/USD, Pakistani Rupee PKR/USD, and Sri Lankan Rupee LKR/USD. Other variables in the empirical analysis include the monthly data for the inflation rate (IR_t), interest rate (DR_t), industrial production growth (IPG_t), and crude oil prices (COP_t). Equity market price indices were obtained for each country: Dhaka Stock Exchange (DSEX) from the Central Bank of Bangladesh; Karachi Stock Exchange (KSE100 Index) from the State Bank of Pakistan; Bombay Stock Exchange (S&P BSE SENSEX) from the Bombay Stock Exchange, India; Sri Lanka Stock Exchange (CSE Index) from Yahoo Financial Services;

[3] Monthly averages were calculated using the daily stock prices and exchange rates at the close for the countries under examination.

and foreign currency exchange information from www.oanda.com. Data for other restricted variables were obtained from the respective central banks of each country and the International Monetary Fund. The time period varied for each country due to the required information being unavailable, but overall, the data covers the period from November 1993 to December 2016.

To test the hypothesis in this study that factors affecting stock market return dynamics are regime-dependent, some basic diagnostic evaluations of the selected financial markets were conducted. Prior to this analysis, therefore, descriptive statistics were calculated and the Augmented Dickey–Fuller (ADF) test undertaken to determine the volatility status and presence of stationary processes in each variable, shown in Table 1 and Table 2, respectively.

Table-1. Descriptive Statistics for all Variables.

VARIABLES	COUNTRIES	Mean	Std. Dev.	Skewness	Kurtosis	Jarque–Bera	Probability	CV
SR	BANGLADESH	0.0070	0.0799	-0.4577	6.9400	97.4871	0.0000	1137.1165
	INDIA	0.0080	0.0617	-0.3962	4.6009	36.8275	0.0000	768.9788
	PAKISTAN	0.0120	0.0781	-0.4716	6.8245	179.0861	0.0000	652.6800
	SRI LANKA	0.0098	0.0579	0.0996	3.7054	5.0823	0.0788	592.9808
ER	BANGLADESH	0.0020	0.0092	2.0164	13.3005	729.0799	0.0000	450.8957
	INDIA	0.0028	0.0171	0.7503	7.0299	213.4231	0.0000	614.0029
	PAKISTAN	0.0045	0.0154	2.0089	15.5799	2012.8270	0.0000	343.9929
	SRI LANKA	0.0038	0.0110	0.9236	10.9846	635.2853	0.0000	291.0290
IR	BANGLADESH	0.0757	0.0181	0.4028	2.9235	3.9286	0.1403	23.9205
	INDIA	0.0728	0.0333	0.6148	3.3125	18.5765	0.0001	45.7166
	PAKISTAN	0.0842	0.0473	0.9913	4.4774	70.5554	0.0000	56.1575
	SRI LANKA	0.0843	0.0540	1.0529	4.5326	64.1590	0.0000	64.0661
DR	BANGLADESH	0.0663	0.0130	-0.1316	1.7490	9.8060	0.0074	19.6812
	INDIA	0.0791	0.0212	0.8292	2.3799	36.1793	0.0000	26.8576
	PAKISTAN	0.1175	0.0368	0.3629	2.2406	12.7337	0.0017	31.3465
	SRI LANKA	0.1606	0.0231	2.7838	10.3034	797.7077	0.0000	14.3642
IPG	BANGLADESH	0.1003	0.0615	-0.0597	2.6724	0.7296	0.6943	61.3020
	INDIA	0.0676	0.0461	0.2568	3.4076	4.9624	0.0836	68.2202
	PAKISTAN	0.0531	0.0821	0.0955	4.0180	12.3816	0.0020	154.4659
	SRI LANKA	0.0474	0.0557	1.6069	10.0857	572.5778	0.0000	117.5794
COP	BANGLADESH	79.9029	26.5153	0.1317	1.7004	10.5504	0.0051	33.1844
	INDIA	52.3192	34.9159	0.6400	2.0631	29.0376	0.0000	66.7364
	PAKISTAN	52.3192	34.9159	0.6400	2.0631	29.0376	0.0000	66.7364
	SRI LANKA	59.8871	34.1887	0.3847	1.8708	17.6578	0.0001	57.0886

Note: The sample consists of average monthly observations of currencies for four SAARC countries. The critical value of the Jarque–Bera Test for Normality from a χ^2 distribution with 2 degrees of freedom is 5.99 for the 5% significance level.

Table-2. Augmented Dickey–Fuller Stationarity Test.

ADF Statistics		BANGLADESH	INDIA	PAKISTAN	SRI LANKA
SR	LEVEL SERIES	-12.1034***	-13.0384***	-14.2211***	-5.8508***
	FIRST DIFFERENCE	-4.9325***	-8.8856***	-6.6646***	-7.6181***
ER	LEVEL SERIES	-6.7116***	-6.2657***	-7.8972***	-6.6031***
	FIRST DIFFERENCE	-6.4733***	-7.3616***	-10.2333***	-6.8134***
IR	LEVEL SERIES	-3.0378	-1.7059	-1.2995	-2.4139
	FIRST DIFFERENCE	-6.5151***	-6.9055***	-8.8786***	-5.5899***
DR	LEVEL SERIES	-2.7059	-1.5030	-1.6343	-2.1383
	FIRST DIFFERENCE	-12.3960***	-11.9753***	-9.9725***	-6.1758***
IPG	LEVEL SERIES	-4.6339***	-3.1274	-3.6294**	-4.6486***
	FIRST DIFFERENCE	-4.0998***	-6.1376***	-6.5933***	-4.5166***
COP	LEVEL SERIES	-2.4654	-2.5552	-2.5552	-2.2844
	FIRST DIFFERENCE	-7.3730***	-10.8888***	-10.8888***	-9.8232***
Test Critical Value	1% level	5% level		10% level	
	-4.2050	-3.5266		-3.1946	

Note: *, **, *** denote significance at the 10%, 5% and 1% significance levels, respectively.

4.1. Regimes in Stock Market Returns

As the purpose of this study is to examine relationships in regime-switching circumstances, whether stock market returns exhibit a regime shift was examined empirically first. Therefore, scatter plots were created to analyze the nonlinearity in the model and demonstrate the impact of each variable on the equity returns (see Appendix B). These charts clearly display the nonlinear behavior between the variables for each market.

To calculate the non-standard asymptotic distribution, a technique proposed by Hansen (1992, 1993) and Garcia (1998) that limited the evaluation of the Markov switching process by treating the transition probabilities as edge parameters were adopted. To facilitate the final choice of a suitable modeling approach, the likelihood ratio test (LR) developed by Garcia and Perron (1996) was conducted, calculated as follows:

$$LR = 2 \times [lnL_{MSM} - lnL_{OLS}]$$

where lnL is the log likelihood ratio of the contending models. Selection of an appropriate model was based on the critical value tests of Davies (1987) and Garcia (1998) and chi-squared distributions. Table 3 shows that the LR test figures are significant at the 1% level in all cases. These results were calculated prior to the actual study to repudiate the null hypothesis that there were no stock market reversals in any of the countries, indicating that the time-dependent behaviors of these markets are more likely to be represented by the nonlinear MSM model. Thus, the implication is that a regime-switching model is suitable for generating hinge dynamics under the influence of regime shifts. Similar results were produced for other emerging markets in earlier studies (e.g., Kanas, 2005; Wang and Theobald, 2008; Chkili and Nguyen, 2011; Chkili *et al.*, 2011).

Table-3. LR Test Statistics.

Countries	*lnL*	*lnL*$_{MSM}$	LR
Bangladesh	164.0641	185.9586	43.789^{++}
India	413.8280	438.7792	49.9024^{++}
Pakistan	324.3060	359.9949	71.3778^{++}
Sri Lanka	341.6122	363.9070	44.5896^{++}

Note: $^{++}$ denotes the null hypothesis of no regime shift is rejected at the 1% significance level.

4.2. The Regime-Dependent Relationship between Stock Market and Currency Returns

An investigation was undertaken into whether there are indications of different regimes existing for stock market returns. The readiness to switch with the data depends on the economic dynamics that lead to a switching behavior. Empirical estimates of the Markov switching model, along with the means and variances involved, are shown in Table 4, and the features of the regime are explained in Table 5. The models for each country identified two regimes (the first referred to as regime/state 0 and the second as regime/state 1) with different volatilities, in which the effect of exchange rate fluctuations and selected macroeconomic variables on stock market returns differ substantially.

The analysis revealed that Bangladeshi stock market returns responded to their own lagged market and oil prices in both the regimes, although the latter had a minor negative impact on the stock market. Furthermore, inflation and industrial production only exerted approximately 380% and 104% negative impacts on stock market returns in state 1. Panel A of Table 5 shows that the transition probability of 0.6242 in regime 0 is higher than that of 0.1048 in regime 1. The significance of these probabilities (P_{11} and P_{22}) suggests that the low volatility regime is more persistent than the high one; in other words, the Bangladeshi stock market remained longer in regime 0 than 1, although the market observed high volatility in both regimes. This finding is confirmed by the average duration (in months) for each regime (d_0 and d_1) exhibiting low volatility for 2.66 months, due to frequent inconsistencies in the market. The results of this analysis indicate the dominance of regime 0, which signifies a bearish trend with low volatility during a crisis in the stock market; however, when there is no crisis, the capital market displays a bullish trend with high volatility owing to the substantial influence of control variables other than exchange rate fluctuations. Moreover, the latter do not play a significant role in the transition between regimes, even though the previous outcomes of stock market returns and oil prices help maintain stability in the market during a crisis.

Table-4. Markov Switching Model Estimations.

Variables	BANGLADESH	INDIA	PAKISTAN	SRI LANKA
Regime 0				
α_0	0.0186*	0.0125**	0.0017	-0.0004
	{1.6860}	{2.1863}	{0.1103}	{-0.0792}
α_1	-0.1333**	-0.0727	0.0427	0.2826***
	{-2.0329}	{-0.8156}	{0.3542}	{3.1692}
α_2	0.6909	-1.0709***	-0.2052	-0.4413
	{1.0226}	{-6.0231}	{-0.3369}	{-1.5864}
α_3	1.3435	0.2233	-0.8524	0.8458***
	{1.5141}	{0.6294}	{-0.8169}	{3.5374}
α_4	-0.7116	0.6275	-3.4385	-0.6499
	{-0.8183}	{0.8792}	{-1.6268}	{-1.4321}
α_5	-0.0689	-0.0329	-0.0591	-0.0092
	{-0.7447}	{-0.3612}	{-0.4145}	{-0.1325}
α_6	0.0023***	0.0003	0.0005	-0.0007
	{2.6906}	{0.4321}	{0.2332}	{-0.9738}
$ln\sigma_0$	-3.1010***	-3.5376***	-2.2225***	-3.4277***
	{-24.7554}	{-44.3775}	{-22.6462}	{-45.3869}
Regime 1				
β_0	0.1208***	0.0137	0.0173***	0.0213**
	{2.9766}	{1.5115}	{2.9822}	{1.8323}
β_1	0.6508**	0.1986***	0.3149***	0.2854***
	{2.1351}	{2.9342}	{3.9694}	{2.6280}
β_2	-1.9662	-1.4456***	-0.7595**	-0.6237
	{-1.3068}	{-4.6519}	{-2.0877}	{-0.7233}
β_3	-3.7820**	-0.6849	-0.1208	0.1552
	{-2.5483}	{-1.4651}	{-0.2612}	{0.3503}
β_4	0.7387	-0.5844	-0.5994	1.6245
	{0.1468}	{-0.3180}	{-0.5930}	{1.2768}
β_5	-1.0433***	-0.0610	-0.0494	0.0232
	{-2.8727}	{-0.6078}	{-0.7870}	{0.1941}
β_6	-0.0070**	0.0019*	0.0016*	0.0030**
	{-2.2199}	{1.7745}	{1.9095}	{2.0421}
$ln\sigma_1$	-2.5086***	-2.7927***	-3.0689***	-2.6855***
	{-18.0935}	{-52.1660}	{-31.7975}	{-30.3167}

Note: Results refer to Equation 4 for the MSM model. The figures in curly brackets show the t-statistics for rejecting the null hypothesis. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table-5. Regime Characteristics of the Markov Switching Model.

Panel A: Regime-Switching Characteristics								
Statistics	**BANGLADESH**		**INDIA**		**PAKISTAN**		**SRI LANKA**	
Transition Probabilities	Regime 0	Regime 1	Regime 0	Regime 1	Regime 0	Regime 1	Regime 0	Regime 1
Regime 0	0.6242	0.3758	0.9950	0.0050	0.9393	0.0607	0.9526	0.0474
Regime 1	0.8952	0.1048	0.0033	0.9967	0.0280	0.9720	0.0653	0.9347
Expected Duration	2.6610	1.1171	198.3705	300.5724	16.46366	35.73076	21.0870	15.3180
Log Likelihood Ratio	185.9586		438.7792		359.9949		363.9070	
Panel B: Diagnostic Tests								
Q(12)	12.5267	(0.4044)	8.3207	(0.6840)	13.3200	(0.3460)	15.7410	(0.2030)
Qs(12)	7.9616	(0.7880)	9.5524	(0.7210)	28.9560***	(0.0040)	3.1605	(0.9940)
J–B	118.5779***	(0.0000)	3.4079	(0.1820)	314.4038***	(0.0000)	7.8646**	(0.0196)

Note: J–B refers to the Jarque–Bera Normality test. *Q(12)* and *Qs(12)* refer to the Box–Pierce serial correlation test for residuals and squared residuals, respectively. The figures in parentheses show the p-values. The expected durations for each regime are d_0 and d_1. ** and *** indicate statistical significance at the 5% and 1% levels, respectively.

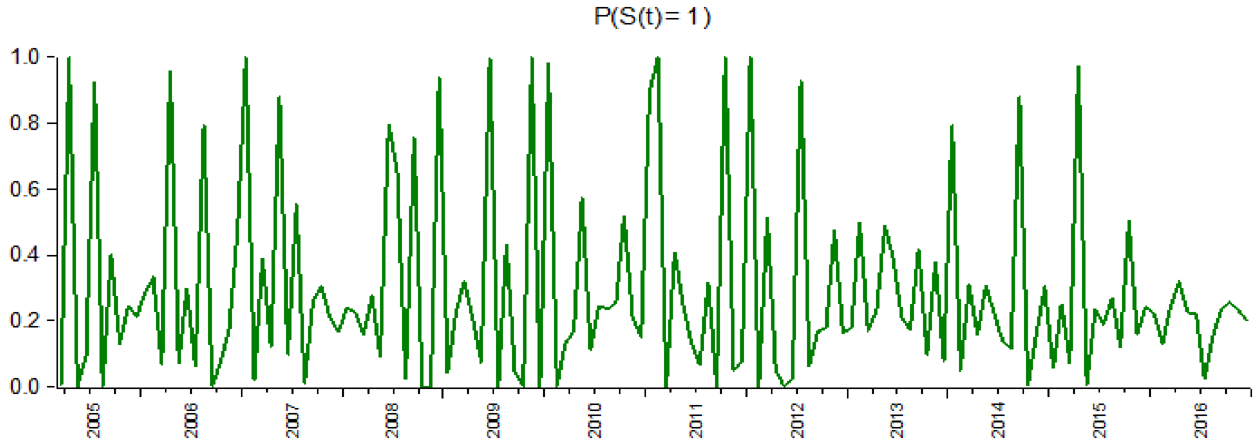
It is noteworthy that the results for India and Pakistan were analogous and revealed very stable economic conditions: the $ln\sigma$ of the returns reported in Table 4 show that both regime 0 and 1 are experiencing a low volatile situation. The mean estimates for the lagged stock market returns and crude oil prices in the preceding period also show a significantly positive response to the stock market returns in regime 1 for both countries. In addition, the relationship between the stock market and exchange rate returns is significantly negative in regime 1, from which can be inferred that stock market returns for India and Pakistan dropped by about 144% and 76% in a month, respectively. Estimations of the transition probabilities for both countries are very close to 1 in both regimes, while the enormity of P_{11} and P_{22} suggests that both regimes are more persistent, or both stock markets remained for longer periods in each regime, though slightly longer in regime 1. These outcomes are also supported by the average duration in months for each regime, elucidating stable market attributes. Overall, the Indian and Pakistani stock markets behaved virtually the same, with the predominance of regime 1 demonstrating a bullish trend with comparatively low volatility when there is no crisis. Under these conditions, despite fluctuating exchange rates, lagged stock market returns and oil prices helped stabilize the markets for the long period of time covered by this study.

The final column of Table 4 provides the estimation results of the MSM model for Sri Lanka, and the mean estimates for one period of lagged stock market returns were found to be significantly positive for both regimes. The inflation rate is also significant in regime 0, leading to an 84% improvement, while crude oil prices are significantly negative in regime 1, with stock market returns declining slightly over one month. Although the Sri Lankan stock market is persistent in both regimes, the transition probability of being in regime 0 is found to be comparatively less volatile than remaining in regime 1. This is upheld by the constant average duration in months for each regime: the low volatile regime 0 lasted 21 months, but the highly volatile regime 1 only lasted around 15 months. Thus, during a crisis, regime 0 prevails as a bear market with low volatility; however, the Sri Lankan stock market significantly triumphed over bearish trends with low volatility.

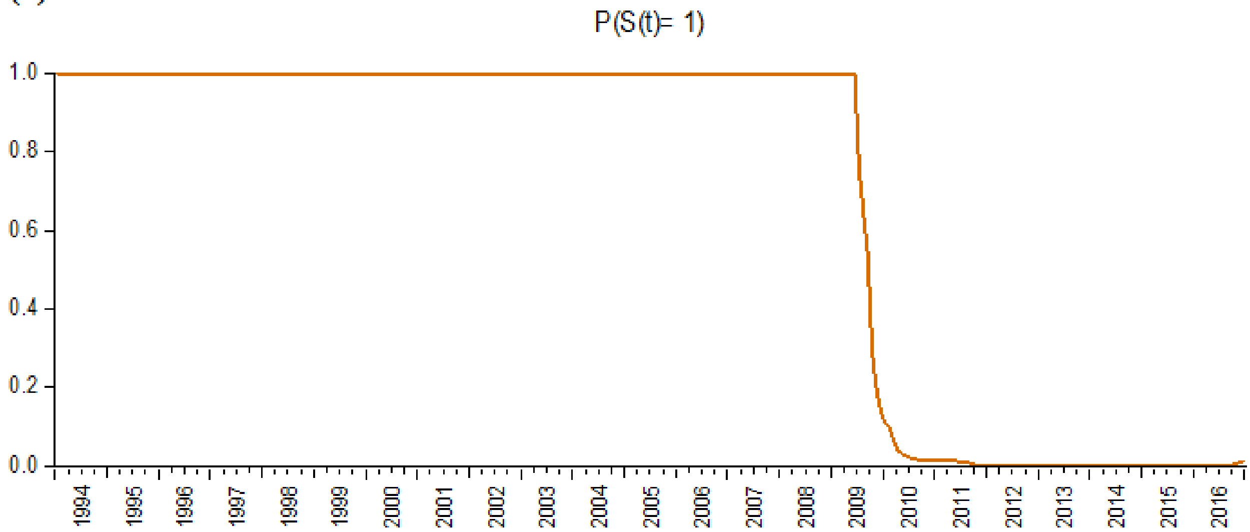
4.3. Smooth Transition Probabilities

The smooth transition probabilities derived from the MSM are presented in Figure 1. The MSM captured all the main highly volatile periods for the selected SAARC countries. Some international crises that affected these markets include the Asian Financial Crisis (1997–1998) and Global Financial Crisis (2007–2008), with each suffering local crises as well.

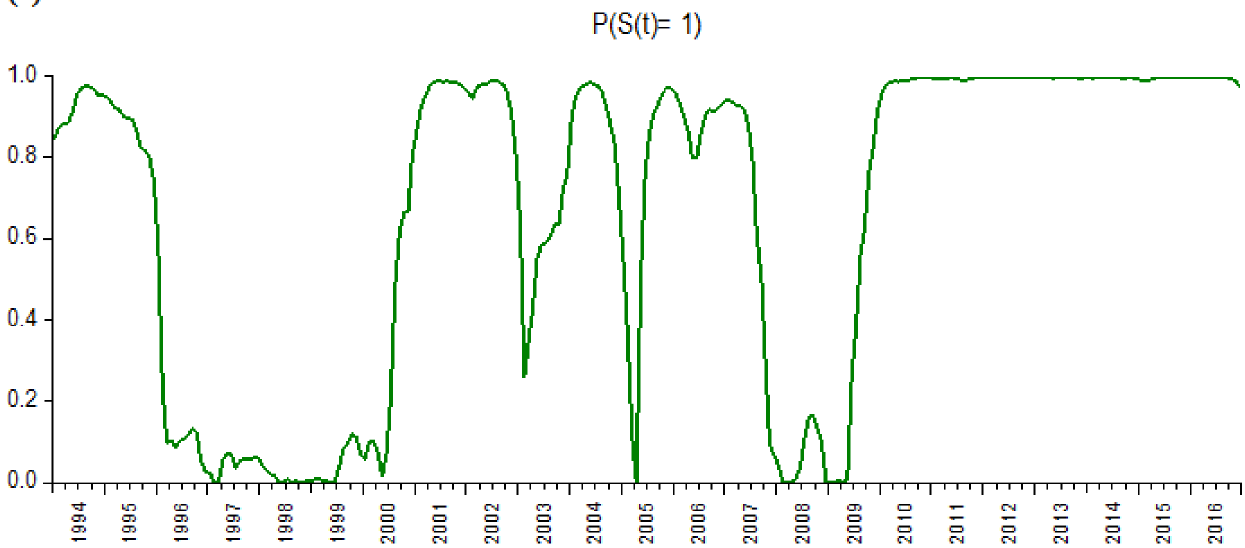
a) Bangladesh



(b) India



(c) Pakistan



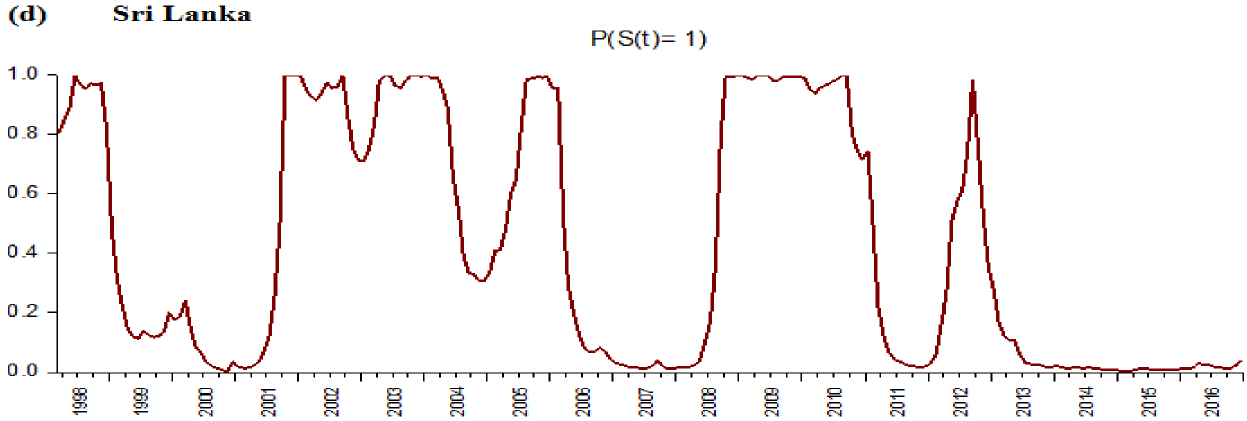


Figure-1. Transition probabilities.

For Bangladesh (Figure 1a), a smooth transition probability for being in regime 1 was estimated, indicating a very high range of volatility, while the stock market experienced a bullish trend when no crisis occurred. Stock market returns, directly affected by exchange rate fluctuations and other control variables, exhibited significant responses to the financial shocks following the Global Financial Crisis and other occasional local crises. Significant increases in volatility were first noticed from mid-2005 to the first half of 2007, followed by a series of fluctuations between 2008 and 2012: the stock market faced a dramatic downturn in 2010 subsequent to the capital market experiencing abnormal turbulence from around 2005 and ending with the burst of the asset price bubble in 2010. The main reasons behind such behavior include: the aftereffects from the 1996 collapse, demand induction due to political conditions since 2007, shortages in the gas and power sector, excess savings, idle business funds, the 2007–2008 Global Financial Crisis, and surplus liquidity in 2009. The repercussions continued for several years afterwards. Similarly, another volatile period delivered a series of shocks to the Bangladeshi financial market in 2014–2015 when the country experienced a significant slowdown in business activity due to political disorder and blockades, and a decline in interest rates. The market recovered in the following year, however, owing to successive attempts at corrective measures.

Figure 1b illustrates the smooth transition probabilities for India, which are particularly interesting for regime 1. There was a very long period, from 1993 to 2008, without any crises; this low volatility preceded a single market deviation only during the Global Financial Crisis, followed by a long-term crisis. Since 1992, India has experienced two incidences of considerable stock market growth, in 1992–1993 and 1999–2000. The first expansion reflected price deregulation driven by a liberal monetary policy; however, investors realized stock prices were overvalued in the primary market, public confidence in the equity market declined following a series of scams and malpractice during 1992 and 1993, the inflow of foreign capital reduced following the Mexican and South Asian crises, and the impact of several global phenomena was felt, resulting in a decline in equity finance up to 1999. In that year, the stock market expanded again on account of the IT boom and a reduction in capital gains tax. As the Indian economy is mainly an open one, the Indian financial market as a whole suffered a depression in 2008–2009. The stock market has experienced huge drops, and its highest ever loss, as weak global signals have created panic among investors, who fear a dramatic slump in US markets. Several factors lie behind this decline: changing the global investment environment, fear of recession in the US economy, global credit crisis and distress, sale of foreign hedge funds to enable reallocation from uncertain emerging markets to stable developed markets, cuts in US interest rates, volatility in the commodities markets, and several other influences from local factors. Consequently, from 2009 onwards, the Indian stock market experienced a depression.

The smooth transition probabilities for Pakistan (Figure 1c) indicates that the market frequently vacillated in high and low volatile regimes. As Pakistan is a partially open economy, the market reacted to financial shocks from internal crises in the main, but the Asian and Global Financial Crises as well. A significant increase in volatility was observed from 1994 to mid-2000, leading to a bearish trend in the market. It involved the collapse of the equity market in 1995, caused by the domestic political crisis and a discouraging macroeconomic outlook, and the devaluation of the Pakistani rupee in October 1997. Then, in 1998, the local capital market suffered a violent crash in the face of such events as the South East Asian financial collapse and global recession. Similarly, the financial shock from the subprime mortgage crisis and major related economic failures also affected Pakistan between 2007 and 2009, which explains the market's transition to a highly volatile regime. Major macroeconomic factors during that period include: the Red Mosque incident, terrorism, reaction to the 2007 Karsaz bombing during the reception for Mrs. Benazir Bhutto on October 18, declaration of a state of emergency, suspension of Pakistan from the Commonwealth, and assassination of Mrs. Benazir Bhutto on December 27, 2007, which resulted in the largest crash of the financial market. As it is evident that Pakistan's stock market returns are closely linked to macroeconomic variables and the business cycle, the remaining highly volatile periods can be rationally attributed to country-specific affairs and risk factors.

The smooth transition probabilities of Sri Lanka being in regime 1 (Figure 1d) suggest that over the period of the study, the market frequently vacillated between high and low volatility. Troughs in the graph illustrate comparatively low volatile crisis trends in the Sri Lankan economy; specifically, the first downturn in the stock market occurred between June 1999 and 2001, indicating the effects of the civil war (Eelam War III), Asian Financial Crisis (1997–1998), and other global events. Another crisis occurred between August 2006 and May 2008, during which time the ceasefire agreement between the Sri Lankan and internal guerilla leaders ended, along with the associated positive political attributes and economic developments, despite the existence of rigid forces, which in turn led to slower growth in the CSE Index. A further two periods of the crisis were observed throughout the 2010s. First, the formidable economic expansion after the civil war ended on May 19, 2009, diminished under the uncertainty in the global markets and domestic market issues (i.e., a series of tighter regulations, stringent trading measures for market insiders, and a high interest rate environment), which disrupted stock market performance. Second, the crisis between late 2013 and 2016 coincided with a decline in the stock market due to a marginal increase in domestic interest rates, political uncertainty, depreciation of the domestic exchange rate, global factors, declining commodity prices, and a drop in oil prices.

Overall, the Indian and Pakistani stock markets were relatively more consistent in regime 1, when there were no crises, and experienced a bullish trend in market performance. In contrast, the capital markets of Bangladesh and Sri Lanka were the least volatile in regime 0, during a crisis, and inclined toward bearish market behavior. These outcomes imply that these stock markets are characterized by a state in which risk is relatively low and investors earn more than when retaining liquidity funds, while they lose money in a state in which risk is substantially higher. These results are consistent with the findings of Kanas (2005) and Chan *et al.* (2011). For instance, Kanas (2005) provides evidence of two regimes in the relationship between the Mexican exchange rate and the stock market returns of some emerging countries. Moreover, the results obtained by Kanas (2005) indicate that a low volatility regime is more persistent than a highly volatile one.

An obvious question is whether there is still evidence that stock market returns can be predicted using macroeconomic variables, after switching control. Fads models[4] provide one possible economic motivation for Markov switching processes: stock market returns are predictable.[5] The predictability of returns can also stem from time variations in the risk premium of an efficient market,[6] while their nonlinear predictability could arise as a result

[4] Fads are any form of collective behavior that often appears suddenly, quickly spreads, is short-lived, and then fades; this is different from trends that develop slowly and last longer. In the main, fads are represented in the model by peaks that generate and deteriorate rapidly.

[5] In a context with fads, Schaller and Norden (1997) demonstrated that returns were correlated with lagged values of the price/dividend ratio, while Chkili and Nguyen (2014) and Sarafrazi *et al.*, (2015) revealed the correlation between stock market returns and exchange rate fluctuations.

[6] See Fama (1990, 1991) for further discussion.

of the kind of stochastic bubbles proposed by Blanchard and Watson (1982). In this study, the empirical estimations for all the markets provided strong evidence of predictability, indicating that the Indian and Pakistani stock market returns are mainly predicted by exchange rate fluctuations, and through other macroeconomic variables for Bangladesh and Sri Lanka.

On the whole, the results of the time-varying MSM models for all the selected countries show that only the Indian and Pakistani stock market returns are negatively influenced by fluctuations in their exchange rates during bull cycles when there are no crises. This significant negative relationship between the stock market and currency returns suggests that equity markets are likely to respond to foreign exchange devaluation with a decrease in prices accompanied by an increase in the required risk premium. For Bangladesh and Sri Lanka, the results corroborate those of previous studies (e.g.Kanas, 2000; Yang and Doong, 2004; Chkili and Nguyen, 2014), suggesting that fluctuations in currency returns exert little effect on stock market return dynamics. For example, Kanas (2000) examined the volatility spillover between exchange rates and stock markets in some developed countries and reported that the transmission of volatility from foreign exchange markets to stock markets was insignificant for all the countries selected. Likewise, Yang and Doong (2004) produced similar results for the G7 countries, stating that fluctuations in exchange rates have less of a direct impact on future stock price changes; this can be explained by means of effective hedging strategies against currency risks through available currency derivatives. Furthermore, Chkili and Nguyen (2014) found that significant impacts from exchange rates only occurred in BRICS countries.

Conversely, a single period of lagged stock market returns and crude oil prices were found to be important control variables that influenced the bear and bull cycles in all the stock markets. Yıldırım *et al.* (2018) estimated that in all countries the response of the stock market to an unexpected oil price shock is positive and statistically significant in highly volatile regimes, suggesting that oil price increases can be estimated by demand-side shock. Sri Lankan stock market returns were further influenced positively by the inflation rate during a bear trend, due to its long civil war, which is in line with Fisher's (1930) prediction of a positive relationship between expected inflation and nominal asset returns. In addition, major constraints were found on Bangladesh's stock market and industrial production growth, which had a negative impact on bull markets, mainly because of demand-side shocks leading to price bubbles on the market during a regime without crises; otherwise, at such times, inflation has no impact on stock market returns (Hondroyiannis and Papapetrou, 2006).

5. CONCLUSION AND POLICY IMPLICATIONS

The evidence of switching behavior in stock market returns is provided by both means and variances. By applying a test amended from an earlier study by Schaller and Norden (1997), switching is shown to be much stronger in all the markets during a crisis. This research also examined investors' insight into foreign exchange risk on the SAARC stock markets. Regime-switching models substantiated nonlinearities in the link between exchange rate fluctuation and equity returns; in particular, the Markov switching dynamic factor model detected regime shifts in the stock market returns as a result of currency returns and other macroeconomic factors and found evidence of two distinct regimes with low and high volatility in each SAARC country. This study revealed the regime-dependent effect of exchange rate fluctuations on stock market returns in India and Pakistan. However, fluctuations in the equity markets in Bangladesh and Sri Lanka were affected more by domestic crises and, despite being just as regime-dependent, by other macroeconomic factors that appeared from time to time in the market.

The inferred probabilities and average regime durations indicated that market switching varied across the selected countries. The Indian market switched regimes only once over the period studied; by comparison, the Pakistani and Sri Lankan markets switched more frequently; meanwhile, the Bangladeshi stock market switched much more sharply between the two regimes—owing to their crises being multiple random events rather than based on a priori dates or structural changes occurring locally—after the onset of local and international financial crises. An increased frequency of regime switching indicates greater uncertainty and a strong tendency toward higher volatility of equity returns during both calm and turbulent regimes.

Evidence for the prediction of regimes was found for all the selected countries. Although both regimes/states were highly persistent in India and Pakistan, and the asymmetric effects of substantial currency depreciation occurred in state 1, casual empiricism suggests that controlled devaluation may eventually be overtaken by market forces, driven either by game-theoretic rounds of further devaluation or by the shifting focus of risk-averse global investors across financial markets. However, interest rates, inflation, and industrial production growth were shown to be insignificant to any change in returns, while the market performance and crude oil prices in the preceding period could be positive for stock market returns during a calm regime; therefore, both stock markets were progressing well but with a declining tendency. Similarly, both states were highly persistent in Sri Lanka, with some exceptions during turbulent regimes when there were high rates of inflation due to the onset of civil war, hindering the stock market. In contrast, the Bangladeshi stock market was quite unstable during both regimes, with the suggestion that since the market was largely affected by long-term demand-side shocks in a calm regime, the effects of inflation and oil prices, apart from industrial production growth, would increase investors' hesitancy in the equity market as well as the likelihood of financial distress and insolvency. This could not be easily dismissed, at least not until the government had implemented strict measures to control those shocks.

In light of the empirical evidence in this study, it is asserted that regime switching in the stock markets of each SAARC country is influenced by both internal and external economic, financial, and political conditions. Policymakers should thus be aware that financial shocks can have considerable real impacts, as proved by not only the recent Global Financial Crisis but also many other domestic crises. Furthermore, when developing an optimal strategy to preserve financial stability in the event of a crisis, those in Pakistan and India should also take note that these shocks are transmitted between foreign exchange and stock markets. Finally, our empirical findings will also assist the central banks of the respective SAARC countries with monetary policies and regulations, and exchange rate regimes. Stock market returns have been studied so extensively that it often seems that very little can be added to the existing knowledge; however, by extending the techniques and findings of Hamilton (1989) and Schaller and Norden (1997), this study does highlight several features of improvement for stock market performance. In conclusion, the authors invite both other empirical researchers to utilize these outcomes and asset pricing theorists to attempt to account for the stylized facts that emerged from this study.

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Appendix-A. Bangladeshi Financial Markets

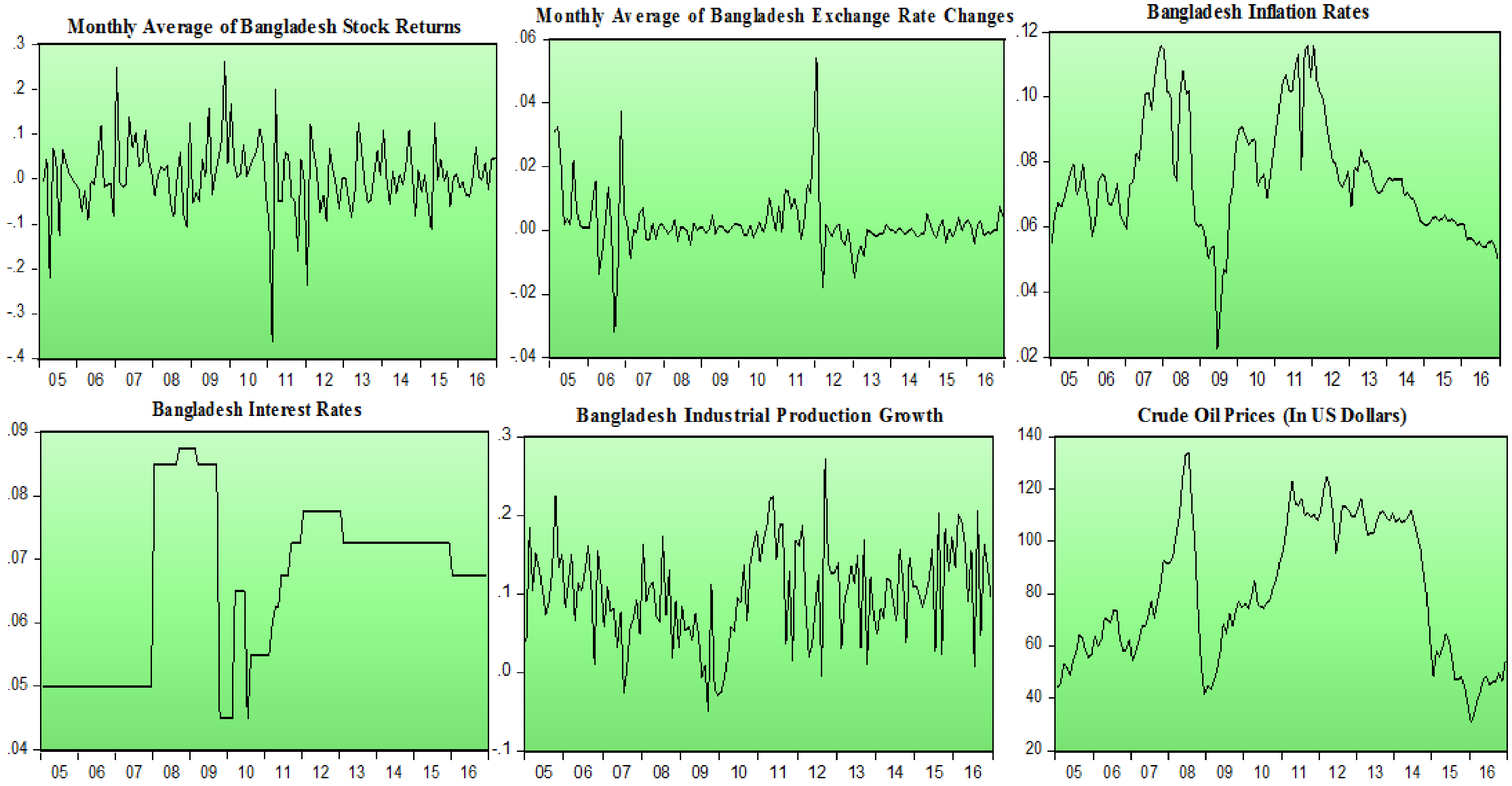

Figure-1. Trend charts of Bangladeshi financial market and macroeconomic factors, overall sample size ranges for a monthly period ranging from January 2005 to December 2016.

Source: Data on stock prices from Central Bank of Bangladesh, exchange rates are from www.oanda.com, and rest from International Monetary Fund.

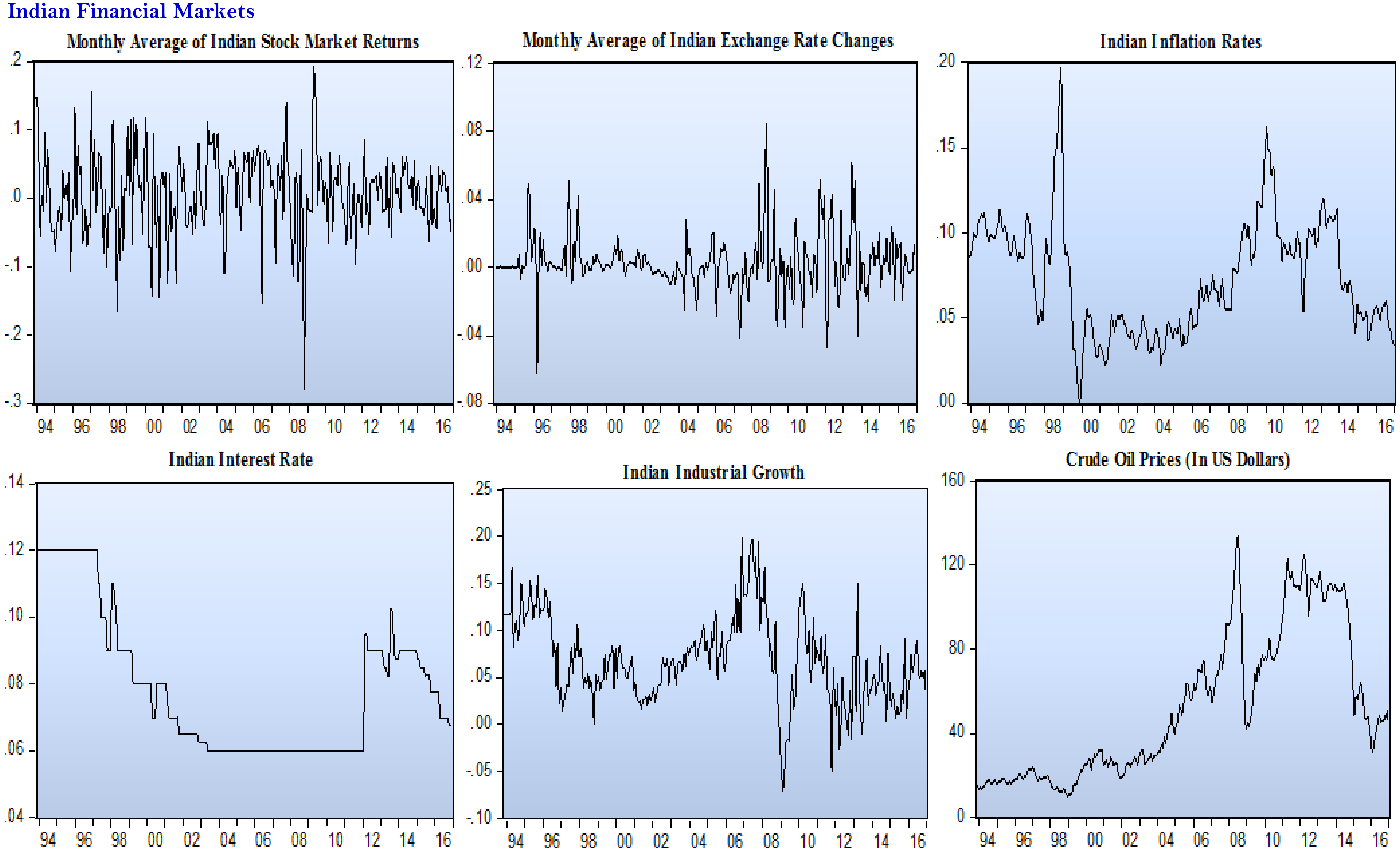

Figure-2. Trend charts of Indian financial market and macroeconomic factors, overall sample size ranges for a monthly period ranging from November 1993 to December 2016.
Source: Data on stock prices from Bombay Stock Exchange, exchange rates from www.oanda.com, and rest from International Monetary Fund.

Pakistani Financial Markets

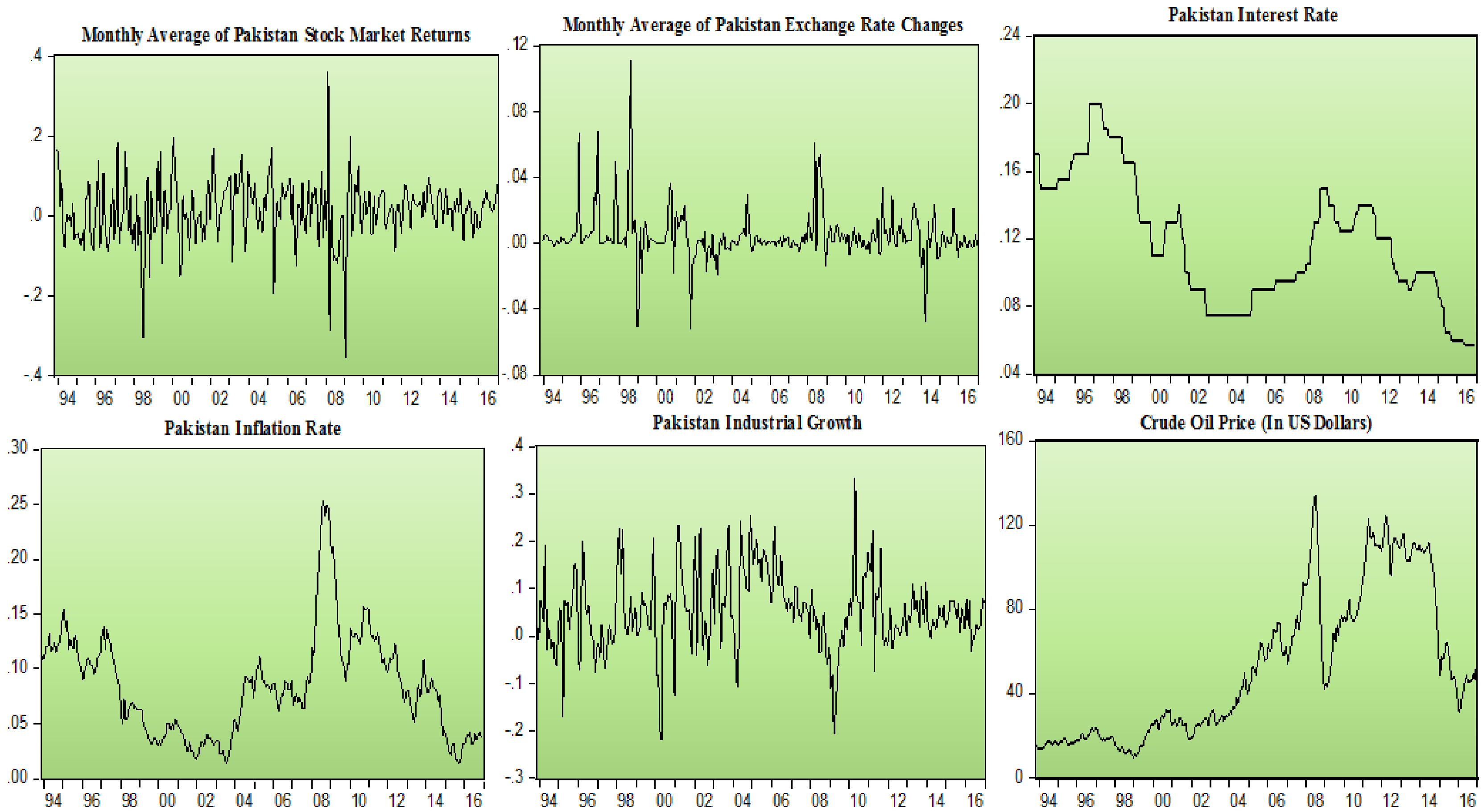

Figure-3. Trend charts of Pakistani financial market and macroeconomic factors, overall sample size ranges for a monthly period ranging from November 1993 to December 2016.

Source: Data on stock prices from State Bank of Pakistan, exchange rates are from www.oanda.com, and rest from International Monetary Fund.

Sri Lankan Financial Markets

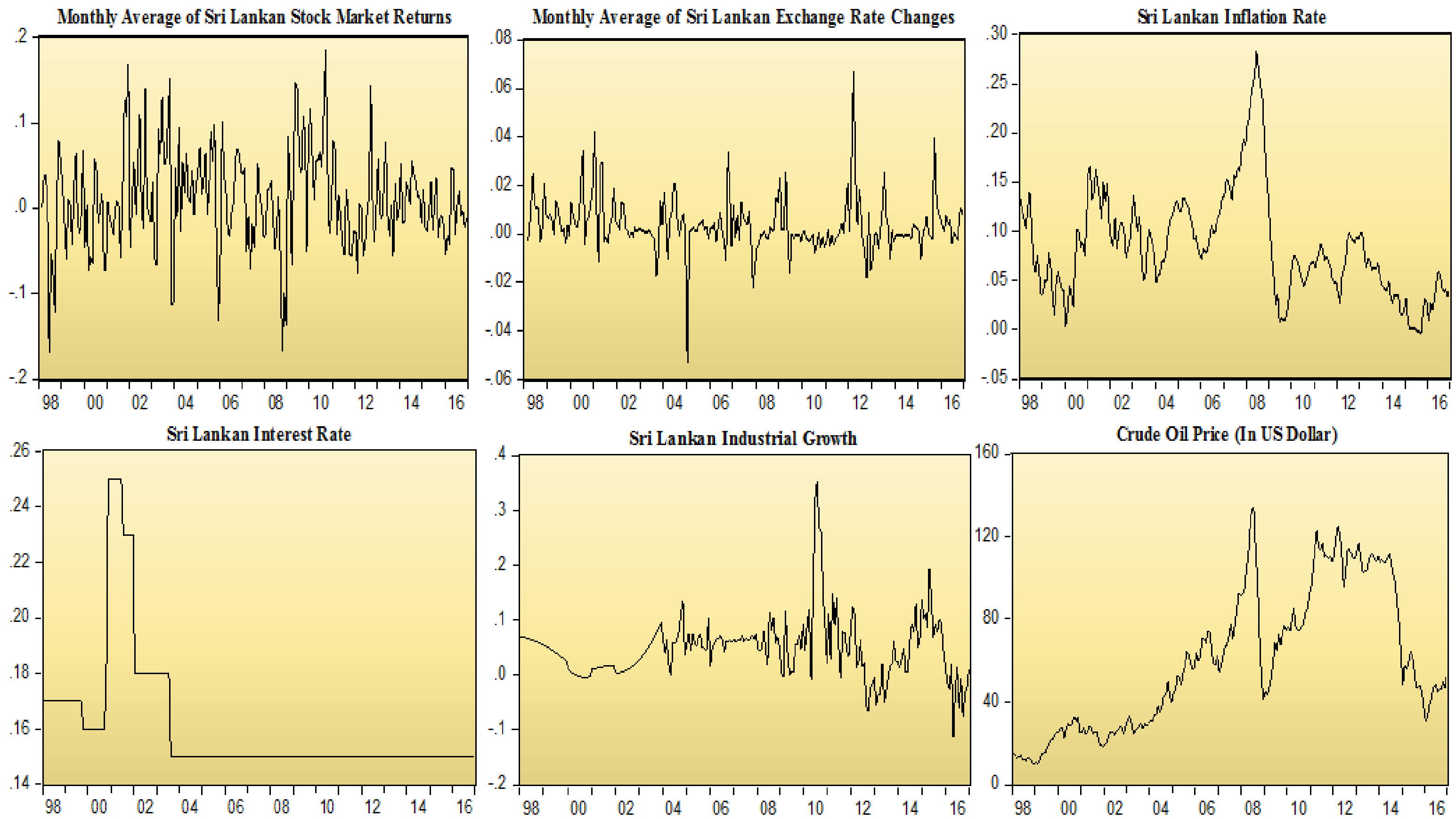

Figure-4. Trend charts of Sri Lankan financial market and macroeconomic factors, overall sample size ranges for the monthly period ranging from January 1998 to December 2016.

Source: Data on stock prices from Yahoo Financial Services, exchange rates from www.oanda.com, and rest from International Monetary Fund.

Appendix-B. Scatter Plots for Analysis of Nonlinearity in the Model

Bangladesh **India** **Pakistan** **Sri Lanka**