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Investigating liquidity constraints as a channel of contagion: a regime switching approach

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Abstract

The present study investigates the timing and repercussion of the subprime crisis of 2008–09 in a regime-switching model. The interdependence and co-movement of financial markets in different countries has been enhanced due to the globalization of international trade, and investment trends can spread globally as a result of investors owning international portfolios. This study uses a regime-switching model to illustrate the timing of the crisis regime and calm regime for United States (US) stock index returns and the corresponding impact on Indian stock index returns. The Indian stocks investigated are classified into “remote” and “reachable” stocks, and different effects are found for these two types. It is found that shocks originating in the US can be transferred to the Indian reachable market as a result of foreign investors. There is, however, a less persistent impact on remote stocks. Accordingly, the study contributes to the literature on the material impacts of the crisis resulting from liquidity constraints and fear of contagion among investors.

Keywords: Financial crisis, Financial contagion, Co-movement, Emerging market, Regime- switching

Introduction

The propagation of a crisis from one country to another can occur in both developed and emerging economies. It generally occurs as a result of a substantial descent in asset prices (Kaminsky et al. 2001; Kyle and Xiong 2001; Yuan 2005). Observations of high volatility in seemingly unrelated economies perplexes researchers and policymakers worldwide (Claessens et al. 2001). The cause of propagation of a financial crisis may be investors’ internationally diversified portfolios, whereby liquidity constraints faced by international investors can have repercussions for all markets where they have holdings. In times of crisis, international investors may compensate for the loss in a crisis country by selling stocks they have invested in other markets not affected by the crisis, thus triggering a panic amongst domestic investors. The concept of stock “reachability” for international investors can be used to reflect the potential transmission of a crisis signal to reachable stocks, which can also be compared to the effects observed in relation to “remote” or unreachable stocks (Boyer et al. 2006). Yuan (2005) suggests that



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there is a noisy signal of a borrowing constraint, which informed investors receive in terms of asset payoffs. The subsequent price fluctuation observed by uninformed investors' associated with information asymmetry and borrowing constraint seeks a bailout from declining prices and causes crisis to spread to emerging markets. Thus the repercussions of the crisis are not confined to the crisis country; the ripples are observed in other countries as well.

Several stock market crises have occurred in emerging and developed markets over the past few decades, namely, the great depression of 1930, the 1992 exchange rate mechanism crisis, the Mexican Peso crisis in 1994, the 1997 East Asian crisis, the Russian collapse of 1998, the 1999 Brazilian crisis, the 2008–2009 Global Financial Crisis (GFC) and the 2009 European sovereign debt crisis. All these crises emerged in a particular country but had worldwide repercussions (Gallegati 2012; Forbes and Rigobon 2001). Before 1997, the term contagion was used to refer to the transmission of a medical disease. However, the scope of the term broadened since the currency crisis in Thailand. Beginning in July 1997, the Asian financial crisis beset East Asia and elevated the economic meltdown worldwide. The repercussions of the Thailand crisis worldwide initiated the use of the term contagion, specified as financial contagion. After the great depression of the 1930s, the subprime crisis of 2008–09 has been marked as the gravest financial crisis (Bekaert et al. 2014; Claessens et al. 2010; Jaffee 2008; Hwang et al. 2013) affecting the financial markets worldwide (Majid and Kassim 2009). Therefore, the present study concentrates on the 2008–09 subprime crisis as a reference point to investigate the channel of contagion.

The study is closely related to the literature on international transmission of shocks where investor asset holdings are the mechanism through which crises propagate. The theoretical models of portfolio rebalancing (Kodres and Pritsker 2002), wealth constraints (Kyle and Xiong 2001; Calvo 1999; Yuan 2005; Boyer et al. 2006), and information asymmetry (Kodres and Pritsker 2002; Gennotte and Leland 1990; Romer 1993; Hong and Stein 2003; Barlevy and Veronesi 2003) establish the worldwide crisis propagation through the asset holdings of international investors as an antecedent to contagion. Kyle and Xiong (2001) demonstrate the ramifications of a crisis in one country for other countries as the investment loss suffered in the crisis country forcing investors to liquidate their holdings in other countries. Similarly, Kaminsky et al. (2004) and Valdes (1997) show that the crisis affects the liquidity of market participants and propagates it to the other markets. The larger liquidity shock in the crisis country increases credit rationing, thus coercing investors to liquidate their holdings in other countries to meet their margin requirements. Consequently, the asset prices in other countries decline and disseminate the crisis to other markets.

Motivated by Kaminsky et al. (2004), Valdes (1997) and Kyle and Xiong (2001), the present study tries to examine whether the liquidity constraints that emerged at the time of crisis in the United States (US) is accountable for its transmission to the Indian market. First, the present chapter clarifies the theoretical explanation of the propagation of the price drop in one market to another, thus affecting the local investors who are not directly connected to the crisis-prone country. The study investigates how the liquidity constraint emerging in the US affects other assets in the Indian market using a regime switching model. Contrary to the aforementioned studies, the present study adopts a varied attribute to further classify emerging market assets. Namely, stocks are

classified as “reachable” or “remote” and the regime-switching model is estimated to test the role of the “reachability factor” in terms of how international investors contribute to the propagation of liquidity constraints. The model portrays the movements of reachable stocks, which move in line with US stocks, and also shows the variability of remote stock price movements. Estimating the asymmetry in the persistence of two regimes during the downturns supports the theory of asymmetric contagion, as validated by Longin and Solnik (2001), Connolly and Wang (2000), Ang and Bekaert (2002) and Ang and Chen (2002). Boyer et al. (2006) estimated the cross-market correlation dynamics of the crisis country return with the returns in what they term “accessible” and “inaccessible” assets during the Asian crisis of 1997. However, the present study extends on this research by also estimating the regime shifts from one state to another state (calm to a crisis and crisis to calm). Further, the change in the regimes coupled with the similarities between the crisis country return (US) with the reachable and remote return in the Indian market during the subprime crisis is investigated.

The objective of the study is to estimate the extent of how the crisis in the US motivated international investors to liquidate their holdings in Indian reachable stocks and its recurrent impact on the remote stocks. The extent of the margin calls arising at the time of crisis motivated international investors to sell reachable Indian stocks, in addition to their domestic stocks (i.e., US stocks). The visibly severe price reduction in reachable stocks compelled local investors in India to reduce their holdings in remote stocks as well. As such, the liquidity constraint faced by international investors initiated contagion in domestic markets.

This research enables inferences about the timing of the subprime crisis of 2008–09 to be made and the material side effects of the crisis on the Indian market to be tested based on the reachability factor of Indian stocks to foreigners. Furthermore, testing the material side effects enables the reactions to the crisis in the Indian market to be investigated based on the reachable factor and the corresponding trigger on the remote factor to be further understood. The adoption of a regime-switching model is necessary to detecting the crisis timings for the reachable and remote stocks of the Indian market in relation to the crisis country. The model assumes that, at a point in time, the stock markets in the US is in one of two regimes, crisis or stable. The regime specifically determines the beginning and end of the crisis to develop a model where the movements of the Indian reachable and remote stocks capture the ramifications of the crisis in the Indian Market.

As opposed to other studies on crisis transmission, the novelty of the present study is to capture the extent to which the reachability of Indian stocks to foreign investors determines the crisis transmission. Further, the study investigates whether Indian stocks can signal a crisis event by making a demarcation between reachability factors of Indian stocks to foreigners and investigating reachable and remote stocks separately. While capturing the timing of the crisis impacts on Indian stocks, the study estimates the material side effects of the crisis on Indian reachable and remote stocks in a Markov regime-switching framework.

The remainder of the paper is organized as follows. Section 2 outlines the literature review. Section 3 presents the methodology applied to capture the timing and the side effects of the crisis emanating from the US on the Indian market. Section 4 discusses the empirical interpretations and section 5 concludes.

Literature review

The contagion experienced by emerging economies as a result of crises is much more significant than for their developed counterparts (Kodres and Pritsker 2002). Although trade and economic linkages justify the co-movements among the financial markets of different countries, the empirical examinations of Karolyi and Stultz (1996) and Cannolly and Wang (2003) disprove the validity of this idea for American and Japanese markets. To these countries, instead of trade and financial linkages, the shocks to the broad based market indices as global shock underline the positive comovement. A common feature of economic crises is the rapid propagation of crisis substantive events, the financial instability in one country or economy leads to contagion elsewhere.

Reasons for contagion are manifold, ranging from the weak fundamentals in the financial system to crony capitalism (Corsetti et al. 1999). An alternate argument by Radelet and Sachs (1998a, b) and Furman and Stiglitz (1998) suggests that panic is triggered by multi-equilibria amid countries where the shift in investors' expectations by the shocks in one country used as a guideline for other countries. Referring to contagion as the promulgation of market instability, one can observe the co-movement in exchange rates, capital flows, and stock prices as concrete indicators. Conceptually, contagion theories can be classified into two broad paradigms (Claessens et al. 2001). The first of which stresses the effect of spillovers by virtue of normal interdependence among markets (Eichengreen et al. 1996; Glick and Rose 1999; Corsetti et al. 1999, Abeyasinghe and Forbes 2005; Forbes 2002; Kali and Reyes 2010, N'Diaye et al. 2010; Chan et al. 2002; Xue et al. 2012; Kaminsky and Reinhart 2000; Van Rijckeghem and Weder 2001, 2003; Baig and Goldfajn 1999). The disturbance which is not caused by changes in macro-economic fundamentals, but instead by the behavior of investors is also considered in terms of the normal interdependence of markets (Boyer et al. 2006; Calvo 1999; Kodres and Pritsker 2002; Kyle and Xiong 2001; Yuan 2005, Rigobon 2003; Masson 1999; Horta et al. 2016; Petmezas and Santamaria 2014). In other words, this school of thought considers the escalation of inherent global or local disturbances across different countries through their real, economic and financial linkages. By contrast, Calvo and Reinhart (1996) avow the transference of crisis as fundamental-based contagion. Studies supporting this fundamental view include Eichengreen et al. (1996), Glick and Rose (1999), Corsetti et al. (1999), Abeyasinghe and Forbes (2005), Forbes (2002), Kali and Reyes (2010), N'Diaye et al. (2010), Chan et al. (2002) and Xue et al. (2012) reinstate the argument of contagion through trade linkages. Similarly, Kaminsky and Reinhart (2000), Van Rijckeghem and Weder (2001, 2003) and Baig and Goldfajn (1999) provide evidence for how the financial vulnerability of countries fundamentally moves together. The common shocks effect portrayed by Radelet and Sachs (1998a, b) in their investigation of the Asian financial crisis emphasized the role of financial panic and the withdrawal of foreign capital flows, leading to the depreciation of both real and nominal exchange rates. Considering both the above schools of thought, it is clear that both economic fundamentals and the information of investors have an effect on the stock market. However, there is little consensus in the empirical literature regarding a formal definition of contagion. In accordance with Pericoli and Sbracia (2003), we define contagion as the intensified shift in the transmission channel after a shock in one market.

The aforementioned studies clearly emphasize fundamental based contagion via trade links (Eichengreen et al. 1996; Abeyasinghe and Forbes 2005) common shocks (Calvo and Reinhart 1996; Chuhan et al. 1998), and financial links (Kaminsky and Reinhart 2000; Baig and Goldfajn 1999; Van Rijckeghem and Weder 2001, 2003). The empirical evidence contributes a demarcation between the influence of fundamentals and investors' behavior in causing stock market co-movements. The studies affirm that although fundamental economic effects influence stock market co-movements, the effectual factor causing stock market co-movement contagion is the investors' behavior in the market, which can only be observed indirectly. Karolyi and Stulz (1996) evidenced that macroeconomic announcements and other public information on economic fundamentals influence stock market co-movement between countries. Nevertheless, the major factor influencing co-movements are the shocks to broad-based market indices (Karolyi and Stulz 1996; Connolly and Wang 2003). Similarly, Connolly and Wang (2003) investigated whether observable co-movement in intraday and overnight returns of the international equity markets attribute to public information on economic fundamentals. The results prove that foreign market returns, rather than news announcements, influence domestic market returns. The observation of King et al. (1994) shows a similar result, whereby a small portion of the international stock co-movement is explained by observable economic variables, though admittedly the changes in correlation between the countries are driven primarily by movements in variables which can only be observed indirectly, such as investor sentiment. In addition, Longin and Solnik (2001), Connolly and Wang (2000), Ang and Bekaert (2002), and Ang and Chen (2002) estimated correlation among market returns and showed that correlations are large during market downturns, which suggests that contagion is asymmetric.

These past findings motivate the hypothesis of this research that investors' behavior best explains the stock market co-movements in addition to macro fundamentals. Studies by Kodres and Pritsker (2002), Kyle and Xiong (2001), Calvo (1999), Yuan (2005), Boyer et al. (2006), Rigobon, (2003), Masson (1999), Horta et al. (2016) and Petmezas and Santamaria (2014) shows that investors' stock holdings cause market contagion. Furthermore, a constrained information asymmetry framework describing contagion has been proposed by Gennotte and Leland (1990), Romer (1993), Kodres and Pritsker (2002), Hong and Stein (2003), and Barlevy and Veronesi (2003). Kodres and Pritsker (2002) show that in the absence of news, the shocks in one market are misinterpreted in another market, and this can be interpreted as information asymmetry causing portfolio rebalancing. Apart from this, wealth constrained investors influence stock market co-movements (Kyle and Xiong 2001; Calvo 1999; Yuan 2005) as they liquidate their assets in different markets and thus, large investment losses in the crisis country trigger depreciation in equity prices in other markets as well.

During the past several years, academics have used varied methodologies to investigate the relationships between the stock markets of different countries during the financial crisis. The literature provides evidence of contagion in the financial markets during the 2008–09 subprime crisis (Fry et al. 2010; Idier 2011; Guo et al. 2011; Galletti 2012; Bekaert et al. 2014; Dungey et al. 2010; Ahmad and Sehgal 2015; Aloui et al. 2011; Lakshmi et al. 2015; Dimitriou et al. 2013; Kenourgios et al. 2013; Jin and An 2016; Kenourgios and Padhi 2012; Kenourgios and Dimitriou 2015; Kenourgios 2014; Leung et al. 2017; Neaime 2016; Guyot et al. 2014; Boamah et al. 2017). More

specifically, the findings reveal that the magnitude of the stock market linkage tends to be higher in crisis periods (Yang et al. 2003; Yang et al. 2006), whereby the highest number of contagion incidents occur in developed markets (Baur 2012; Calomiris et al. 2012) and the incidents propagate to smaller economies (Breuss 2011; Karunanayake et al. 2010; Kenourgios et al. 2011).

There is also an extensive body of literature on financial contagion which measures the volatility spillovers among markets. For example, Calvo and Reinhart (1996) used the principal component models, Glick and Rose (1999) adopted the spillover model, Baur (2003) used regression-based models of asymmetries and non-linearities and finally, models of interdependence were applied by Bekaert et al. (2005). Similarly, Bertero and Mayer (1990), King and Wadhvani (1990), Calvo and Reinhart (1996), Baig and Goldfajn (1999) and Hon et al. (2007) employed correlation breakdown models. However, Forbes and Rigobon (2002) highlighted a number of limitations in the literature on financial contagion with the prior methods, such as heteroskedasticity problems and omitted variables in measuring correlations.

Motivated by the thought-provoking study by Forbes and Rigobon (2002), the recent literature on financial contagion employs methodologies such as models based on extreme value theory (Longin and Solnik 2001; Hartman et al. 2004; Bae et al. 2003; Butler and Joaquin 2002; Chan-Lau et al. 2004), autoregressive conditional heteroscedasticity (ARCH) models (Hamao et al. 1990), Markov switching models (Ramchand and Susmel 1998; Ang and Bekaert 2002; Chesney and Jondeau 2001; Pelletier 2006; Guo et al. 2011; Mandilaras and Bird 2010; Billio et al. 2005; Gravelle et al. 2006), dynamic copulas with or without regimes (Rodríguez 2007; Okimoto 2008; Aloui et al. 2011; Jondeau and Rockinger 2006; Patton 2006, 2009; Chollete et al. 2011; Ning 2010; Sun et al. 2009), conditional asymmetries and correlations models like Dynamic Conditional Correlations (DCC) using GARCH (Celik 2012; Chiang et al. 2007), Fractionally Integrated Asymmetric Power ARCH (FIAPARCH) models (Kenourgios and Dimitriou 2015; Dimitriou et al. 2013), the Asymmetric Generalized DCC (AG-DCC) model (Cappiello et al. 2006) and a multivariate regime-switching Gaussian copula model and the AG-DCC model (Kenourgios et al. 2011). Further, studies by Kou et al. (2019) and Chao et al. (2019) adopted machine learning methods to study the mechanisms of outbreak and the contagion of systemic risk in the financial market network. Many of the aforementioned studies emphasize that the choice of methodology is important when investigating abnormal behavior in financial markets.

Ang and Bekaert (2002) and Ang and Chen (2002) investigate stock market co-movements to see whether market co-movement is stronger in market downturns and find evidence of asymmetric contagion. Ang and Bekaert (2002) studied international asset allocation with regime shifts to see whether the existence of high volatility in a market downturn regime invalidates the benefits of international diversification. Using a regime-switching model, the results validate international diversification where investors can dynamically make portfolio decisions in response to the regime switches. Further, the existence of highly volatile bear market regimes does not invalidate the benefits of international diversification; rather it suggests that a switch toward lower volatility assets may be advisable. Similarly, Ang and Chen (2002) studied the correlation asymmetry between US stocks and the aggregate US market in downside and upside moves to understand the consequences for portfolio allocation. Comparing the

GARCH-in-Mean (GARCH-M) model, Poisson Jump model, Regime switching normal distribution model and Regime switching GARCH model on the asymmetric correlation of stock returns, Ang and Chen (2002) evidenced that the regime-switching normal distribution model is the best to model the correlation asymmetries. The authors also find that correlations between markets are stronger during market downturns, thus showing contagion. Similarly, Baele (2005) investigated the effect of globalization and regional integration in transmitting global shocks to local markets. Using a regime-switching model, the study allows the shocks intensities to change over time and the authors found evidence of contagion from US markets to the European markets in terms of an increased probability of switching from one market to another at times of high market volatility.

In addition to the studies investigating the propagation of crises, there are studies investigating the impact of policy interventions and regulatory measures on the level and rapidity of cross and within country contagion. Kosmidou et al. (2015) and Kosmidou et al. (2019) investigated the effectiveness of policy interventions from the European Union/European Central Bank/International Monetary Fund (EU/ECB/IMF) to prevent contagion across European member states. During medium to high volatility periods, the news announcements concerning policy interventions by the ECB, EU, and IMF decrease the speed of contagion from banking-specific news spreading to both the stock market and the industrial sector. On the other hand, the policy news announcement by national governments decelerate the contagion from banking only for the industry sector and not for the overall stock market. In short, the simultaneous release of policy-related news of the ECB, EU, IMF, and the national governments seems to be beneficial in reducing contagion.

The present study uses a different attribute of emerging stock markets to investigate how liquidity constraints during crisis motivate investors to liquidate their positions in other markets, whereby the reachable and remote factors are applied to reflect the accessibility of stocks to international investors. Using the regime-switching model of Hamilton (1989), this study illustrates international investors' motivation in liquidating their holdings of reachable stocks in the Indian market, thus transmitting shocks to Indian stocks. Defining Indian stocks as reachable, if they are accessible to international investors, and remote, if they are not, we try to capture to what extent investors influence contagion as a result of their liquidity constraints. The regime-switching model further identifies the duration for which returns are affected in different regimes of calm and crisis.

Methodology

The time series variables are subject to periods of dramatic changes to their usual trends. A dramatic change in macroeconomic or financial time series variables is likely to reflect financial panics, wars, or other sudden changes in the market. The regime-switching model is an effective means of modeling dramatic changes in a time series. In this paper, we investigate the special case developed by Hamilton (1989). Specifically, we investigate the shift in stock index returns occurring on the basis of either the calm or crisis regime, respectively. The regime at any given date can be considered to be the outcome of a Markov chain, for which the realizations are unobserved. Characterizing the two regimes and the law governing the transition between the two regimes is the

task of the regime-switching model. The parameter estimates reflect the regime process on any particular date and enable forecasts of future values to be generated.

A single variable r_t , stock index return, is modeled to quantify the outcome of a dramatic change in the behavior of the time series under investigation. The change in the time series data prior to a crisis (i.e., in a calm regime) and during a crisis (i.e., in a crisis regime) is modeled. The typical historical behavior is modeled with first-order autoregression, whereby the data prior to the crisis is modeled as

$$r_t = \mu_0 + \phi r_{t-1} + \varepsilon_t, \tag{1}$$

where $\varepsilon_t \sim N(0, \sigma^2)$ and the observed data for $t = 1, 2, \dots, t_0$. The model assumes that at date t_0 , the time series undergoes significant change. The significant change in the average level of the series at date t_0 following a crisis is described by the model as

$$r_t = \mu_1 + \phi r_{t-1} + \varepsilon_t \tag{2}$$

According to the model for $t = t_0 + 1, t_0 + 2, \dots$

Where t in eq. (1, 2) explain the data prior to and after the crisis respectively. An evaluation in to the data for t in eq. (2) compared with (1) necessitates the significant change observed to the time series following the crisis.

However, these two models are not satisfactory as a time series model for this context. Changing the intercept from μ_0 to μ_1 enhance the forecast accuracy but this is not sufficient. Thus, instead of relying on the change from μ_0 to μ_1 , the model also assumes that an imperfectly predictable force produces this change. In other words, the change itself is considered as a random variable. Hence, instead of just considering model (1) and (2) expressing data up to date t_0 and postdate t_0 , we adopted a complete time series model describing the probability law governing the change from μ_0 to μ_1 . This approach more accurately describes the consequences of a dramatic change in the behavior of the variable r_t . The model below encompasses both the aforementioned models:

$$r_t = \mu_{s_t} + \phi r_{t-1} + \varepsilon_t \tag{3}$$

The defined switch from μ_0 to μ_1 assumes that there are two possible regimes, namely zero and one, from which a particular observation of r_t is drawn. This unobserved random variable is known as the “state” of the process. The unobserved state is denoted by s_t , which takes an integer value of either 0 or 1. The random variable s_t assumes the value $s_t = 0$ for $t = 1, 2, \dots, t_0$ and $s_t = 1$ for $t = t_0 + 1, t_0 + 2, \dots$

Here, the number of variables is one, the autoregressive lag order is one, the number of possible regimes is two and the model assumes that r_t depends on the current and most recent values of s_t , on lags of r_t , and on a vector of parameters, θ . Thus, the probability of a regime prevailing is $p(r_t | z_t; \theta)$.

where $z_t = (s_t, s_{t-1}, r_{t-1})$.

This model is an extension of the model developed by Hamilton (1989), in which Engel and Hamilton (1990) evaluated the vector systems without autoregressive elements, such that $\phi = 0$. The model shows that the mean vector and the variance matrix were functions of the state, which is defined as follows:

$$r_t | s_t \sim N(\mu_{s_t}, \sigma_{s_t}^2), s_t = 0, 1.$$

The model proposes the existence of an unobservable variable, s_t , which portrays the state or regime the event was in at date t by assigning the value of zero or one. When

the unobserved variable $s_t = 0$, the noticeable change in the variable r_t is assumed to have been drawn from the $N(\mu_0, \sigma_0^2)$ distribution. When $s_t = 1$, the variable r_t is distributed as $N(\mu_1, \sigma_1^2)$. Therefore, when $s_t = 0$, the mean vector is μ_0 and when $s_t = 1$, it is μ_1 .

Here, the number of variables is one namely the stock index returns of the respective series, the autoregressive lag order is zero, number of possible regimes is two, and the model assumes that r_t depends only on the current values of s_t and on a vector of parameters, θ . Thus, the probability of a regime switch is.

$$p(r_t | s_t; \theta), \text{ where } \theta = (\mu_0, \mu_1, \sigma_0^2, \sigma_1^2).$$

A probabilistic model showing the change from $s_t = 0$ to $s_t = 1$ gives a complete description of the probability law governing the observed data. The two-state Markov chain clearly specifies that s_t is a realization of the two-state options with a transition probability. This can be represented as:

$$p(s_t = j | s_{t-1} = i) = p_{ij} \tag{4}$$

Following Hamilton (1989) and Engel and Hamilton (1990), the Markov chain for the evolution of the unobserved state variable is given by;

$$p(s_t = 0 | s_{t-1} = 0) = p_{00},$$

$$p(s_t = 1 | s_{t-1} = 0) = p_{01},$$

$$p(s_t = 0 | s_{t-1} = 1) = p_{10},$$

$$p(s_t = 1 | s_{t-1} = 1) = p_{11},$$

(Thereby,)

$$p = (p_{00}, p_{01}, p_{10}, p_{11}).$$

It is presumed that the process for s_t depends on the past realizations of r and s only through s_{t-1} . In the model, the unobservable variable s_t is not directly observed. Instead, it is deduced based on the observed behavior of r_t . The parameters which describe the probability law governing r_t are the variances σ_0^2 and σ_1^2 , the autoregressive coefficient ϕ (with or without autoregressive dynamics), the two intercepts μ_0 and μ_1 , and the two state transition probabilities p_{00} and p_{11} .

The parameter estimates of the model give the smoothed regime probabilities based on the full sample. Thus, the probability with which a regime is supposed to have transpired at each time can be determined. The peaks and troughs of the data in the series can be determined. However, in our model, the smoothed regime probabilities, which aim to capture the real timings of the crisis, were allowed to follow regime specific error variance, which was assumed to be constant across regimes. Therefore, the model as includes a constant error variance, σ^2 , along with the means of μ_0, μ_1 and the transition probability p_{00} and p_{11} .

Data

We study the daily stock index returns of reachable and remote stocks for US investors over the period from April 2007 to June 2016. The classification of reachable and remote stocks applies to Indian stocks. In the developed market, all stocks are reachable to both foreign and local investors but this is not the case with emerging markets. The International Finance Corporation (IFC) publishes the IFC investable (IFCI) stock index

series for each of the emerging markets. The IFCI index determines the legal market openness to foreign investors by screening stocks according to size and liquidity. The size and liquidity requirement is dependent on a base market capitalization of \$50 million or more and a base trading volume of \$20 million or more before 12 months stocks accession to the IFCI index. The readily available return information for the IFCI index typifies the reachable stock market index in terms of what foreign investors would receive from investing in the Indian market. The NSE 500 index is used as a proxy for the whole market. All the stocks from the global portfolio that are not in the IFCI index are included in the remote index, which represents those stocks which are only reachable for Indian investors. Specifically, the remote index has been constructed following Boyer et al. (2006), considering NSE 500 as the proxy for the Indian total index and IFCI as follows:

$$R_{Rmts,t} = M_{Is,t-1} \times R_{Is,t} - M_{Rchs,t-1} \times R_{Rchs,t} / (M_{Is,t-1} - M_{Rchs,t-1})$$

Here, R represents index returns, M is index market capitalization, Is , $Rchs$ and $Rmts$ refers to the Indian, reachable and remote stock index respectively and t denotes the time period.

The data have been compiled from the Bloomberg database. The regime-switching model estimates detect the timing, as well as the side effects of the crisis among Indian investors.

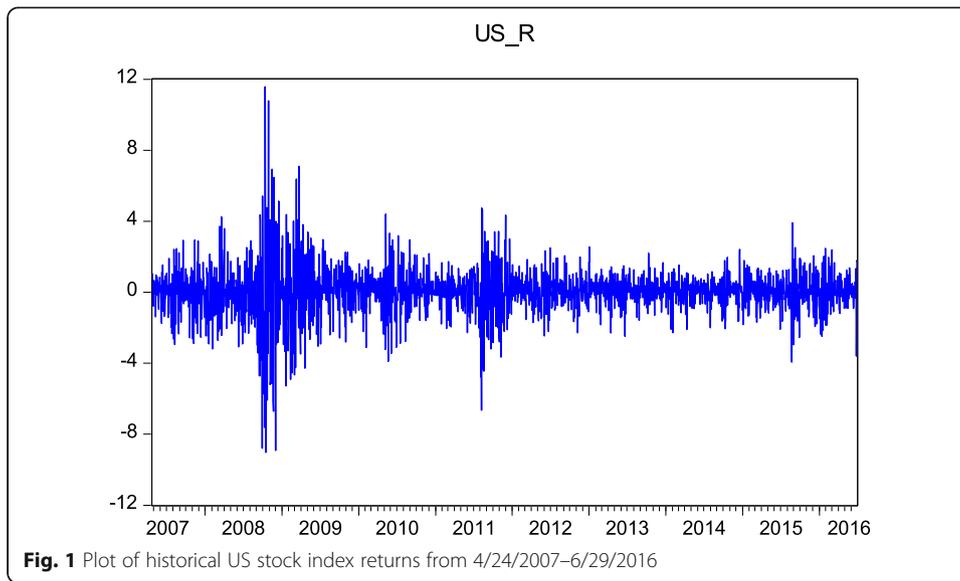
Empirical results and interpretation

This study investigates the side effects of the global financial crisis of 2008–09 on the Indian market. Past studies have delineated various timelines to determine the timing of the crisis in the US (Bank for International Settlements (BIS) 2009; Federal Reserve Board of St. Louis 2009; Guillen 2009). The present study tries to capture the timing of the crisis to adduce its side effects, focusing on liquidity constraints, on the Indian economy. The unobservable state of financial calm and crisis regime is modeled using a regime-switching model.

Figures 1, 2 and 3 show the Markov switching model of heteroscedasticity, as defined by Kim et al. (1998), for stock index returns of US stocks, reachable Indian stocks and remote Indian stocks.

Figures 1, 2 and 3 and the corresponding Table 1 reveal the non-normal unconditional sampling distribution, thus confirming the presence of skewness and excess kurtosis in the data. This is to be expected based on the findings of Fama (1963) and Mandelbrot (1963). The marked values and statistics showing the peak and heavy tails in the distribution of the stock index returns evidences the need to consider heteroscedasticity (Turner et al. 1989). The popularly adopted specification in the study of stock return volatility or heteroscedasticity is the GARCH model by Engle (1982) and Bollerslev (1986). However, the SWARCH (switching ARCH) model proposed by Hamilton and Susmel (1994) allow parameters of an ARCH process to be defined differently for different regimes in a regime-switching model. This effectively addresses the heteroscedasticity in stock index returns. Following Engel and Hamilton (1990), this study considers the below two-state regime switching model of stock index returns.

$$r_t | s_t \sim N(\mu_{s_t}, \sigma^2), s_t = 0, 1.$$

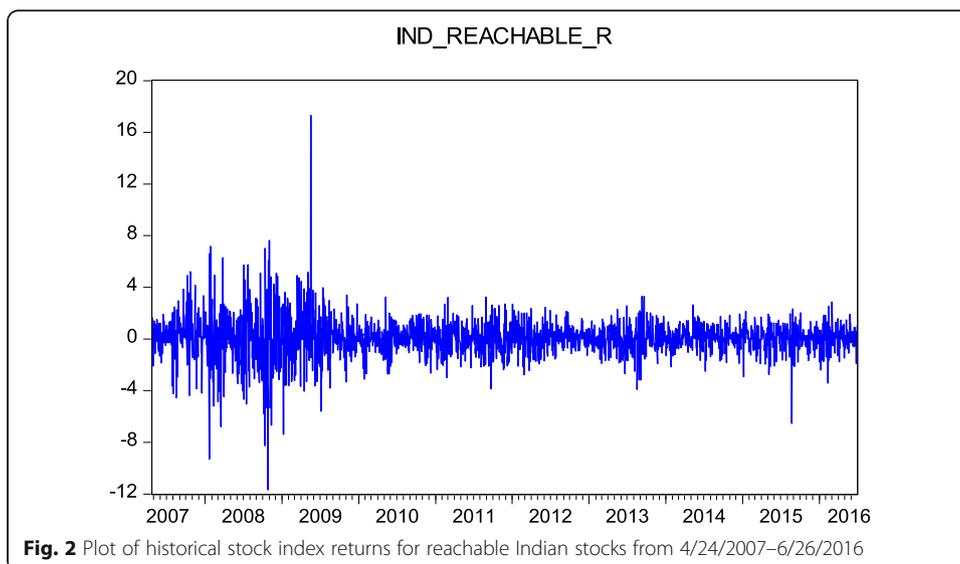


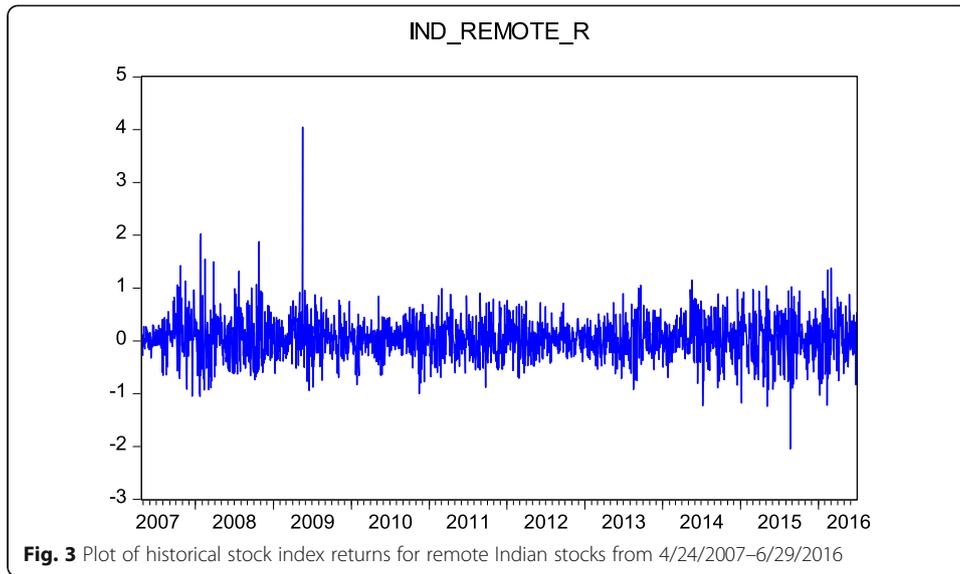
The model assumes that r depends only on the current values of s_t and on a vector of parameters, θ .

Thus, the probability of a regime prevailing is $p(r_t | s_t; \theta)$.

where $r \cong usr, irchr, irmtr$ which is the stock index returns for the three series of US (usr), Indian reachable ($irchr$) and Indian remote stocks ($irmtr$).

Here, s_t is the unobserved variable that takes the value of zero or one and characterizes the state or regime the event was in at date t . When $s_t = 0$, the observed change in the variable r_t , namely the $usr, irchr, irmtr$ values, are presumed to be drawn from the $N(\mu_0, \sigma_0^2)$ distribution and when $s_t = 1$, the observed change in the variables $usr, irchr, irmtr$ are presumed to be drawn from the $N(\mu_1, \sigma_1^2)$ distribution. Therefore, the model assumes that the variable returns depend on the current values of s_t and on a vector of parameters, θ , which is defined as follows:





$$\theta = (\mu_0, \mu_1, \sigma_0^2, \sigma_1^2).$$

The Markov chain shows the transmission probabilities for the change from $s_t = 0$ to $s_t = 1$, thereby giving a complete description of the probability law governing the observed data. The two-state Markov chain clearly specifies that s_t is a realization of the two-states, with the following transition probability:

$$p(s_t = j | s_{t-1} = i) = p_{ij}. \tag{4}$$

Following Hamilton (1989) and Engel and Hamilton (1990), the Markov chain for the evolution of the unobserved state variable is given by:

$$p(s_t = 0 | s_{t-1} = 0) = p_{00},$$

$$p(s_t = 1 | s_{t-1} = 0) = p_{01},$$

$$p(s_t = 0 | s_{t-1} = 1) = p_{10},$$

$$p(s_t = 1 | s_{t-1} = 1) = p_{11},$$

for which,

$$p = (p_{00}, p_{01}, p_{10}, p_{11}).$$

As noted above, the stock index returns for the three series of US (*usr*), Indian reachable (*irchr*) and Indian remote stocks (*irmtr*) are represented by r . As s_t is a random variable, the incidence of changes to the stock index returns occur in the time series to infer the value $s_t = 0$ and $s_t = 1$ for calm and crisis regimes, respectively. Here, μ_0 and μ_1

Table 1 Descriptive statistics

Sl. No:	Variables	Mean	Median	Std. Dev	Skewness	Kurtosis
1	US Return	0.035685	0.075576	1.353654	-0.069699	12.44939
2	Indian Reachable Return	0.045814	0.025035	1.477971	0.231311	16.04324
3	Indian Remote Return	0.041719	0.038470	0.374275	0.663970	9.854970

are the means of the stock index returns for the calm and crisis regimes. However, the present study tries to capture the real timings of the crisis, without considering regime-specific error variance. In other words, the error variance is assumed to be constant across regimes. Therefore, the parameters required to estimate θ are restricted to $\mu_0, \mu_1, \sigma^2, p_{00}$ and p_{11} .

The side effects of the subprime crisis on reachable and remote stocks of the Indian economy were analyzed with the corresponding decade-long changes in trends. The parameter estimates of the regime switching model considered constant transition probabilities and the Markov probabilities that represent the unconditional probabilities of a change in regime. The state variable s_t in the model follows a two-state Markov chain, clearly specifying that s_t is a realization of one of the two-states, with constant transition probability, namely $P(s_t = j | s_{t-1} = i) = p_{ij}$ whereby $(i, j = 0, 1)$.

Table 2 shows the estimation result of the regime switching model. The transition probabilities of the US stock index returns, Indian reachable and remote stock index returns during financial calm and crisis periods are estimated through p_{00} and p_{11} . In the case of US stock index returns, the state at $t - 1$ was the calm state ($s_{t-1} = 0$), with a 15% chance that time t will also be a calm state ($s_t = 0$). This is notated as $P(S_t = 0 | S_{t-1} = 0) = p_{00}$. On the contrary, if the state at the time $t - 1$ is the crisis state ($s_{t-1} = 1$), then there is a 98% chance that the state at time t will also be a crisis state ($s_t = 1$), noting that $P(S_t = 1 | S_{t-1} = 1) = p_{11}$. This indicates that the probabilities of being in a calm or a crisis state are approximately 15% and 98%, respectively, which suggests there is no considerable state dependence in terms of staying in the original state of financial calm for an extended period of time. There is an 85% chance of transition probabilities to switch from a calm regime to a crisis regime for the US index returns since the inception of the financial crisis from July 2008 to May 2009. Investigating Indian reachable stocks, if the state at $t - 1$ was a calm state ($s_{t-1} = 0$), then there is a 25% chance that state at the time t will also be a calm state ($s_t = 0$), which is notated as, $P(S_t = 0 | S_{t-1} = 0) = p_{00}$. On the contrary, if the state at the time $t - 1$ was crisis state ($s_{t-1} = 1$), then results show that there is a 98% chance that the state at time t will also be crisis state ($s_t = 1$), whereby, $P(S_t = 1 | S_{t-1} = 1) = p_{11}$. Similarly, for remote stock index returns, if the state at $t - 1$ was a calm state ($s_{t-1} = 0$), then results show that there is a 6% chance that state at time t will also be a calm state ($s_t = 0$), which again is notated as $P(S_t = 0 | S_{t-1} = 0) = p_{00}$. Further, if the state at time $t - 1$ was a crisis state ($s_{t-1} = 1$), results show that there is a 99% chance that the state at time t will also be crisis state ($s_t = 1$), thereby $P(S_t = 1 | S_{t-1} = 1) = p_{11}$.

Table 2 Parameter estimates for Markov Regime-Switching Model from April 2007 to June 2016

Parameter	Unites States	India	
	Crisis Return	Reachable Return	Remote Return
p_{00}	0.1501	0.2546	0.0593
p_{11}	0.9875	0.9884	0.9967
μ_1	-4.9414 (0.3428)	- 4.9776 (0.3504)	1.9702 (0.2080)
μ_0	0.1083 (0.0257)	0.1238 (0.0281)	0.0355 (0.0074)
$\sigma^2 \sigma^2$	0.1925 (0.0158)	0.2914 (0.0160)	-1.0275 (0.0151)

Standard error values in parenthesis

The Indian reachable and remote stocks also do not show any state dependence in terms of staying in one regime for a long time. Since in the scenario of the subprime crisis, the transition probabilities for switching from a calm regime to a crisis regime increases to 98%, thus evidencing a comparatively 85% chance of transition probabilities to switch from calm to crisis regime for US stock index returns. The disruption to the Indian market during the subprime crisis is evidenced by a shift to a crisis regime, which is reflected in the time series of conditional transition probabilities. The constant transition probability shows the expected duration of stay in the regime for the respective indices.

The estimated means of the growth rate of the US stock index returns in the calm state is 0.1083. On the other hand, it falls to -4.8331 ($\mu_0 + \mu_1$) in the crisis state. This shows that, during the subprime crisis period, the US stock index returns fell by an average of 4.83% per day. Similarly, the estimated mean of the growth rate of the Indian reachable stock index returns in the calm state is 0.1238. However, in the crisis state, the estimated mean growth rate of the Indian reachable stock returns falls to -4.8537 ($\mu_0 + \mu_1$). This means that, during the subprime crisis period, the Indian reachable stock index returns also falls by an average of 4.85% per day. In contrast, the estimated mean of the growth rates of the Indian remote stock index returns in the calm state is 0.0355 but in the crisis state, the mean raises to 2.0057. This implies that, during the subprime crisis period, the Indian remote stock index returns rise by an average of 2.00% per day. The less significant oscillation of remote stocks between crisis and calm periods explains this effect. The negative growth rate of the US stock index returns and the reachable stock index returns are consistent with the state of a crisis regime. Conversely, the remote stocks positive growth rate, despite the crisis regime, suggests that while reachable stocks were affected by the crisis, its impact on the remote stocks is not clearly visible.

In addition, the model sheds light on a variety of behaviors. In particular, it allows for asymmetry in the persistence of the two regimes, exemplifying that the regimes are stronger in market downturns (Engel and Hamilton, 1990). The large and positive μ_0 (0.1083, 0.1238 and 0.0355) and small constant transition probability p_{00} (0.1501, 0.2546 and 0.0593) shows that the upward moves (calm regime) are short but sharp. Likewise, the negative and small values of μ_1 (-4.9414 , -4.9776 and 1.9702) and the large constant transition probability p_{11} (0.9875, 0.9884 and 0.9967) reveals that the downward moves (crisis regime) are gradual. This exemplifies asymmetric behavior for the US, Indian reachable and remote returns. Crises initiated in the US affect the Indian reachable market in a similar manner, and thus the resulting contagion is asymmetric.

Figures 4, 5 and 6 show the estimated smoothing probabilities of the shift in regime from a state of calm to crisis. The regime-switching model assumes that the disruptions of a crisis in time series shift regimes from one state to another, which can be represented by a series of conditional probabilities. The figures point out the timings of the crisis, as well as the conditional probability of the financial crisis, which jumps from zero to one during 2008–09 in the regime-switching model. The smoothed regime probabilities infer ex-post in which state the returns are at each time and also reflect the recurrent regime shifts in stock index returns. This analysis can be conducted based on estimates of the transition probabilities.

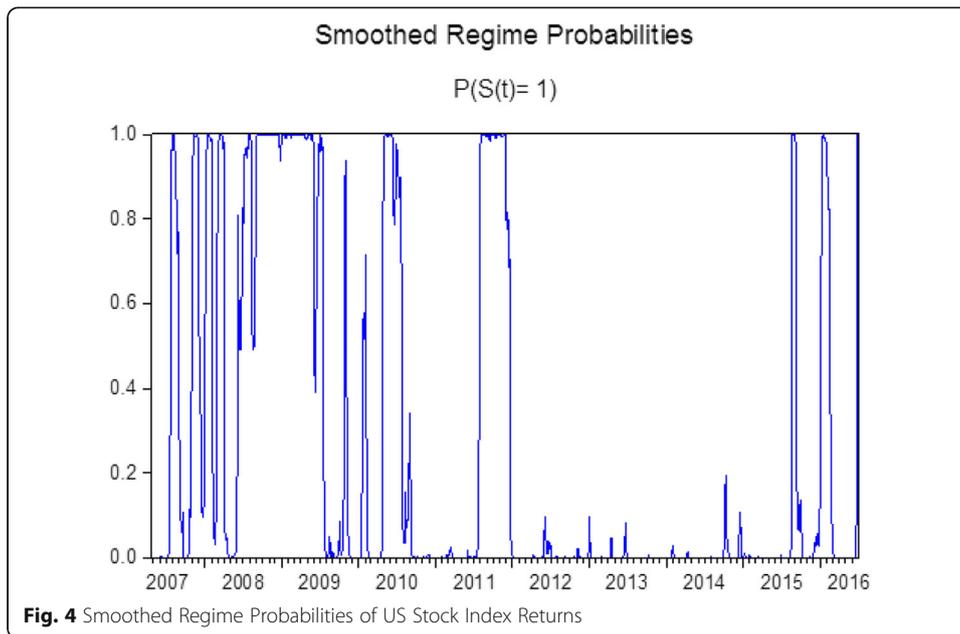
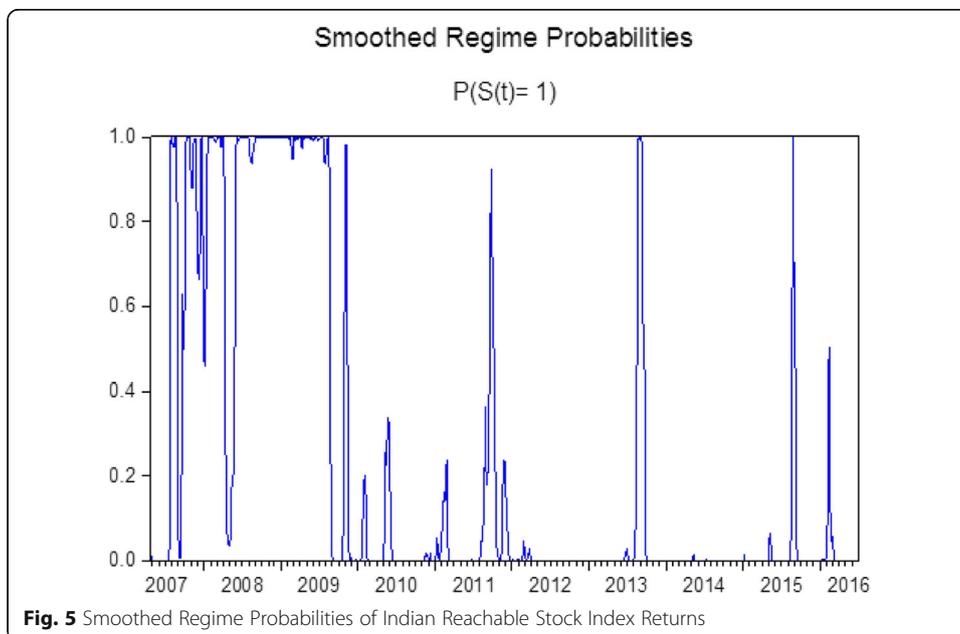
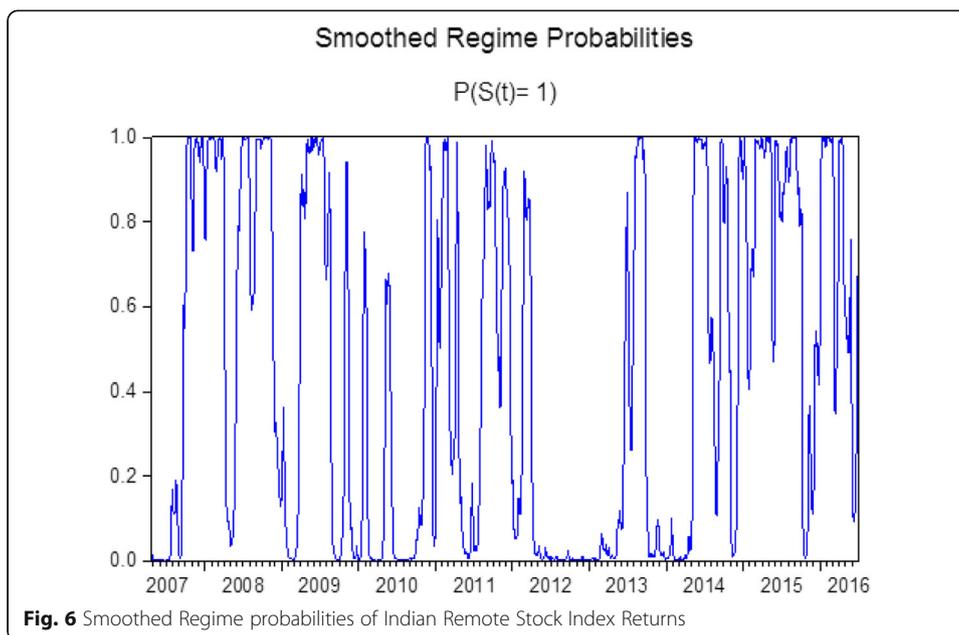


Figure 4 shows a shift between a crisis regime and a calm regime between 2007 and 2008 for the US index returns. From 2008 onwards, the state of crisis regime persists, with a shift in the series that lasts for a period of 1 year until 2009. More specifically, for the US, the period of the crisis regime from 8/06/2008 is maintained with the probability close to one until 5/21/2009. The shift to a calm regime is exemplified by the regime probability returning to close to zero by 7/29/2009. Hence, the figure exemplifies cogent shifts in the US Stock index returns in the subprime crisis period.

Figure 5 shows the smoothed regime probabilities of Indian reachable stock index returns through the period 2007 to 2016. In accordance with US index returns, Indian reachable index returns show a consistent shift of the state through the period 2008 to





2009. The figure for the US Index returns exemplified the crisis period for the US market. The reachability of Indian stocks to the US market suggests that the fear of crisis transmission as a result of its reachability factor is justified. The regime-switching model of the reachable Indian stock returns mirrors the start and the end of the US crisis regime. Following the commencement of the subprime crisis of the US, the conditional probability of a crisis regime for Indian reachable stocks jumps to one in 6/12/2008. This scenario lasts for one year and by 9/08/2009, is the probability returns to close to zero, which evidences that the crisis of 2008–09 in the US had a similar effect on the Indian reachable stocks. One possible explanation for this is that, to make up the margin call needs that emerged at the time of the US crisis, investors were compelled to sell Indian stocks where they have reachability. This would ultimately lead to a price decline in Indian reachable stocks, which suggests that the fear of contagion for the Indian reachable market is justified. Finally, this study investigates whether this impact persists only for the reachable stocks or whether it also has an impact on the Indian remote stocks.

The smoothed regime probabilities of the Indian remote stock index returns through 2007 to 2016 reported in Fig. 6 show mixed events of regime shifts. During the time of the crisis in the US, Indian remote stocks have a tendency to move to a crisis state for a limited period of time and then return back to the calm state for a limited duration. The influence on reachable Indian stocks can be expected to have an automatic impact on remote stocks. This might be a cause for the remote stocks to oscillate between calm and crisis regimes of a short duration. A period of crisis transition occurs from 5/05/2008 (0.04) to 6/26/2008 (.99). On 6/26/2008, the Indian remote stocks reach a crisis regime following the sudden shift beginning on 5/05/2008. As of this point, the series shows a tendency to move to the calm regime, but again reaches a crisis on 8/08/2008 (0.59). The probability of the crisis regime being maintained reaches one on 9/16/2008 and the remote stocks remain in the crisis regime until 11/11/2008. A similar shift is observed approximately every four months. This suggests that the regimes of remote

stocks are stagnant, as is the case for the reachable stocks. More specifically, the crisis impact on the Indian reachable stocks exemplifies a similar scenario to the US Index returns and the remote stocks show that the impact of the crisis is short-term in nature and regime shifts with a short duration can be observed.

This study contributes to the empirical literature on investor-influenced contagion as a result of liquidity constraints on international investors. International investors acting to liquidate their holdings in other markets as a result of a crisis in their home market leads to increased price volatility in both markets and an automatic crisis effect is reflected in the other market. Consequently, the Indian reachable stocks show a prediction for following crisis regime movements from the US market. The remote stocks also show a tendency to move to a crisis regime at the same time, but they also oscillate back forth between crisis and calm regimes in consecutive periods.

Conclusion

The paper explores the timings of the crisis as well as its side effects on Indian reachable and remote stocks to validate the hypothesis that liquidity constraints on investors influenced contagion at the time of the 2008–09 financial crisis. The subprime crisis of 2008–09, which was initiated in the US, is investigated to assess its impact on the Indian market due to liquidity constraints emerging from the reachability factor. The reachability factor suggests that the Indian stocks' reachability to international investors provided a means for them to meet their liquidity constraints. The regime switching model, which accounts for the non-normal unconditional heteroscedasticity of the stock index returns, finds evidence consistent with a regime change occurrence for the respective series of stock index returns. The estimated probabilities over the state of the regime model suggest that, although the global crisis began in 2007, the lasting tendency to stay in the crisis regime is only observed in the 2008–09 period for the US and Indian reachable stock index returns. In contrast, the remote stock index returns moves back to a calm regime more rapidly, though it also returns to a crisis state in a short period.

The present study on equity market contagion is limited to testing the transmission of the crisis based on the reachability factor from the US to the Indian market. Extending the study to the other markets, for example by analyzing the Eurozone Debt Crisis considering the reachability factor, is worth exploring. Contagion has relevance for optimal asset allocation, risk measurement, and investment diversification. Understanding how the important decisions taken on these factors can be better informed by considering contagion as a factor remains unexplored. A further limitation of the study is that it could not consider how the bond market responds to crisis transmission. Investigating stock returns (both reachable and remote) and government bond index return comovement during calm and crisis periods would assist in understanding the spread of the crisis between risky and safe assets. An additional investigation into the impact of policy interventions on reachability factor in preventing or speeding up contagion is also an avenue for future research.

Abbreviations

ARCH: autoregressive conditional heteroscedasticity; BIS: Bank for International Settlements; DCC: Dynamic Conditional Correlations; AG-DCC: Asymmetric Generalized DCC; FIAPARCH: Fractionally Integrated Asymmetric Power ARCH; EU/ECB/IMF: European Union/European Central Bank/International Monetary Fund; IFC: International Finance Corporation; SWARCH: switching ARCH; US: United States

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Authors' contributions

RS contributed to the development of the conceptual idea and SS contributed to the development of the model. Both authors read and approved the final manuscript.

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Availability of data and materials

The datasets used and/or analyzed during the current study can be provided on reasonable request.

Competing interests

We declare that we don't have any competing interests.

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