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ORIGINAL ARTICLE

Synchronization in Cycles of China and India During Recent Crises: A Markov Switching Analysis

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Abstract
We study the impact of recent crisis episodes viz. the Great Recession of 2007–09, the Euro Area crisis of 2010–12 and the COVID-19 pandemic of 2020–21 on the Emerging Market Economies (EMEs) of China and India using data from January, 1986 till June, 2021. A Markov-switching (MS) analysis is applied to discern economy-specific cycles/regimes and common cycles/regimes in the growth rates of the economies. We apply the univariate MS Autoregressive (MS-AR) model to characterize country-specific negative growth, moderate growth and high growth regimes of China and India. We examine the extent of overlap of the identified regimes with the Great Recession, the Eurozone crisis, and the COVID-19 pandemic. Thereafter, we study the regimes depicting common phases in growth rates of China-India and China-India-US by using multivariate MS Vector Autoregressive (MS-VAR) models. The multivariate analysis shows the presence of common negative growth during the turbulent periods during the study period. These results can be explained by the existence of strong trade and financial linkages between the two EMEs and the Advanced economies. The pandemic triggered a recession in the Chinese, Indian and U.S. economies and its impact on growth is much worse than the Great Recession and the Eurozone crises.

Keywords Great Recession · Eurozone Crisis · COVID-19 · China · India · Economic Growth · Markov Switching

JEL Classification C24 · F44 · G01

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Introduction

In the last two decades, the global economy was unsettled by turbulent crises in the advanced economies of United States (U.S.) and Eurozone (E.Z.). Post the Great Recession of 2007–09 and the Eurozone debt crisis of 2010–12, economic growth was arrested in numerous economies around the world. Additionally, an external shock in the form of the COVID-19 pandemic arrested growth in numerous economies of the world. The growth momentum of emerging economies has been halted due to this unprecedented health crisis. As a consequence of the pandemic, compared to the last year, growth in the global economy is expected to fall by as much as 3 per cent in 2021. IMF's *World Economic Outlook (WEO) Update (April 2020)*, reports this to be much more severe than the growth contraction resulting from the Financial Crisis of 2008–09. The impact of the recent crises has been studied by several studies[1] in the literature including Banerji and Dua (2010). The paper by Banerji and Dua (2010) investigates the synchronization of recessions in major developed and emerging economies during the global recession (post the U.S. recession of 2007–09) and conclude that unlike other economies the two Emerging Market Economies (EMEs) viz. China and India did not undergo a recession but only a milder slowdown.

According to International Monetary Fund (IMF)'s World Economic Outlook (2016), China and India held 17% share in total world output (based on Purchasing Power Parity) in 2007 which is expected to increase to 28% by 2020. Table 1 Panels A and B show the trade (depicted by the share in total trade) and financial linkages (represented by claims of banks vis-à-vis the advanced nations) of China and India with the U.S. and E.Z. Both the U.S. and E.Z. economies are important trading partners of China and India along with the existence of significant financial ties among the nations as well. In this backdrop, the present study examines the impact of the Great Recession and the Eurozone sovereign debt crisis on China and India. In view of the recent most crisis episode due to the COVID-19 pandemic being an external shock to growth, we compare the impact of the Great Recession and the Eurozone Debt Crisis with the pandemic.

To discern economy-specific and common cycles/regimes in growth rates of China and India, we use Markov-switching (MS) analysis. The research by Hamilton (1989, 1990) brings to fore a Markov-switching framework which can be utilized to characterize regime shifts in economic time series such as business cycles and growth rate cycles. MS models introduce a hidden or 'unobservable' state variable which is assumed to follow a Markov chain process[2] and depicts different regimes or *states of the world*.

[1] Several studies in the extant literature have examined the recent crisis episodes. These include Bems et al. (2010), Blanchard et al. (2010), Fidrmuc and Korhonen (2010), Gore (2010), Imbs (2010), Gianone et al. (2011), Milesi-Ferreti and Tille (2011), Gopinath et al. (2012), Anand et al. (2012), Berkmen et al. (2012), Checherita-Westphal and Rother (2012), Chor and Manova (2012), Massa et al. (2012), Ball (2014), Eichengreen et al. (2014), and Reinhart and Rogoff (2014) among others.

[2] It is standard to assume that the regimes are generated by a first-order Markov chain process.

Table 1 Trade and Financial Linkages between China, India, Eurozone and U.S

Panel A Trade Linkages-Share of Trade	2005		2015	
Countries/Region	Share of imports (%age)	Share of exports (%age)	Share of imports (%age)	Share of exports (%age)
China				
Eurozone	9.5	14.8	10.1	11.4
US	7.4	21.4	8.2	17.0
India				
Eurozone	17.9	16.4	8.8	11.9
US	8.0	16.5	4.9	13.4

Panel B Financial Linkages-Consolidated Foreign Claims of Reporting Banks (Ultimate Risk Basis)

	2005 Q4		2014 Q4	
Claims vis-à-vis	Share of eurozone banks (%age)	Share of US banks (%age)	Share of Eurozone banks (%age)	Share of US banks (%age)
China	25.3	13.0	17.4	12.7
India	32.2	25.3	17.5	30.2

Source Direction of Trade Statistics, IMF, 2015

Source Quarterly Review, Bank of International Settlement, 2015

Dua and Tuteja (2017a, b) study economic growth rates and stock market returns, and export growth rates, respectively. Their findings suggest that both China and India were somewhat affected by the crises. Dua and Tuteja (2017b) study the impact of the Great Recession and the Eurozone debt crisis on China and India. They focus on the trade channel of transmission of the crises i.e. on exports from China and India to the U.S. and Euro Area respectively. The paper finds that the exports from China and India to both the destinations were affected as a result of the crisis episodes with major exporting sectors of the two economies displaying negative rates of growth. Further, they conclude that a dampening of the economic activity in the U.S. and Eurozone in the wake of the crises led to a reduction in the rate of growth of exports from China and India due to a fall in the demand for exports. The paper by Dua and Tuteja (2017a) focuses only on the effect of the Eurozone debt crisis on China and India. The paper finds that given strong trade and financial linkages, the crisis may have marred prospects of recovery in the aftermath of the recent Great Recession in both the economies. The study finds China to be more resilient to the crisis possibly due to stronger macroeconomic fundamentals at the time.

This paper extends the existing literature by incorporating the multivariate MS-VAR framework. In this regard, this paper additionally examines the common cycles/regimes in the growth rate cycles of China and India by utilizing MS-VAR models. Further, we include a much longer period for the analysis i.e. from January, 1986 to June, 2021.

In this paper, we first estimate the economy-specific growth rate cycles for China and India using a univariate Markov-switching Autoregressive (MS-AR) framework. Subsequently, we investigate the common regimes in the growth rate cycles of the two countries using a multivariate Markov-switching Vector Autoregressive (MS-VAR) model.

The rest of the paper is organized as follows: Sect. 2 discusses the recent crises viz. the Great Recession, Eurozone Debt Crisis and the COVID-19 pandemic. Section 3 presents the data. Section 4 explicates the methodology and empirical estimation strategy. The subsequent Sect. 5 presents the results and discussion. The last section concludes.

Crises in the U.S., Eurozone and the Covid-19 Pandemic

In the last decade, the developed economies of US and EZ experienced major crises in 2007–09 and 2010–12 respectively.

The domino effects of the ‘subprime crisis’ that started with the bursting of the housing bubble in the United States (hereafter, U.S.) in 2007, led to a subsequent financial crisis in 2008. Several banking giants such as Lehman Brothers, Merill Lynch, Washington Mutual, Wachovia, Freddie Mac and Fannie Mae along with numerous small banks were embroiled in the financial crisis and declared bankruptcy. This was followed by a full-blown recession in the U.S. and several other economies of the world, also known as the ‘Great Recession’. The global financial markets bled out experiencing a simultaneous downfall due to ‘contagion effects’. In order to curb the recession and high unemployment that was setting in, many economies of the world bailed out distressed financial institutions and undertook fiscal expansion. This subsequently strained governments around the world since they had to overstretch in an attempt to tackle the real effects of the crisis on their economies by undertaking fiscal expansion.

The paper by Gore (2010) reasons that the Great Recession marks the end of the global development cycle that started in the 1950s. He argues that contradictions in the global development trajectory are at the heart of the recession which was precipitated by misdirected incentives, promotion of exotic and complex instruments and slackness in the regulation of the financial sector. Using cross-country regressions, the study by Giannone et al. (2011) finds that higher the adoption of policies aimed at liberalization of credit markets in an economy, lower the country’s resilience to the recent recession during 2008–09. The study by Ball (2014) attempts to quantify the long-term impact of the global recession on the output of 23 economies using the potential output pre-and post-crisis and concludes that the average size-weighted loss is 8.4%. Reinhart and Rogoff (2014) have shown that despite the recovery following the Great Recession, only two of twelve countries in their sample could attain pre-crisis levels of per capita Gross Domestic Product (GDP). In fact in some of the cases, the 2007–09 crisis was much more severe than the Great Depression of the 1930s.

The Eurozone (EZ) is a major subset of the European Union and is comprised of seventeen nations, namely Austria, Belgium, Cyprus, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Malta, the Netherlands, Portugal, Slovakia, Slovenia, and Spain. The Maastricht Treaty of 1992 established budgetary and monetary criteria such as size of the budget deficit, government debt, inflation rates, long term interest rates and exchange rates for potential member countries to enter the European Economic and Monetary Union and adoption of a single currency, the Euro. In 1999, eleven EU nations adopted the common currency Euro, and formed the Euro Area. The monetary policy of the Euro Area was henceforth governed by the European Central Bank. Several member nations joined EZ thereafter, and by 2011 the number of Euro Area member countries increased to seventeen. Till 2007, EZ experienced a general growth momentum along with mounting twin deficits viz. fiscal deficit and current account deficit.

As a consequence of the economic uncertainty following the 'Great Recession' and an injection of liquidity by the governments, public debt levels of EZ economies started mounting. This was especially true of the PIIGS economies viz. Portugal, Ireland, Italy, Greece and Spain. Portugal had been struggling with slow growth, Ireland was dealing with a fragile banking sector which had financed a property bubble, Italy was consistently showing signs of slowing down and disinflationary pressures, Greece was battling low tax collections and high budget deficits, and finally Spain was confronting a property bubble. The Eurozone sovereign debt crisis was characterized by high bond yield spreads in state-backed sovereign bonds/securities, large public debt levels and a collapse of the banking and financial sector. In order to grant relief to the distraught economies, the European Central Bank responded with a bailout package and most of the economies have had to take up austerity measures and economic reforms. In fact, Eichengreen et al. (2014) have compared the Eurozone crisis to the "Lost Decade" in Latin America during the 1980s and point out that the Eurozone economies have been consistently floundering in terms of their economic performance.

Some of the noteworthy points about the crisis resulting from the spread of the COVID-19 pandemic are its unprecedented nature, the huge output loss, uncertainty regarding the duration and intensity of this surprise and the demands of innovative policy, both medical and economic, to counter the effects of the crisis. The latter is fraught with difficulties owing to the push and pull among the public health measures on the one hand and the expansionary economic activity measures on the other. The worst recession since the Great Depression of 1929 is currently staring the global economy in its face. This is because lockdowns imposed to slow the spread of the various are likely to shrink the economic activity and growth drastically. The COVID-19 pandemic is an unanticipated health shock to the global economy. In order to analyse the impact of such a shock, we consider the various pathways for transmission of this shock across the world. A health shock is expected to lower productivity and labour supply and cause disruptions in supply chains. Additionally, it would lead to an increase in medical costs which may be borne by the employer (in the formal sector) or the employee (in the informal sector). The containment measures will adversely affect mobility and impact the travel and tourism and entertainment sectors. Further, the fear of layoffs leads to fall in expected disposable income and this coupled with rising uncertainty makes consumers averse to spending. This in turn leads to further business losses and retrenchment of workers. Finally,

Table 2 Descriptive Statistics

	y_t^{CHI}	y_t^{IND}	y_t^{US}
Mean	13.92***	6.06***	2.22***
Std. Dev	5.27	4.71	3.08
Skewness	0.72***	0.16	– 2.50
Excess Kurtosis	1.18***	0.24	19.45***
Jarque–Bera	41.76***	1.91	5248.91***
Minimum	– 48.10	– 14.05	– 23.36
Maximum	29.00	16.97	18.88

Note: *ytCHI* denotes the rate of growth of China, *ytIND* denotes the rate of growth of India, and *ytUS* denotes the rate of growth of U.S. respectively. *, ** and *** denote 10%, 5% and 1% levels of significance respectively

healthcare expenditure increases sharply. These effects are amplified and transmitted globally through trading partners and financial borrowers or lenders via the global value chains. Recent work on the COVID-19 pandemic includes Dev and Sengupta (2020), Song and Zhou (2020); Feyisa (2020) and He and Harris (2020) which show that the global economy is adversely affected due to the crisis.

Data

This section focuses on the data utilized in the present study.

The Economic Cycle Research Institute (ECRI) provides data on the coincident index of economic activity and the corresponding growth rates for 22 major economies of the world. In order to examine the impact of recent crises in the advanced economies on Chinese and Indian growth rates, we collect monthly data on the growth rate of the coincident index of economic activity from ECRI.[3] We analyse the data for the countries of China,, India, and U.S. over the period January, 1986 to June, 2021. We also utilize dates for the U.S., E.Z. and COVID-19 crises which are sourced from the website of ECRI.

Table 2 provides the summary statistics for the Chinese, Indian and U.S. growth rates (depicted by $\boldsymbol{y_t^{CHI}}, \boldsymbol{y_t^{IND}} and y_t^{US}$ respectively). The average growth rate of economic activity is highest for China.

According to latest data collected from the National Bureau of Economic Research (NBER, 2012) and the Economic Cycle Research Institute (ECRI, 2021a), the recession in the U.S. ensued from December, 2007 to June, 2009. It is notable that this includes the sub-period of the global financial crisis which occurred from September, 2008 till June, 2009 (as per the timeline provided by the Federal Reserve Bank of St. Louis on its website). We utilize data from ECRI (2021b) on the growth

[3] A similar analysis was also conducted with the Production index sourced from the International Financial Statistics of the International Monetary Fund (IMF). The results are similar and available with the authors on request. You may also see Dua and Tuteja (2017a) for an analysis of the same.

rate cycles in the economies of France, Germany, Italy and Spain, which are part of the Eurozone. The data reveals that these economies were experiencing a slowdown from February, 2011 to November, 2012; from August, 2010 to December, 2012[4]; July, 2010 to December, 2012; and from April, 2010 to November, 2012 respectively. Therefore, we define the Eurozone crisis period from April, 2010 to December, 2012. Similarly, the dates for the slowdown/ recessions in the Chinese, Indian and U.S. economies given by ECRI are December 2019 till March 2020; January 2020 till April 2020 and February 2020 till April 2020 respectively. The COVID-19 crisis is therefore defined from December 2019 to April 2020. The results from the DF-GLS, KPSS and Lee-Strazicich unit root tests indicate that the series are stationary.[5]

Methodology And Estimation Strategy

This section describes the methodology and estimation steps for the econometric exercise undertaken in the paper.

Methodology

Researchers have attempted to model the nonlinearity inherent in the time series. One obvious manner in which the time-varying and nonlinear behaviour of the series may be captured is to assume that it is different across various *states of the world* (alternatively, known here on as *regimes*). In a general setting, this allows the researcher to assume and model the mean or volatility of the variable differently depending on the realization of the *state of the world*. In the case of a two-state Markov switching model, for example, if $S_t = 1$ then the process was in regime 1 and $S_t = 2$ indicates that the process was in regime 2. The simplest probabilistic law or specification that governs a transition from state 1 to state 2 is obtained by assuming that S_t which is a discrete-valued random variable capturing the *state of the world* to be the realization of a Markov chain.

A discrete-time Markov chain process is a stochastic process $S_t, t = 0, 1, \dots$ which can take a finite number of values and is governed by the 'Markov assumption' which states that the probability of transition at each point of time depends only on the current state and nothing else. If the transition probabilities do not vary with time then such a process is called a time homogenous Markov chain. Let p_{ij} denote the transition probability from state i to state j i.e. the probability of being in state j in the next period, given that the present period state is i. Then, the probability that $S_{t+1} = j$ or the conditional distribution of a future state $S_{t+1} | S_0, S_1, \dots, S_{t-1}, S_t$ is

[4] Germany was also undergoing a slowdown from January, 2014 to August, 2014 but it was not accompanied by a slowdown in the other Eurozone economies and is, therefore, not considered in the analysis.

[5] Results are available on request.

dependent only on the current state and is independent of the realization of all past states

$$P\{S_t = j|S_{t-1} = i, S_{t-2} = k, \dots, y_{t-1}, y_{t-2}, \dots\} = P\{S_t = j|S_{t-1} = i\} = p_{ij} \quad (1)$$

If there are K states then the transition probability matrix will be

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdot & \cdot & p_{1K} \\ p_{21} & p_{22} & \cdot & \cdot & p_{2K} \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ p_{K1} & p_{K2} & \cdot & \cdot & p_{KK} \end{bmatrix} \quad (2)$$

The properties on the probabilities are.

1. $p_{ij} \geq 0, \forall i, j \in \{1, \dots, K\}$ i.e. probabilities are non-negative.
2. $\sum_{j=1}^{K} p_{ij} = 1, \forall j = 1, \dots, K$ or the probability that state i will be succeeded by one of the K-states must sum to unity which means the process must transit into one of the K states.

The Markov-switching time series models allow for regime-shifts, which are an outcome of the unobserved Markov chain process, in the parameters of autoregression (AR)/ vector autoregression (VAR). The estimation is conducted using Maximum Likelihood Estimation (MLE) or (Expectation–Maximization) EM algorithm.

First, we attempt to identify the regimes in the economy-specific models for China and India. In order to do that, we model the behaviour of the univariate time series (say y_t) which denotes the real activity in the economy using the Markov-switching specification. We assume that there are three states of the world or regimes.[6] In general, we could adopt a Markov Switching Intercept Autoregressive Heteroscedasticity (MSIAH) specification or a Markov Switching Mean Heteroscedasticity (MSMH) specification to model the process. The other variants of the process are MSI, and MSIA which indicate the absence of regime-switching in autoregressive (A) parameters and heteroscedasticity (H) respectively. The MSM specification (Hamilton 1990) includes regime-dependent means, while the MSMH contains regime-dependent means and variances.

We then describe a 2-state first-order Markov-switching autoregression (MS-AR) model (proposed by Hamilton 1989; 1990) according to the various alternative specifications discussed in Guidolin (2011) as,

Markov Switching Intercept Autoregressive Heteroscedasticity (MSIAH) Model:

[6] We need to test for the number of regimes in the process before specifying the model. One may alternatively, utilize the rule of thumb given in Krolzig (1997).

$$y_t = \mu_{S_t} + \sum_{j=1}^{k} \phi_{S_t j} y_{t-j} + \sigma_{S_t} \varepsilon_t \tag{3}$$

Markov Switching Intercept Autoregressive (MSIA) Model:

$$y_t = \mu_{S_t} + \sum_{j=1}^{k} \phi_{S_t j} y_{t-j} + \sigma \varepsilon_t \tag{4}$$

Markov Switching Intercept Heteroscedasticity (MSIH) Model:

$$y_t = \mu_{S_t} + \sum_{j=1}^{k} \phi_j y_{t-j} + \sigma_{S_t} \varepsilon_t \tag{5}$$

Markov Switching Intercept (MSI) Model:

$$y_t = \mu_{S_t} + \sum_{j=1}^{k} \phi_j y_{t-j} + \sigma \varepsilon_t \tag{6}$$

Markov Switching Mean Heteroscedasticity (MSMH) Model:

$$y_t - \mu_{S_t} = \sum_{j=1}^{k} \phi_j (y_{t-j} - \mu_{S_{t-j}}) + \sigma_{S_t} \varepsilon_t \tag{7}$$

Markov Switching Mean (MSM) Model:

$$y_t - \mu_{S_t} = \sum_{j=1}^{k} \phi_j (y_{t-j} - \mu_{S_{t-j}}) + \sigma \varepsilon_t \tag{8}$$

where $\mu_{S_t} = \mu_1, \mu_2$ denote the regime-dependent intercept in states 1 and 2 respectively; $\phi_{S_t} = \phi_{1j}, \phi_{2j}$ is the vector of regime-dependent autoregressive coefficients[7] in states 1 and 2 respectively and $\sigma^2_{S_t} = \sigma^2_1, \sigma^2_2$ is the regime-dependent variance in states 1 and 2 respectively. Further, $S_t = 1, 2$ denotes the random variable governing the switching process in the model which is the realization of a two-state Markov chain process.

The MS-AR model will be utilized to elicit cycles/regimes intrinsic to the growth rates inferred from the probabilities derived for the *states of the world*.

Wang and Theobald (2008) have proposed constructing the time-varying market volatility for each of the markets based on the full information set by using the smoothed probabilities and the parameter estimates under.

$$E\left[\widetilde{\sigma}^2_t | \mathcal{F}_T\right] = \widetilde{\sigma}^2_1 E\left[S_t = 1 | \mathcal{F}_T\right] + \widetilde{\sigma}^2_2 E\left[S_t = 2 | \mathcal{F}_T\right] \tag{9}$$

[7] The optimal number of regimes which are assumed to be two in the above specification and lags j will be selected on the basis of Krolzig (1997).

where $\widetilde{\sigma}_1^2$ and $\widetilde{\sigma}_2^2$ are the estimated conditional variances for regimes one and two respectively and $\mathcal{F}_T$ is the full information set upto time T.

Upon identification of the economy-specific regimes, we intend to delineate the common regimes in the Chinese and Indian growth rates. In order to accomplish that, we specify a multivariate vector autoregression (VAR) model for the growth rates which may have any one of the MSIAH/ MSIH/ MSI/ MSIA/ MSMH/ MSM specifications discussed for the univariate model in the previous sub-section.

The general form of the Markov Switching Intercept Autoregressive Heteroscedasticity (MSIAH) model for the K-regime MSVAR (p) process is given by

$$y_t = \mu_{S_t} + \sum_{j=1}^{p} A_{j,S_t} y_{t-j} + \varepsilon_t \tag{10}$$

The corresponding general form for the K-regime MSVAR(p) model with Markov Switching Mean Heteroscedasticity (MSMH) specification is as follows

$$y_t - \mu_{S_t} = \sum_{j=1}^{p} A_{j,S_t} (y_{t-j} - \mu_{S_{t-j}}) + \varepsilon_t \tag{11}$$

where y_t is the $N \times 1$ vector of endogenous variables, μ_{S_t} is a $N \times 1$ vector of regime-dependent mean returns; A_{j,S_t} is the $N \times N$ matrix of regime-dependent (V)AR coefficients; $S_t = 1, 2, \ldots, K$ is a latent state variable driving all the parameter matrices and is an irreducible, aperiodic ergodic K-state Markov chain process with transition matrix

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdot\ \cdot & p_{1K} \\ p_{21} & p_{22} & \cdot\ \cdot & p_{2K} \\ \cdot & \cdot & \cdot\ \cdot & \cdot \\ \cdot & \cdot & \cdot\ \cdot & \cdot \\ p_{K1} & p_{K2} & \cdot\ \cdot & p_{KK} \end{bmatrix} \tag{12}$$

$$P\{S_t = j | S_{t-1} = i, S_{t-2} = k, \ldots, y_{t-1}, y_{t-2}, \ldots\} = P\{S_t = j | S_{t-1} = i\} = p_{ij} \tag{13}$$

Such a process will be called a K-state Markov chain with transition probabilities $\{p_{ij}\}_{i,j=1,2,\ldots,K}$. The residuals follow a standard Gaussian distribution conditional on the state i.e. $\varepsilon_t \sim N(0, \Sigma_{S_t})$. The $N \times N$ matrix Σ_{S_t} represents the state S_t factor in a regime-dependent variance–covariance matrix such that

$$\Sigma_{S_t} = \begin{bmatrix} \sigma_{1,1,S_t} & \cdot\ \cdot\ \cdot & \sigma_{1,N,S_t} \\ \cdot & \cdot\ \cdot\ \cdot & \cdot \\ \cdot & \cdot\ \cdot\ \cdot & \cdot \\ \cdot & \cdot\ \cdot\ \cdot & \cdot \\ \sigma_{N,1,S_t} & \cdot\ \cdot\ \cdot & \sigma_{N,N,S_t} \end{bmatrix} \tag{14}$$

The contemporaneous correlation between the growth rates in the two economies p and q in regime S_t will be given by.

$$\rho_{p,q,S_t} = \frac{\sigma_{p,q,S_t}}{\sigma_{p,S_t}\sigma_{q,S_t}} \tag{15}$$

It is notable that for $K = 1$ the model reduced to a standard single-regime VAR process. A regime classification measure[8] (RCM) proposed by Ang and Bekaert (2002) indicates the adequacy of a K-regime model as it is based on the intuition that a good regime-switching model should discriminate between the states clearly so the smoothed probabilities would be either close to zero or one.

Estimation Strategy

In order to discern the impact of recent crises in the U.S. and E.Z. as well as the COVID-19 pandemic on the growth rate of the Chinese and Indian economies, we employ a Markov-switching framework (in the time domain). The central idea is to discern the regimes in the Chinese and Indian growth rates. We then compare the endogenously selected slowdown/recession dates for the two countries with the time periods of Great Recession, E.Z. and COVID-19 crises. This approach, therefore, does not entail imposition of any prior knowledge of the periods of crises on the model. First, the univariate Markov-switching AR model (Hamilton 1989; 1990) is utilized to delineate cycles/regimes in the emerging economies' growth. Subsequently, we use the multivariate Markov-switching VAR model to identify the periods of synchronized slowdowns/recessions in the Chinese and Indian economies. In both the cases, the identified periods are compared with the dates of the Great Recession, E.Z. and COVID-19 crisis.

To gauge the state of economic activity in China and India, we consider the smoothed growth rate of the coincident index for the two countries. Thereafter, we utilize Markov-switching AR/VAR models to elicit the slowdown and pickup phases in the growth rates and assess the slowdown periods when there has been a dip in the economic activity of the two EMEs.

Since Markov-switching models require the assumption of stationarity, in the first step, we test for non-stationarity of the time series using the Dickey-Fuller Generalized Least Squares (DF-GLS) and Lee and Strazicich minimum LM unit root tests. The latter is employed since we suspect that the data series for the growth rates may be affected by structural breaks and, therefore, the standard unit root tests would not be valid (Perron 1989). The unit root test by Lee and Strazicich (2003) allows for multiple structural breaks in the null hypothesis of a unit root. We then undertake the Box-Jenkins methodology for lag selection and determine the appropriate

[8] The RCM statistic for a model with two regimes is defined as $RCM = 400 \times \frac{1}{T}\sum_{t=1}^{T} \Pr[S_t = j|\mathcal{F}_t](1 - \Pr\left[S_t = j|\mathcal{F}_t\right])$, where the constant term of 400 is used to normalize the statistic between 0 and 100, $\Pr[S_t = j|\mathcal{F}_t]$ is the smoothed probability conditioned on the availability of the full information set $\mathcal{F}_t$. The literature often uses a standard benchmark of 50 for the RCM statistic.

Markov-switching model[9] for the univariate models in each of the growth rates. We decide the appropriate lag for the multivariate Markov-switching model by considering the AIC/BIC and HQ criterion for lag selection in a VAR model. Subsequently, the Markov-switching univariate and multivariate models are estimated using the Expectation–Maximization (EM) algorithm (Dempster et al., 1977). We also report a regime classification measure (RCM) proposed by Ang and Bekaert (2002) which indicates the adequacy of a K-regime Markov-switching model.

Results and Discussion

This section presents findings from the univariate and multivariate analysis of Chinese and Indian growth rates using the Markov-switching framework.

As mentioned earlier, we measure the rate of growth in the Chinese and Indian economies by using the smoothed growth rates given by ECRI. We, then, employ the univariate MS-AR models to identify the slowdowns and pickups in the growth rates of the two EMEs. Our methodology does not impose any a priori knowledge of the existence of the U.S. and Eurozone or COVID-19 crises. The model endogenously constructs the *states of the world* which are then compared with the dates for crises in the U.S. and E.Z. economies and the recent pandemic, respectively. Subsequently, we undertake a multivariate analysis using the growth rates in both the economies to elicit common regimes which correspond to synchronized slowdowns and pick-ups in Chinese and Indian growth rates. These periods are again compared with the dates for the crises in the advanced economies as well as the pandemic.

Prior to application of the Markov-switching models, we undertake two tests viz. Hinich Bi-spectral test (Brockett et al. 1988) and Tsay's test (Tsay 1986) to check for the linearity of the series. The results in Table 3 Panels A and B show that the null hypothesis of linearity is rejected in all the cases at 1% level.

Economy-Specific Regimes

The estimation results of the univariate three-state Markov-switching MS-AR models for growth rates in China and India are reported in Table 4. Figure 1 Panels A and B give the corresponding smoothed probabilities of the negative growth regime in the Chinese and Indian growth rates. Since the estimations are based on a univariate modelling framework, they yield economy-specific regimes.

To begin with, we explore the results for the growth rates of China. The underlying model is a three-state Markov-switching model with switching intercept with no

[9] The autocorrelation function (ACF) and partial autocorrelation function (PACF) of the series are plotted. The plausible ARMA (autoregressive moving average) models are selected, estimated and examined. The best ARMA models are selected on the basis of information criterion-Akaike Information Criterion (AIC), Schwarz Bayesian Criterion (SBC) and Hannan Quinn (HQ), parsimony, stability-stationarity and invertibility, and inspection of the Q-statistic for autocorrelation in the residuals (Enders 2008). We then go on to formulate the corresponding parsimonious Markov-switching model based on Krolzig (1997).

Table 3 Tests for Non-linearity

Panel A: Hinich Bi-spectral Test

Variable	Test Statistic (z)	P value	Conclusion
y_t^{CHI}	22.74	0.00	Non-linear
y_t^{IND}	11.68	0.00	Non-linear
y_t^{US}	125.63	0.00	Non-linear

Panel B: Tsay's Test for Non-linearity

Variable	F Test	P value	Conclusion
y_t^{CHI}	3.53	0.00	Non-linear
y_t^{IND}	1.55	0.00	Non-linear
y_t^{US}	8.46	0.00	Non-linear

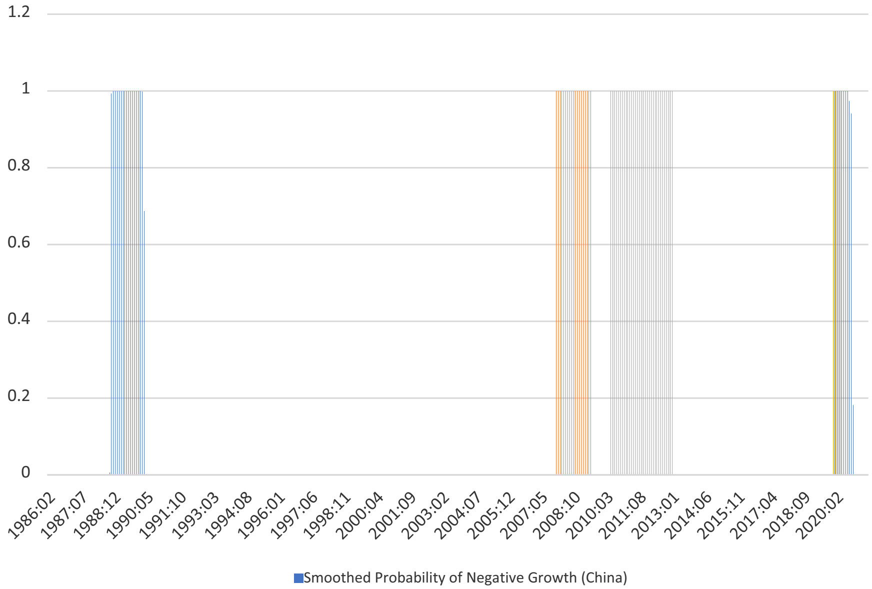
Note: *ytCHI* denotes the rate of growth of China, *ytIND* denotes the rate of growth of India, and *ytUS* denotes the rate of growth of U.S. respectively. *, ** and *** denote 10%, 5% and 1% levels of significance respectively

Table 4 Parameter Estimates for Univariate Three-state Markov-switching AR Models

	y_t^{CHI}	y_t^{IND}
Model	MSI	MSI
Lags	0	0
μ_1	− 2.319***	− 17.799***
μ_2	7.025***	0.656***
μ_3	11.397***	3.928***
σ	3.592***	4.821***
LogL	− 941.826	− 974.196
p_{11}	0.927***	0.196
p_{21}	0.072	0.803
p_{12}	0.006	0.000
p_{22}	0.959***	0.934***
p_{13}	0.000	0.084
p_{23}	0.090**	0.328
p_{33}	0.91***	0.588***
LR	28.13***	31.66***
LR^{Wolfe}	27.86***	31.35***
RCM	18.43	18.16

$\boldsymbol{y_t^{CHI}}$ denotes the rate of growth of China and $\boldsymbol{y_t^{IND}}$ denotes the rate of growth of India. *, ** and *** denote 10%, 5% and 1% levels of significance respectively

Panel A: China



Panel B: India

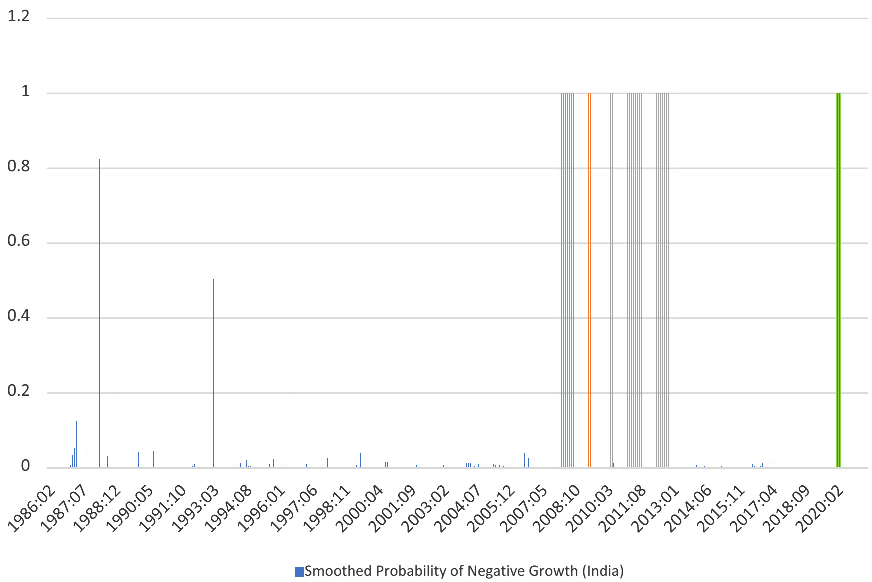


Fig. 1 Smoothed Probabilities (MS-AR) Panel **A** China, Panel **B** India

lag i.e. MSI-AR(0). The LR statistics show that the linear model is inadequate. The average growth rate is -2.3% in state one, 7.0% in state two and 11.4% in state three. Therefore, regime one depicts a negative growth rate regime, state two is the moderate growth state or a slowdown and the last state is the high growth rate regime. The transition probabilities are given by p_{11}, p_{22} and p_{33} are more than 0.9 for all three of the regimes indicating high persistence. Clearly, the moderate regime in economic activity is the most persistent in this case. The average duration of the slowdown and pickup regimes is 28 months. The RCM value of 18.43 indicates that the MS model fit is good.

Now, we turn to the results of the univariate three-state Markov-switching model for the Indian growth rate. The model specification is similar to that for the Chinese case i.e. Markov-switching with intercept switching and no lag or MSI-AR(0). The mean growth rate in state one is -17.8%, that in state two is 0.65% and in the third state is 3.9% which indicates that the first state corresponds to the negative growth regime, the second state is the moderate growth and the last state is the high growth regime. The transition probabilities for the Indian growth rate are 0.196 (negative-regime), 0.934 (moderate growth regime) and 0.588 (high growth-regime) which shows that the moderate growth regime is more persistent. The RCM value of 18.16 shows that the MS model specification is adequate.

In Fig. 1 Panel A and B plot the smoothed probabilities of a negative growth phase along with the periods for the U.S. crisis (i.e. USC) and Eurozone crisis (i.e. EZC) along with the COVID-19 (COVID) pandemic. From Fig. 1A for the Chinese negative growth rate in economic activity, it is evident that the Markov-switching models have captured Asian Crisis and COVID-19 episodes[10] Figure 1B presents the smoothed probability for the negative growth in economic activity of India. Several low-probability episodes are highlighted including a slowdown in 1992–93, that triggered by the Asian crisis in 1997–98 and the U.S. recession in 2001, the U.S. and the E.Z. crises. Like the Chinese case, both the recent crises seem to be associated with a slowdown in Indian economic activity but not a recession. However, currently both the EMEs seem to be stuck in a negative growth rate regime or recession due to the ongoing COVID-19 pandemic.

Common Regimes

Table 5 presents the results of the multivariate three-state Markov-switching MS-VAR model which includes growth rates for China as well as India. This model is a multivariate counterpart of the univariate framework presented earlier and yields common regimes of slowdowns/ pickups in the growth rates of both the economies. The smoothed probability of slowdowns in economic activity of both China and India is given in Fig. 2.

[10] According to ECRI (2021a), the U.S. economy experienced a recession from March, 2001 to November, 2001.

Table 5 Parameter Estimates for Multivariate Three-state MSI Markov-switching VAR Model

	y_t^{CHI}	y_t^{IND}
μ_1	− 2.490***	− 3.503***
μ_2	1.044***	− 1.548***
μ_3	1.62***	4.85***
ϕ_{CHI}	0.880***	0.013***
ϕ_{IND}	0.318***	0.825***
σ_{ii}	1.688***	7.649***
LogL	− 1818.35	
p_{11}	0.381***	
p_{21}	0.394***	
p_{12}	0.040***	
p_{22}	0.959***	
p_{13}	0.177***	
p_{23}	0.079	
p_{33}	0.744***	
RCM	8.208	

$\boldsymbol{y_t^{CHI}}$ denotes the rate of growth of China and $\boldsymbol{y_t^{IND}}$ denotes the rate of growth of India. *, ** and *** denote 10%, 5% and 1% levels of significance respectively

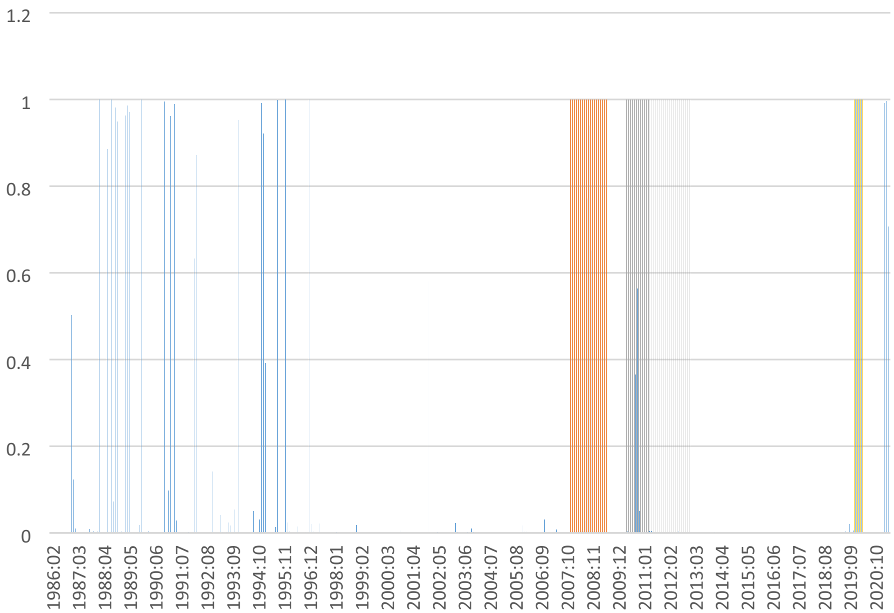


Fig. 2 Smoothed Probabilities (MS-VAR) for China and India

Table 6 Parameter Estimates for Multivariate Three-state MSI(1) Markov-switching VAR Model

	y_t^{CHI}	y_t^{IND}	y_t^{US}
μ_1	− 2.472***	− 3.482***	− 1.700***
μ_2	1.076***	− 1.602***	− 0.544**
μ_3	1.530***	5.000***	1.305***
ϕ_{CHI}	0.884***	0.030***	− 0.066***
ϕ_{IND}	0.322***	0.808***	0.056
ϕ_{US}	0.112***	− 0.009	0.880***
σ_{ii}	1.652***	7.651***	1.830***
LogL	− 2502.13		
p_{11}	0.386***		
p_{12}	0.410***		
p_{21}	0.041***		
p_{22}	0.958***		
p_{13}	0.178***		
p_{23}	0.066***		
p_{33}	0.756***		
RCM		1.003	

Note: *ytCHI* denotes the rate of growth of China, *ytIND* denotes the rate of growth of India,and *ytUS* denotes the rate of growth of U.S. respectively. *, ** and *** denote 10%, 5% and 1% levels of significance respectively

The Markov-switching multivariate specification is that with switching intercepts and zero lags i.e. MSI-VAR (1). The LR statistics indicate that the linear VAR specification is inadequate for modelling the series. From Table 5, we infer that the mean rates of growth for China and India in the first state are -2.5% and -3.5% respectively. On the other hand, during the second state symbolizing moderate growth both the Chinese and Indian economies experience 1% and -1.5% growth. Finally, the last state depicting high growth shows much higher growth rates of 1.6 and 4.8% respectively. Therefore, we can clearly identify the first state as the regime depicting common slowdown periods, the second state as that associated with common moderate growth periods and the last state is associated with common high growth periods. The transition probabilities for the common slowdowns and pickups are 0.381, 0.959 and 0.744 respectively with the moderate phase being more persistent. The RCM value of 8.2 suggests that the MS model is adequate.

In Fig. 2, we plot the smoothed probability of common slowdowns in economic activity of China and India and periods of U.S., Eurozone, and COVID-19 crises. The analysis demarcates four broad episodes of common slowdowns viz. the slowdowns due to the Asian Crisis of 1997–98, U.S. recession of 2001, Great Recession of 2007–09 and Eurozone crisis of 2010–12. It is notable that the recent crisis in the U.S. as well as the E.Z. triggered common slowdowns in both Chinese and Indian economic activity. Dua and Tuteja (2017a, b) find similar results which indicate that the growth rates for exports of China and India to the E.Z. are stuck in a low growth rate regime since 2011. Moreover, our results suggest that the two EMEs

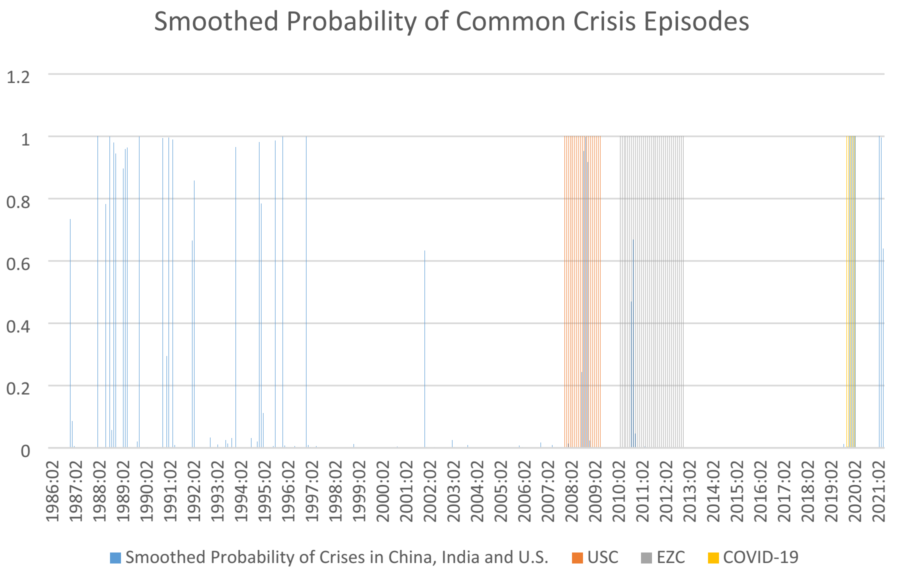


Fig. 3 Smoothed Probabilities (MS-VAR) for China, India and U.S

are currently undergoing a common recession phase which has persisted due to the COVID-19 pandemic.

Table 6 gives the results of the multivariate three-state Markov-switching MS-VAR model for growth rates of China, India, and U.S. (denoted$\boldsymbol{y}_t^{US}$)[11]. The results show that average growth rates for China, India and U.S. in the first state are − 2.5%, − 3.5% and − 1.7% respectively. In the second state, however, mean growth rates for China, India and U.S. are 1%, − 1.6% and − 0.5% respectively. In the last state, the mean growth rates are 1.5%, 5% and 1.3% and this state depicts the common high growth phase. We identify the first state as the regime demarcating the periods of common negative growth and the second regime is synonymous with the periods of common moderate growth. The transition probabilities for the three states are 0.386, 0.958 and 0.756 respectively and the moderate growth phases are much more persistent. The RCM value of 1 suggests that the MS model has very good fit. In Fig. 3, we plot the smoothed probability of slowdowns in economic activity of China, India and U.S. The figure shows that the Great Recession is a common and long period of common slowdowns in the three economies. However, the pandemic has resulted in synchronized recession across the economies.

Therefore, the Markov Switching analysis of growth rates reveals three states for China and India which correspond to the behaviour of the economy during negative, moderate and high growth states. The negative episodes include those

[11] The coincident index for the U.S. is stationary and the results for the same are available with the authors on request. For a Markov-switching analysis of regimes in the coincident index see Dua and Sharma (2016).

that are possibly triggered by the recent U.S. and Eurozone crises. It is notable that the pandemic resulted in a severe recession across the economies.

Discussion

Several studies in the literature have attempted to explain the causes for transmission of crises from the U.S. and Eurozone to the emerging and developing economies. There are two broad channels of transmission-trade ties and financial linkages. Fidrmuc and Korhonen (2010) advance evidence in favour of the 'decoupling hypothesis' for China and India. They, however, show that the U.S. crisis impacted emerging Asian countries and close trade ties can explain the business cycle correlation between OECD and large Asian economies. Imbs (2010) examines the pattern of international business cycle synchronization of OECD nations over the last three decades. The author finds a significant and unprecedented rise in the business cycle correlations post the crisis of 2008–09. He attributes the heightened co-movement to high goods trade in the case of developing countries and close financial links for the OECD nations. Berkmen et al. (2012) attempt to explain the differences in output impact of the global financial crisis and emphasize the financial channel in the case of emerging economies and the trade channel in the case of developing economies.

Among the studies that focus only on the trade channel of transmission are Bems et al. (2010), Gopinath et al. (2011) and Dua and Tuteja (2017b). Bems et al. (2010) show that about 70% of the slowdown in trade resulting from the Great Recession was accounted for by a fall in demand, especially those for durables. Gopinath et al. (2012) investigate the Great Trade Collapse of 2008–09 (following the Second Great Contraction) and find that there was decline of 30% in the trade value of differentiated manufacturing goods exports. Focusing on the trade channel of transmission, Dua and Tuteja (2017b) show that exports from China and India to both the U.S. and EZ were affected due to the crisis episodes.

The paper by Blanchard et al. (2010) discusses the channels of transmission of a crisis in the US to EMEs. The study sheds light on the initial and short-run impact of the financial crisis in U.S. on emerging market economies (EMEs) characterised by imperfect capital mobility and exposure to foreign currency debt. In the theoretical model, transmission of global shocks to EMEs is assumed to occur through the Balance of Payments (BoP) accounts. To maintain an equilibrium in the BoP, a current account deficit has to be financed either by a surplus on the capital account or a change in the foreign exchange reserves. Therefore, the impact on the EME is expected to occur due to either trade shocks (on the current account), financial shocks (on the capital account), deterioration of the terms of trade (which affects both the current and the capital account) or a depletion of the foreign exchange reserves.

Conclusion

We employ Markov-switching models, both univariate and multivariate, to delineate the economy-specific and common regimes in China and India to examine the impact of the Great Recession, the Eurozone crisis and the COVID-19 pandemic on the economic activity in the two EMEs. It is noteworthy that we do not impose any a priori knowledge of the existence of the Great Recession, the Eurozone crisis and the COVID-19 pandemic. The Markov-switching model endogenously constructs the *states of the world* which are then compared with the dates for crises in the U.S. and E.Z. economies and the pandemic respectively.

The results of the Markov-switching models of growth rates reveals three states for China and India which correspond to the behaviour of the economy during negative growth, moderate growth and high growth states. Both the economy-specific and common slowdown episodes include those that are possibly triggered by the recent U.S. and Eurozone crises. The model also picks up negative growth rate regimes in the two economies due to the COVID-19 crisis. The impact of the COVID-19 pandemic on global growth is much more severe than the economic crises in the previous decade or so. Our results from the MS analysis on transmission of the global financial crisis and Eurozone debt crisis are supported by the existence of close trade and financial ties of the Chinese and Indian economies with the U.S. and Eurozone economies.

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Data availability This paper uses proprietary data which is available from the Economic Cycle Research Institute, New York and cannot be shared by the Authors.

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