FINANCIAL STRESS, SPILLOVERS AND FINANCIAL CYCLE IN INDIA

A thesis submitted to the University of Hyderabad for the award of the degree of

DOCTOR OF PHILOSOPHY

IN

ECONOMICS

By

SRUTI MUNDRA
Registration No. 17SEPH14

Thesis Supervisor
Dr. Motilal Bicchal

SCHOOL OF ECONOMICS
UNIVERSITY OF HYDERABAD
HYDERABAD-500046
JULY 2023

Dedicated to My Parents and Husband...

School of Economics
University of Hyderabad
Hyderabad-500046, India

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The candidate has satisfied the UGC Regulations of publications and conference presentations before the submission of her thesis. Details are given below.

Publications:
1. Mundra, S. and Bicchal, M. (2023), "Asymmetric Effects of Monetary Policy and Financial Accelerator: Evidence from India", *The Journal of Economic Asymmetries,* 27(June 2023), e00296.
2. Mundra, S. and Bicchal, M. (2021), "Evaluating Financial Stress Indicators: Evidence from Indian Data", *Journal of Financial Economic Policy,* 13(1), 116-135.

Presentations in conferences:
1. Presented a paper: "Asymmetric Effects of Monetary Policy Transmission Mechanism in India", International E-conference, St. Joseph's College of Commerce on Disruptions in Business and Economy: Challenges and Opportunities to a Sustainable Future in Collaboration with St. Xavier's College, Kolkata, held on November 30, 2021.
2. Presented a paper: "Financial Stress Spillovers from India's Major Trading Partners", in Virtual Symposium as part of National Webinar on Aatma Nirbhar Bharat, Arun Jaitley National Institute of Financial Management, Faridabad, held on December 24, 2021.
Further, the student has passed the following courses towards fulfilment of coursework requirement for Ph.D, during August-December 2017.

Course Code	Course Title	Credits	Pass/Fail
EC-801	Advanced Economic Theory	4	Pass
EC-802	Social Accounting and Database	4	Pass
EC-803	Research Methodology	4	Pass

Signature of PhD Supervisor

27/07/23

SUPERVISOR
SCHOOL OF ECONOMICS
UNIVERSITY OF HYDERABAD
Hyderabad-500 046. (IN)

Dr. Motilal Bicchal

Dean

DEAN
SCHOOL OF ECONOMICS
UNIVERSITY OF HYDERABAD
Hyderabad-500 046. (INDIA)

Acknowledgements

I would like to express my deep sense of gratitude and profound respect to Dr. Motilal Bicchal for his supervision, advice and guidance from the very beginning of this research. His constant support and pursuit, dedicated encouragement, utmost care and continuous mentoring has helped immensely in completing this thesis within the time. I am very grateful for his sincere supervision and time and energy in reviewing my thesis and providing constructive comments and suggestions during the course of this study.

I am thankful to Prof. Naresh Kumar Sharma, former Head of the Department and Prof. R. V. Ramana Murthy, Dean of School of Economics for providing the conducive atmosphere, which enabled to complete this study.

I immensely acknowledge my doctoral committee members, Prof. Debashish Acharya and Prof. Raja Sethu Durai for their inspiration and valuable comments on my work and all other faculty members of the School of Economics for their co-operation.

I owe special thanks to my friends Devika and Cyril who have always stood behind me during the need of the hour. They always extended their helping hand in every possible way.

On a personal note, I would like to thank my parents and husband for their constant encouragement and support that provided me a great level of confidence in carrying out this work.

Sruti Mundra

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Financial globalization in the 1970s marked the beginning of financial innovation, institutional changes, financial volatility, and crisis-prone financial markets in advanced and emerging economies (Gourinchas and Obstfeld, 2011). The past three decades witnessed bouts of financial volatility and frequent financial crisis such as the Tequila crisis in 1994-95, the 1997 Asian financial crisis, Russia's 1998 currency crisis, the collapse of long-term capital management in the United States in 1998, the dotcom bubble crash in the 2000s, the Argentinean and Turkish crises in 2001, the global financial crisis in 2008-09 and the Eurozone crisis in 2011. This series of financial crises demonstrated the significance of comprehending the causes and repercussions of financial crises (Andres Solimano, 2010).

Accommodative financial and monetary regimes provide a conducive environment for financial imbalances to build up. Rapid credit expansion, growth in leverage, above-average capital accumulation, and rise in asset prices fuel the procyclicality in the financial system. A financial crisis typically arises from unwinding financial imbalances built up by favorable economic conditions (Borio, 2013). The common characteristics associated with the financial crisis are large-scale balance sheet problems, significant alterations in financial and real asset values, credit volume, disruption in access to external financing, and obstruction in financial intermediation. It is seen that financial crises are usually followed by booms in asset and credit markets, finally leading to asset bubble busts and credit crunches. It then translates into financial contagion, spillovers, and firesales in financial markets (Claessens and Kose, 2013).

A widely accepted elucidation of the cyclical fluctuations of financial systems being prone to rapid expansions followed by corrections is Minsky's Financial Instability Hypothesis. Minsky

(1992) characterizes a capitalist economy with capital assets as a financial system where banking activity generates profits. It identifies three types of economic units: hedge, speculative and ponzi finance. Hedge financing units can fulfill their obligations, and the system is in equilibrium; speculative financing units can repay only the interest but not the principal amount; ponzi units cannot repay the principal and the interest due. When the share of speculative and ponzi units rise in the economy, the system deviates from a stable financing regime to an unstable regime. During stable times, the financial system consists of mainly hedge finance units but prolonged prosperity transitions to a system with larger units engaged in speculative and ponzi finance. The likely consequences of this system is the sudden collapse in the asset prices .

Theoretical and empirical literature emphasizes the macroeconomic consequences of disruptions in the financial system. One branch of inquiry focusing on the borrower balance sheet channel finds lenders' inability to assess the borrower’s risk and creditworthiness, monitor their investments, and enforce repayment. Due to the above reasons, borrowers face an external finance premium, hence a higher cost to raise funds externally than internal funds. The external finance premium is inversely proportional to the net worth of the potential borrower. During the financial stress phase, the borrower's net worth is low, translating into higher external finance premium, affecting their expenditure volume and aggregate demand. Also, lenders are required to pledge collateral for borrowing. Financial shocks that reduce the prices of borrowers' assets used as collateral will tighten the collateral constraint. This reduces production and spending, which further reduces asset values. The net worth of borrowers and external finance premium serves to propagate and amplify shocks to the real economy, and it is called the financial accelerator model (Bernanke and Gertler, 1989).

Another transmission channel is the bank balance sheet channel comprising bank lending and bank capital channel. In accordance with the bank lending channel, on the liability side, a monetary policy tightening shock reduces money supply and money demand. On the asset side, it produces changes in asset composition, contracting credit supply (Bernanke and Blinder, 1988). Under the bank capital channel, regulatory capital requirements can impose an upper bound on bank assets and lending. Deteriorating bank capital ratios or bank capital losses, such as loan defaults, can also affect the cost and availability of credit and worsen economic conditions. Adverse shocks affecting the balance sheets of financial institutions can curtail the availability of credit supply, thereby reducing economic activity. Such shocks have magnified effects when banks cannot fully insulate their lending supply and borrowers are highly dependent on bank credit.

It is crucially important for policymakers to be equipped with tools that detect potential misalignment in the financial system during the initial stage. This requires empirical methods to improve the monitoring of the current state of financial stability and to be able to recognize and assess the causes of financial stress. In this context, it becomes imperative for central banks, policymakers, and regulatory authorities to monitor and supervise financial stability. Specifically, detecting financial stress is essential in the micro and macroprudential policy frameworks. Many institutions are now using early warning systems to track the development of financial stress pertaining to the whole financial market. The Federal Reserve Bank of Kansas City, the European Central Bank, and St. Louis have built composite indexes to assess financial stability. International organizations like the International Monetary Fund (IMF), the Bank for International Settlements (BIS), and the Organisation of Economic Co-operation and Development (OECD) have developed indicators for various nations.

Financial crises often produce effects across institutions, markets and have international consequences. This emphasizes the importance of gathering better knowledge of transmission mechanisms through which spillovers increase significantly following a shock to a specific country or a set of countries. The relevant literature has identified the links and fundamental conditions that can make the economy vulnerable to spillovers during heightened financial stress. Empirical work highlights the importance of trade and financial linkages through which shocks are normally transmitted. Fischer (1998) mentions the limited ability of emerging economies to manage significant, frequent, and disruptive spillovers that arise due to shocks and crises originating elsewhere. The study also finds that international capital markets are highly susceptible to spillovers.

A resilient economy focusing on the financial cycle requires a broader macroprudential stability framework. The goal is to dampen the procyclicality of the financial cycle. The key principle is to preserve prudential buffers during the upturn phase of the financial cycle to withdraw these in a controlled manner during a downturn. It also prescribes restraining risk-taking during the upturn phase and associated vulnerabilities. Alongside, the policies like monetary policy and macroprudential policy should co-ordinate and reinforce each other in building-up unsustainable financial imbalances and avoid sending conflicting signals (Borio, 2002; Borio, 2009).

It is crucial to determine probable indications of financial stress early before it becomes a full-blown crisis. In order to monitor and assess financial stress, there is a need to build a comprehensive indicator covering the entire financial system. Apart from the surveillance of the financial system, a financial stress examination is crucial for recognizing the impact of financial stress on economic activity. Since financial markets have become increasingly integrated globally, it leads to the transmission of financial stress spillovers. Besides this, emerging markets are strongly affected by such spillovers and turn out to be the most vulnerable to the inevitable spillover effects. The reoccurrence of such financial crises has drawn attention to the procyclicality of the financial system.

1.2 Scope and motivation of the study

A variety of financial stress indices, in recent times, have been proposed to identify the level of stress in the financial market. We find the existing literature is void of a study that compares these FSIs obtained using various methods and the most efficient FSI among them that can trace all the major and minor events. Specifically, in the Indian context, none of the studies accounted time-varying nature of stress prevalent across different financial markets. In addition, understanding the impact of monetary policy during financial stress is crucial for stabilization policy. However, most research in this area has focused on investigating the effect of financial stress on the macroeconomy using linear models (see, for example, Hakkio and Keeton, 2009; Cevik et al., 2013; Park and Mercado, 2013; Mallick and Sousa, 2013). These studies ignored regime-switching and the nonlinear effect of monetary policy shock. Particularly, the related literature on India is confined to linear relationships to examine the propagation of monetary policy shocks on the real economy. The literature presents evidence of financial crises usually originating in one country but later transmitted across countries. Also, empirical work on measuring such spillover effects focuses mainly on the sectors of financial markets; it largely ignores trade and financial flow channels that exist across countries. We attempt to fill these gaps in the case of an emerging market economy, India. Lastly, previous studies on financial cycle have primarily explored the interlinkages between financial and real cycles and the impact of monetary policy on the real cycle alone. Limited studies have explored the impact of monetary policy decisions on financial cycle. In recent times, macroprudential policy has emerged to be an important tool to stabilize the financial system. The literature lacks a study that investigates the behaviour of macroprudential policy with financial cycle. This study attempts to fill these gaps.

The present study contributes to the existing literature in various means; first, it computes various financial stress indicators, some of which are computed for the first time in the Indian case, incorporating the systemic nature of financial stress in the construction of FSIs and evaluating their usefulness in terms of real-time assessment; secondly, it examines asymmetric effects of monetary policy in India using financial stress index; thirdly, it studies the transmission of financial stress spillovers to an emerging market, India; and lastly, it analyses the behaviour of monetary policy stance and macroprudential norms in the various phases of the financial cycle in India.

1.3 Objectives of the study

In light of this background, the objectives of the present study are set as follows:

1. To assess alternative financial stress indicators for India.
2. To examine the asymmetric effects of the monetary policy during low and high financial stress regimes in India.
3. To examine the spillovers of financial stress from the top five trading partners to India through bilateral trade relations and financial linkages.
4. To assess the co-movement of monetary policy and macroprudential policy stance towards financial cycle phases in India.

1.4 Methodology and database

The study constructs several stress indicators for India and describes a detailed methodology for constructing indicators. The variables selected cover four segments of the financial market: banking, equity, foreign exchange, and bond markets. These variables are then standardized using normal standardization (NS) and cumulative distribution function (CDF). Then, the financial stress indices are generated using four different aggregation methods. These methods are variance equal weights, principal component method, exponentially weighted moving average (EWMA), and dynamic conditional correlation (DCC)-GARCH.

To examine the asymmetric effects of monetary policy shocks, a threshold vector autoregression (TVAR) model is estimated, and nonlinear impulse response functions are generated. The Financial Stress Index (FSI) is used as the threshold variable that endogenizes the regime-switching. The FSI is based on the dynamic conditional correlation-generalized autoregressive conditional heteroscedasticity (DCC-GARCH) method. The model is estimated with endogenous variables. The endogenous variables in the TVAR model are the industrial production index, consumer price index, weighted average call rate, and FSI.

To investigate the financial stress spillovers, we use FSI and apply a generalized vector autoregressions (VARs) variance decomposition by Diebold and Yilmaz (2012) to measure the financial stress spillovers. The generalized forecast error variance decompositions are constant to the order of variables. The spillovers index represents the degree of cross-variance spillovers. It is computed as the proportion of spillovers across all asset markets to the total forecast-error variance. They also measure gross and net directional spillovers received by a specific asset market and transmitted by a specific asset market, enabling to determine the recipients and transmitters of spillovers. The top trading countries are the United States, China, Singapore, Hong Kong, and the United Kingdom. The FSI of each trading partner's country is computed using variance equal weights to measure the financial stress. India's exports and net Foreign Institutional Investors (FIIs) proxy trade and financial spillovers.

Towards the fourth objective, non-food bank credit and BSE Sensex are used to create a composite scale of the financial cycle derived from the low-frequency component of wavelet analysis. The co-movement of the financial cycle phase is assessed with weighted average call rate and time-varying risk weights and provisioning norms on certain sectors. We compute pro-cyclicality ratios and follow the research approach of Kurowski and Smaga (2018) to determine the procyclical or countercyclical stance of monetary and macroprudential policies.

1.5 Scheme of the study

The remaining part of the study consists of the following five chapters.

Chapter 2 discusses various definitions of financial stress and explains variables employed in the computation of the financial stress indices. It also describes the steps involved in the computation of various financial stress indices. It assesses the efficiency of these indices in tracing crisis events in India.

Chapter 3 estimates a TVAR model to examine the asymmetric effects of monetary policy shocks and derives a nonlinear impulse response function.

Chapter 4 analyses financial stress spillovers from top trading partners of India. It estimates the financial stress indices of each country, spillover index, directional spillovers, and net spillovers from/to India.

Chapter 5 computes the financial cycle for India using wavelet analysis. It then assesses the co-movement of financial cycle phases with monetary policy stance and macroprudential norms to determine the outcome as procyclical or countercyclical.

Chapter 6 concludes the thesis with a summary of the study and the policy implications of the study.

CHAPTER 2

EVALUATING FINANCIAL STRESS INDICES FOR INDIA

2.1 Introduction

The aim of this chapter is to construct and assess alternative financial stress indices (FSI) for India. These indices aim to measure a build-up of stress before a full-blown crisis, providing insight into fluctuating stress levels. Such financial stress measures are useful for assessing financial instability and can be fed into policy decisions to flux out the stress before it blows out on the full scale. The study uses several representative variables in the FSI computation to cover all four financial market segments: banking, equity, foreign exchange, and bond. The study following the methodology of Holló et al. (2012) computes two systematic financial stress indexes and compares them with frequently applied methods, equal-variance weighting and principal component analysis (PCA). In the developing index, Holló et al. (2012) compute the cross-correlation matrix of the submarket to incorporate the systemic nature of stress prevalent across various financial markets, which is derived using the exponentially weighted moving average (EWMA) method. However, one drawback of the EWMA method is that it arbitrarily assigns the exponential smoothing parameter. This study following Polat and Ozkan (2019), overcomes the problem of arbitrary usage of the smoothing parameter by employing DCC- GARCH. This is the first study that comprehensively evaluates the systemic nature of financial stress in India by computing systemic stress indices and their usefulness in real-time assessment from an emerging market perspective.

2.2 Review of Literature

Much of the literature concentrates on the determinants and episodes of crisis limited to only one or two segments of the financial market. Among them, studies examining precursors and causes of banking distress include Demirgüç-Kunt and Detragiache (1998), C. Borio and

Drehmann (2009), Davis and Karim (2008), Kaminsky and Reinhart (1999), Logan (2000) and Hardy and Pazarbasioglu (1999). Reinhart et al. (2000) present reliable early warning signals for banking and currency crises. Other studies focusing on currency and debt crisis are Frankel and Rose (1996), Eichengreen et al. (1996), and Detragiache and Spilimbergo (2001). Nevertheless, Balakrishnan et al. (2009) contend that the above work is unsuitable for inquiring about financial crisis events as it considers only binary variables: either crisis or no crisis. Moreover, these episodes are dealt with as banking or exchange market events.

The construction of financial stress indices is, however, surrounded by complexity as there is no agreement on a single definition or method for measuring it. The literature provides alternative definitions of financial stress. Illing and Liu (2006) is an initial work on this subject. They define stress as a continuous variable with a spectrum of values, where extreme values are called crises. Morales and Estrada (2010) determine stress levels by combining bank profitability and the default probability. Grimaldi (2010) defines stress as the product of the vulnerability of markets and shocks. The stress level is determined by the interaction between financial vulnerabilities and the size of shocks. The prevalence of financial conditions is directly proportional to market vulnerability, whereby a shock may result in stress. Hakkio and Keeton (2009) describe stress as the malfunctioning of financial markets. It is characterized by great uncertainty about the fundamental value of assets, the behavior of other investors, asymmetry of information, reduced inclination to hold risky assets (flight to quality), and reduced inclination to hold illiquid assets (flight to liquidity). Holló et al. (2012) define stress in broader terms by combining friction, stress, and strains in the financial system. Cardarelli et al. (2011) define the episodes of financial stress as extreme values of a composite variable. The composite variable is derived from the number of market-based indicators. These different definitions of financial stress give rise to different problems in measuring financial stress, viz., the selection of variables, frequency of data, aggregation scheme, and the evaluation criteria to pin down a particular measure of financial stress. This complicates the task of measuring the financial stress.

The growing literature on financial stress indices embodies alternative methods of measuring financial stress and evaluation criteria for determining the usefulness of the FSI indices. In this context, the following survey provides a review of some relevant studies.

Illing and Liu (2006) constructed a financial stress index for Canada based on variables from the banking sector, foreign exchange market, debt market, and equity market. They combine variables using factor analysis, credit weights, and variance-equal weights. Hanschel and Monnin (2005) combine several banking sector variables using the variance equal method to construct a Swiss banking index. Cardarelli et al. (2011) employ variance weighted average of banking, securities, and currency markets to build a stress index for 17 developed economies. Using the same approach, Yiu et al. (2010) compute a measure for Hong Kong's economy with four financial sectors.

Hakkio and Keeton (2009), henceforth HK, derive a monthly Kansas City financial stress index (KCFSI) by applying the principal component method to eleven variables. Kliesen and Smith (2010), using the HK methodology, present St. Louis fed’s financial stress index (STLFSI). Brave and Butters (2011) applied the HK method to a hundred variables selected from the different segments of the financial market.

Another strand of literature explores the systemic dimension of financial stress. Bandt De and Hartmann (2000) define systemic risk as the risk when financial instability is so widespread that it impairs the functioning of the financial system, resulting in a loss in the output. Holló et al. (2012) rely on this notion of systematic stress and use the portfolio theoretic aggregation approach, which considers the time-varying cross-correlation between sub-indices. They propose a composite indicator of systemic stress (CISS) for the Euro area using data from different market segments: equity, bond, money, forex markets, and financial intermediaries. Along this line, Louzis and Vouldis (2012) and Cerqueira and Murcia (2016) construct FSI indices for Greece and Spain, respectively.

In the Indian context, Shankar (2014) estimates the financial condition index using the principal component method on thirteen financial market variables encompassing four money market variables and three variables, each from the bond market, forex market, and stock market. Subsequently, following a similar methodology, Khundrakpam et al. (2017) and Roy et al. (2015) construct the financial condition index using principal component analysis to identify early warning signals. Guru (2016) builds a financial sector stress index (FSSI) using the PCA method by combining three segment-specific indices: currency, banking, and stock markets. However, none of the studies accounted time-varying nature of stress prevalent across different financial markets. The present study incorporates the systemic nature of financial stress in constructing FSIs and assesses their usefulness in real-time assessment.

2.3 Data and methodology

The variables selected capture vital features of financial stress, covering all four segments of the financial market: banking, equity, foreign exchange, and bond markets. The monthly data are used over the period January-2001 to October-2018. The data set is collected from the Center for Monitoring the Indian Economy (CMIE) economic outlook and Reserve Bank of India databases. The details about the sources of the data are given in Appendix I. The following section provides an economic rationale for choosing variables as a representative indicator of the stress in each market segment. At the outset, Table 2.1 provide an outline of various variables used by some important studies in the construction of FSI. The characteristics of the variables are mentioned in Table 2.2.

2.3.1 Selection of variables

2.3.1.1 Banking Sector

There is no standard definition of a banking crisis as institutions differ across countries, and also, due to the unavailability of suitable data, it is difficult to define. Among others, Demirgüç-Kunt and Detragiache (1998) identify a crisis if any one of the four conditions holds: (i) non-performing assets exceed 10 percent, (ii) cost of bank rescue being at least 2 percent of GDP, (iii) extensive bank runs (iv) large scale nationalization of banks due to banking problems. While Vila (2000) considers the banking crisis in terms of a fall in the large bank equity price. The following variables are selected to represent the stress indicator of the banking sector.

i) Beta of the banking sector

The literature suggests the use of the banking sector beta for measuring banking stress (among others, Balakrishnan et al. 2009, Park and Mercado 2013). The banking sector β is considered a measure of risk attributed to banking-specific events. The stress in the banking sector is calculated as follows:

$$\beta = \frac{cov(r,m)}{var(m)}, \tag{2.1}$$

Where r and m are total returns to the Nifty banking index and Nifty market index, respectively. If $\beta > 1$ means the banking sector exhibits relatively more stress than the market over the past twelve months.

ii) Bank credit

The boom periods witness the rapid expansion of domestic credit, making the system more vulnerable to shocks. Therefore, several studies consider the credit variable a key early warning indicator to detect the possibility of a system-wide financial crisis. Misina and Tkacz (2009), Alessi and Detken (2018), and Geršl and Jašová (2018) use credit-based variables as early warning indicators to identify distress in the banking sector. Hanschel and Monnin (2005) and

Louzis and Vouldis (2012) use both market and balance sheet data for bank credit. The monthly changes in the bank credit are used as one of the indicators in the FSI index.

iii) Spread between Certificate of Deposit and 15-91 days T-bills

Another indicator of the banking sector stress is the spread between the certificate of deposit (CD) and 91 days T-bills. During financial stress, the spread is found to be more catholic as investors prefer risk-free T-bills. The higher spread, therefore, signifies flight to liquidity and flight to quality on account of heightened financial stress in the market.

2.3.1.2 Equity market

A significant and rapid decline in the equity market index suggests uncertainty and weak fundamentals across the market stocks, which signify the market-wide equity crisis.

i) Equity volatility

The higher volatility in the market index reflects more stress in equity markets. The relevant studies use a different method to measure volatility (see Grimaldi 2010 and Duca and Peltonen 2011). The volatility is measured as a standard deviation of the Nifty 50 index over a 2-month rolling window.

ii) Stock-bond correlation

The Stock-bond correlation variable is found to be decisive during normal times but turns out negative in high-stress periods. This time-varying correlation in the periods of uncertainty represents the flight to quality phenomenon (see, Hakkio and Keeton, 2009 and Andersson et al., 2008). The stock-bond correlation between 10-year government bond return and equity market index-Nifty return is considered in Holló et al. (2012) and Hatzius et al. (2010).

2.3.1.3 Foreign Exchange market

The literature broadly defines a foreign exchange crisis as a situation in which the following events are observed: a significant currency devaluation, a loss of international reserves, and a substantial surge of interest rates. Frankel and Rose (1996) define a currency crash as a nominal depreciation of the currency by at least twenty-five percent. Sachs et al. (1996) specify the necessary conditions for the currency crisis: an overvalued real exchange rate and low international reserves. Patel and Sarkar (1998) and Illing and Liu (2006) consider the exchange rate CMAX as an indicator of crisis, as defined below. The exchange rate CMAX and change in the international reserve are used as variables of the foreign exchange market stress.

i) Exchange rate CMAX

The literature on international finance considers the exchange rate *CMAX* as a measure of exchange rate volatility. It is the ratio of the exchange rate at time t to the maximum exchange rate over the last year. It is calculated as:

$$CMAX_t = \frac{x_t}{max[x \in (x_{t-j} \ \ j=0,1...,T)]} \tag{2.2}$$

where x_t is the exchange rate between INR and the US dollar at the time t and T is the moving window of 12 months.

ii) Changes in the international reserve

The central banks typically maintain a certain level of foreign exchange reserve as an insurance buffer against abrupt foreign currency turmoil. Therefore, any significant changes in the reserves can indicate heightened stress in the currency market.

2.3.1.4 Bond market

The spread between risky and risk-free bond yield is the most common indicator of a debt crisis. The spread is a function of expected losses, and it diverges when the expectations of future losses increase. Hence, the spread is considered an important indicator of heightened stress in the bond market.

i) Inverted term spread

The spread between a 10-year government yield and a 15-91 days Treasury bill rate is considered to proxy interest rate shocks (among others, Illing and Liu 2006). The equilibrium interest rate is defined as the long-run yield on government bonds, and when the short-term interest rate rises above the long equilibrium yield, it produces a negative yield curve. The negative yield scenario indeed suggests significant stress in the bond market.

ii) Spread between commercial paper rate and Treasury bill rate

In times of market stress, usually, the demand for commercial papers falls as creditors prefer more liquid instruments like treasury bills, indicating lower liquidity with increased uncertainty in the financial market. Therefore, the spread between the commercial paper rate and the 15-91-day treasury bill rate is used as a proxy variable for the credit crunch (see, Kliesen and Smith 2010).

2.3.2 Methodology

2.3.2.1 Transformation of variables

The foremost step in the construction of an FSI is putting all individual raw stress indicators on a common scale. The two methods for standardization, namely, normal standardization (NS) and cumulative distribution function (CDF), are used. The NS approach assumes that the variables under consideration are normally distributed. The standardized indicator, y_t is obtained using its sample mean $\bar{x}$ and standard deviation σ as follows:

$$y_t = \frac{(x_t - \bar{x})}{\sigma} \tag{2.3}$$

In the second method, the CDF normalizes the variables by transforming the observations of each series into their respective empirical CDFs[1]. The CDF is calculated as follows: First, the observations in the data set are arranged in ascending order such that the ordered sample denoted by $x_{[1]} \leq x_{[2]} \leq \ldots. \leq x_{[n]}$. The rank is assigned to each realization of x_t. The data are then transformed as z_t on their empirical CDF, as:

$$z_t = \begin{cases} \frac{r}{n} & for\ x_{[r]} \ \leq \ x_t,\ r = 1,2, \ldots, n-1 \\ & 1\, for\ x_t \geq \ x_{[n]} \end{cases} \tag{2.4}$$

where x_t is the original variable, z_t is the transformed series, *r* is the ranking number of x_t and *n* the number of observations in the sample.

2.3.2.2 Aggregation method

Four different aggregation methods are used to generate FSI indices. These methods are variance equal weights, principal component method, exponentially weighted moving average (EWMA), and dynamic conditional correlation (DCC)-GARCH.

i) Variance-equal weight-based index

The variance-equal method assumes that the variables under consideration are normally distributed. The name variance-equal is due to the use of the normal standardized variables, and the average of those standardized variables is called the variance-equal weight series. The above-mentioned nine representative variables are used to derive this index.

ii) Principal component analysis (PCA) based index

[1] Inverted CDF is calculated for bank credit, stock-bond correlation, changes in international reserve and inverted term spread

This method combines the normal standardized variables into a single index by forming a linear combination of each variable. In doing so, it captures the common information set from the variables. The index is obtained first, applying the PCA method to the variables, and then based on the results of cumulative variance, the number of principal components is selected. Four principal components are selected as they capture around 62 percent of the information of the data set. The Eigenvalue represents the variance accounted by each component in the total variance. The weighted average of Eigen value with indicator loadings of each variable produces the weight, and the FSI index is derived.

iii) The systemic stress index based on the exponentially weighted moving average (EWMA)

Hollo et al. (2012) proposed the composite index of systemic stress (CISS) by modeling time-varying cross-correlations among sub-markets using the exponentially weighted moving averages (EWMA) method. This index uses the CDF to transform the variables. The computation of CISS is explained as follows:

$$CISS=(w \circ s_t) \times C_t \times (w \circ s_t)' \qquad (2.5)$$

where $w = (w_1, w_2, w_3, w_4, w_5,)$ are the weights of sub-index vector[2] and $s = (s_1, s_2, s_3, s_4, s_5,)$ are the vector of submarket Indices. The product $(w \circ s_t)$ is the Hadamard-product matrix in time t, and $(w \circ s_t)'$ is the transpose matrix. The C_t is the matrix of time-varying cross-correlation coefficients $(\rho_{ij,t})$ between sub-Indices i $(i = 1,2,3,4)$ and j $(j = 1,2,3,4)$. The C_t the matrix is expressed as:

[2] Hollo et al (2012) derived the weight from the impulse responses of output to shock to submarket index using VAR models. We consider equal weight to each submarket.

$$C_t = \begin{pmatrix} 1 & \rho_{12,t} & \rho_{13,t} & \rho_{14,t} & \rho_{15,t} \\ \rho_{21,t} & 1 & \rho_{23,t} & \rho_{24,t} & \rho_{25,t} \\ \rho_{31,t} & \rho_{32,t} & 1 & \rho_{34,t} & \rho_{35,t} \\ \rho_{41,t} & \rho_{42,t} & \rho_{43,t} & 1 & \rho_{45,t} \\ \rho_{51,t} & \rho_{52,t} & \rho_{53,t} & \rho_{54,t} & 1 \end{pmatrix} \tag{2.6}$$

The time-varying cross-correlations ($\rho_{1j,t}$) are estimated with variance ($\sigma_{i,t}$) and covariance ($\sigma_{ij,t}$) as:

$$\rho_{ij,t} = \sigma_{ij,t}/\sigma_{i,t}\sigma_{j,t} \tag{2.7}$$

The volatility ($\sigma^2{}_{i,t}$) is derived as the weighted exponentially moving average (EWMA) of the previous period volatility and the square of demeaned sub-indices ($\tilde{s}^2{}_{i,t}$) as[3]:

$$\sigma^2{}_{i,t} = \lambda\sigma^2{}_{i,t-1} + (1-\lambda)\tilde{s}^2{}_{i,t} \tag{2.8}$$

The covariance ($\sigma_{ij,t}$) is derived as the weighted exponentially moving average (EWMA) of previous period covariance and the product of demeaned sub-indices ($\tilde{s}_{i,t}\tilde{s}_{j,t}$) as:

$$\sigma_{ij,t} = \lambda\sigma_{ij,t-1} + (1-\lambda)\tilde{s}_{i,t}\tilde{s}_{j,t} \tag{2.9}$$

Hollo et al. (2012) assumed that the weight (λ) in equations (8) and (9) is constant. They consider a 0.93 value for λ in deriving CISS. Here, 0.75 is used as the study uses monthly data, as in Huotari (2015).

iv) The systemic stress index based on the dynamic conditional correlation model (DCC)

The CISS method uses the EWMA model, where λ is an ad-hoc selection and does not reflect the information content of the underlying data. To overcome this problem, the multivariate GARCH model, DCC-GARCH methodology proposed by Engle (2002), is used to derive the

[3] The demeaned sub-Indices are computed by subtracting their theoretical mean of 0.5.

composite index of systemic stress. As a first step in the computation of the index, all variables are transformed with the CDF. In the second step, the sub-market index is calculated as the arithmetic average of the representative transformed variables of each sub-market. In the third step, time-varying conditional correlations of sub-indices are obtained using the DCC-GARCH method. Lastly, the FSI index is derived by multiplying all four sub-index with equal weight.

The DCC model for multivariate time series (r_t) is expressed as:

$$r_t| =_{t-1} \sim N(0, D_t R_t D_t) \tag{2.10}$$

$$H_t = D_t R_t D_t \tag{2.11}$$

where R_t represents the time-varying conditional correlation matrix and is defined by a definite matrix Q_t as:

$$R_t = diag\{Q_t\}^{-1}\, Q_t diag\{Q_t\}^{-1} \tag{2.12}$$

$$D_t^2 = diag\{\omega_i\} + diag\{\kappa_i\} \circ\ r_{t-1}r_{t-1}' + diag\{\lambda_i\} \circ D_{t-1}^2 \tag{2.13}$$

This expresses the assumption that each series follows a univariate GARCH process. Equation (10) provides the assumption of normality, giving rise to a log-likelihood function. Engel (2002) shows that the log-likelihood function that maximizes the parameters can be expressed as:

$$L = -\frac{1}{2}\sum_{t=1}^{T}(n\, log(2\pi) + 2\, log|D_t| + r'\, D_t' D_t' r_t - \varepsilon_t'\epsilon_t + log|R_t| + \epsilon_t' R_t'\, \epsilon_t) \tag{2.14}$$

Once time-varying conditional correlations, C_{t} between each pair of sub-market indices are estimated, then the FSI index is obtained as follows:

$$FSI = (w \circ s_t) \times C_t \times (w \circ s_t)' \quad (2.15)$$

2.4 Assessing financial stress index

This section provides an assessment of the derived FSI indices and their usefulness for India. The performance of the FSIs is assessed by mapping them with known periods of past episodes of financial stress. The FSIs are examined to see whether the peaks in the index always occur with known financial stress. Alternatively, we assess to what extent the index would trace the known crisis events during the sample period. Illing and Liu (2006) compared the index to match the Bank of Canada's internal survey to determine the stressful events for the Canadian financial system. Various stress periods are identified for India after going through RBI's various quarterly review report on macroeconomic and monetary developments.

The four constructed FSIs series are plotted in Figures 2.1 to 2.4. It can be seen that the sharpest spike in all the indices was seen in the 2008s global financial crisis. The variance-equal and PCA-based FSIs indexes locate a few stress episodes and have an overly volatile behavior. Further, these two FSI show significant stress at the end of the sample, which is not identified with any known stress periods, undermining the usefulness of these FSI as an indicator of financial stress. The PCA-based FSI does not show any spike around recent events like demonetization in India, while equal variance-based FSI shows a relatively minor peak vis-à-vis the EWMA and DCC-based FSIs. On the other hand, all the spikes of the EWMA and DCC FSI series in the figures are associated with the stress events in the Indian economy. This is because the computation of the EWMA and DCC FSIs uses the time-varying information of the correlations of different markets. Consequently, the EWMA and DCC FSIs index are seen to trace all the known systemic events, as evidenced in Figures 2.3 and 2.4. An assessment of the FSIs on their ability to trace the identified events is provided below.

The first stress episode in the sample data is identified around the second half of 2005 when crude oil prices surged from US $ 33.7 per barrel in March-2004 to US $ 60.9 per barrel in March-2006. The oil shocks in an emerging country like India, where the oil consumption is entirely imported, often create substantial stress on the supply-side decisions of an economy. However, this stress episode is captured only by the EWMA and the DCC-based FSI.

The next and the most stressful event in the entire sample is the global financial crisis, which originated in the US sub-prime mortgage market and is appropriately mapped by all the FSIs. Initially, India's financial markets remained relatively resilient. However, with a rapid rise of default in the US sub-prime mortgages and losses in the credit market, the turmoil was deepened, and it spilled over to other asset markets and then to the world financial market. As the crisis unfolded rapidly, the Indian financial markets started witnessing immense pressure from the first quarter of 2008-09. This onset of the crisis is efficiently captured by only DCC FSI, as seen in panel a of Figure 2.5. It further intensified, especially after the collapse of Lehman Brothers in mid-September 2008. This is observed as an abrupt spike in all FSIs in Figures. In tandem with the trends in major international financial markets, the Indian equity markets also declined, Rupee depreciated, and yields softened in the government securing market, RBI (2008-09, Q3). However, the Indian financial markets recovered sooner than their counterparts and recorded improvements from the first quarter of 2009-10, RBI (2009-10, Q2). This early sign of recovery is reflected in DCC FSI as in panel a of Figure 2.5. The moderation in the economy lasted in the subsequent period with a minor stress event around October-2009 due to a 2G scam, which led to the cancelation of hitherto allocated spectrum licenses. In a nutshell, beginning from the second quarter of 2009 until the Greece debt crisis, there was a moderation period in the financial market with a minor spike related to the 2G scam. This assessment can be mapped only with DCC and EWMA FSIs in Figures 2.3 and 2.4, the period which is shown as a valley with low and stable index values of FSIs.

The next significant peak in all FSIs can be traced to the beginning of the European debt crisis from the second quarter of 2011, RBI (2011-12, Q2), and since then, the Indian equity and currency markets witnessed a volatile period as shown fluctuations in the Figures of DCC and EWMA. This period could be accounted for down gradation of the sovereign rating of nine Euros which intensified the global financial market stress. The European turmoil exerted pressures on the domestic currency and equity markets until the third quarter of 2011, RBI (2011-12, Q3). After that, taking cues from a favorable international environment, EWMA and DCC FSI signaled a steady decline in financial stress until March-2012. The EWMA and DCC FSI surged again on account of the re-emergence of the Euro area debt crisis, increasing volatility in the Indian markets in the early first quarter of 2012-13, RBI (2012-13, Q1). Again, the beginning of recovery is well traced in DCC FSI as in panel b of Figure 2.5. This volatile period is also fuelled by the development of the domestic political economy, the unearthed coal scam in September-2012.

A sharp, abrupt increase in DCC FSI is seen in the month of May-2013, while EWMA captures it a month later, as in panel c of Figure 2.5. The global markets witnessed renewed turbulence following the US Federal Reserve's signal to taper off the quantitative easing program. This unusual move led to the reversal of the global interest rate cycle triggering bond sell-offs across the global markets. The Indian financial markets also witnessed intense pressure due to outflows in debt and equity markets, amounting to ₹ 522 billion and ₹ 116 billion, respectively[4]. The rupee also depreciated by 7.5 percent[5], RBI (2013-14, Q1). In September 2013, the

[4] Between May 22 and July 24, 2013.
[5] Between May 22 and July 15, 2013.

decision by the US Fed to continue its pace of asset purchases calmed the markets, following which Rupee strengthened and the Indian equity market turned around, RBI (2013-14, Q2). The next spike in all FSIs except the principal component was observed in November-2016 due to twin shock-demonetization, and the unanticipated US presidential election results impacted domestic financial markets. Table 2.3 provides a snapshot of the number of times each FSIs index traces the identified stress period of the financial market.

Overall, an assessment of event identification and the behavior of the FSIs suggests that only the EWMA and the DCC FSIs track all major stress episodes. However, the DCC FSI even captures the minor events and reverts to the normal periods, locating the stable and unstable periods accurately.

2.5 Conclusion

The global financial crisis was a bitter reminder of the spillover effects of financial turmoil on emerging market economies. The aftermath of the event shows the adverse repercussion effect of the crisis on the real economy. It is, therefore, imperative for policymakers to monitor the prevailing level of financial stress across the market.

This chapter computes the stress indices of Hollo, Kremer, and Lo Duca (2012) by using two different methods for computing a time-varying cross-correlation matrix, the EWMA, and the DCC-GARCH. The derived indices are evaluated with other popular financial stress indexes, equal-variance weighting, and principal component weighting in tracing stress events. The results suggest that the derived FSI indices, mainly the DCC-GARCH FSI, locate all the major and minor events efficiently. It also detects the evolution of stress and revision to normal periods correctly, which other alternative indices do not demonstrate.

Table 2.1: Summary of Various Financial Stress Index Variables

Indicators	**Illing & Liu, (2006)**	**Hakkio & Keeton (2009)**	**Cardarelli et al., (2011)**	**Holló et al., (2012)**	**Duca & Peltonen (2011)**
Banking sector beta	✓		✓		
Time-varying stock volatility: GARCH(1,1)			✓		
Change in stock index			✓		
TED spread		✓	✓	✓	✓
Two-year swap spread		✓			
Idiosyncratic volatility of bank stock prices		✓		✓	✓
Cross-section dispersion of bank stock returns		✓			
Stock bond correlation		✓		✓	
Stock market volatility				✓	✓
Government bond volatility				✓	✓
Euro interbank offered rate volatility				✓	
10-year interest rate swap spread				✓	
Inverse price-book-ratio				✓	
The corporate bond yield spread	✓	✓	✓	✓	
CMAX of equity market index	✓			✓	
Covered interest rate differential	✓				
Bid-ask spread on 90day government treasury bill	✓				
CMAX of exchange rate	✓				
Bank bond yield spread	✓				
Commercial paper spread	✓				
Inverted yield curve	✓		✓		
Time-varying exchange rate volatility: GARCH(1,1)			✓		
Implied volatility of overall stock prices (VIX)		✓			
Exchange rate volatility				✓	✓

Table 2.2: Financial Market Variables Included in the FSI

Financial Market	Variable	Characteristics of Chosen Variables
Banking sector	Bank beta	Uncertainty about fundamentals, flight to liquidity, flight to quality
Banking sector	Change in bank credit	Uncertainty about fundamentals
Banking sector	Spread between Certificate of Deposit and 15-91days T-bills	Flight to liquidity, flight to quality
Equity market	Equity volatility	Flight to quality, flight to liquidity
Equity market	Stock bond correlation	Flight to quality
Foreign exchange market	Exchange rate CMAX	Uncertainty about fundamentals, flight to liquidity, flight to quality
Foreign exchange market	Change in international reserves	Uncertainty about fundamentals
Bond market	Inverted term spread	Flight to quality, flight to liquidity
Bond market	Spread between commercial paper rate and treasury bill rate	Increased asymmetry of information, flight to quality

Table 2.3: Summary of Financial Stress Periods

Events / Series	Rise in Crude oil Prices	Global Financial Crisis	2G spectrum Scam	Euro-Debt Crisis	Coal Scam	Fed tapering	Demonetiz ation
Equal Variance		✓		✓			✓
PCA		✓		✓			
EWMA	✓	✓	✓	✓		✓	✓
DCC-GARCH	✓	✓	✓	✓	✓	✓	✓

Source: Authors' compilation

Figure 2.1: The Financial Stress Index for India Using Variance-Equal Weights

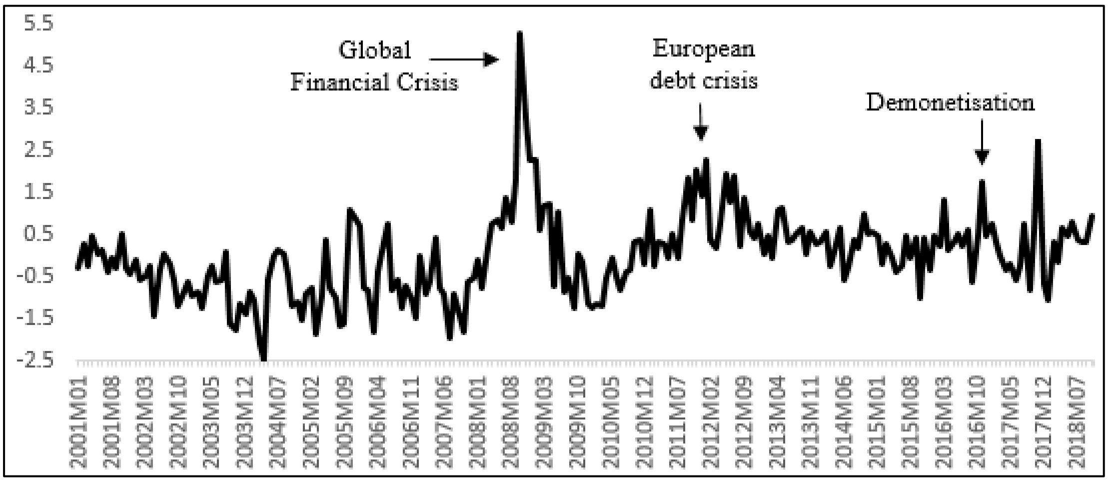


Figure 2.2: The Financial Stress Index for India Using Principal Components

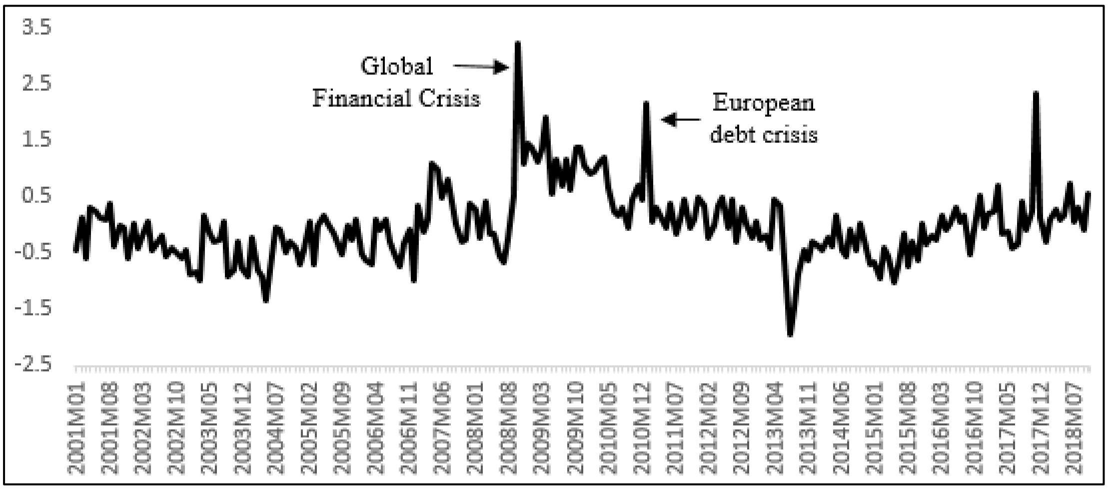


Figure 2.3: The Financial Stress Index for India Using EWMA

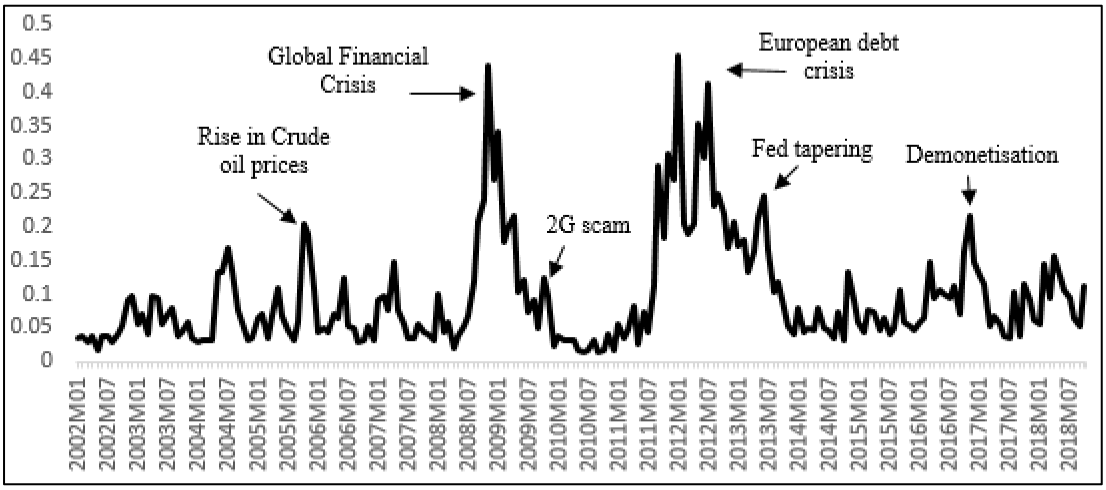


Figure 2.4: The Financial Stress Index for India Using DCC-GARCH

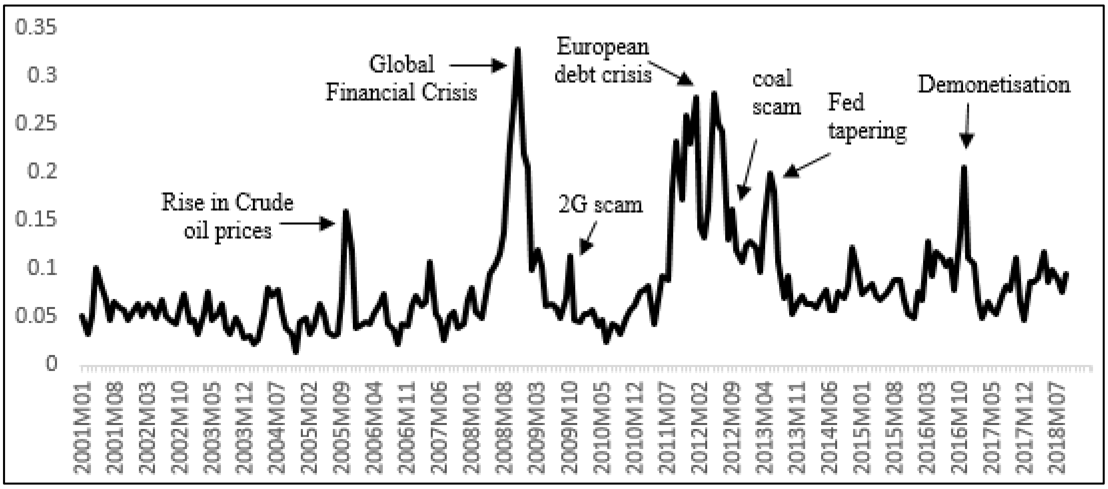
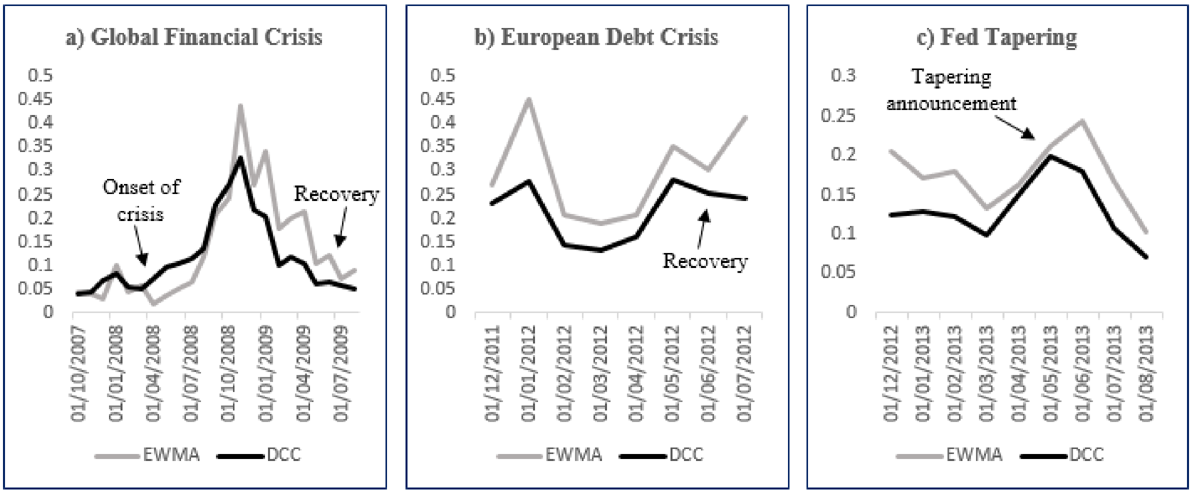


Figure 2.5: Comparison of EWMA and DCC FSIs in Tracking Stable and Unstable Periods



CHAPTER 3

ASYMMETRIC EFFECTS OF MONETARY POLICY AND FINANCIAL ACCELERATOR

3.1 Introduction

The present chapter contributes to the literature on the nonlinear impact of monetary policy during low and high financial stress in the case of India. Furthermore, the study shows that the financial accelerator mechanism proposed by Bernanke and Gertler (1989) and Bernanke et al. (1996) amplifies and propagates shocks to the real economy.

To measure the asymmetric effects of monetary policy, a threshold vector autoregression (TVAR) model is estimated. Specifically, the effects of expansionary and contractionary monetary policy shocks and the magnitude of such shocks in low and high-financial stress regimes are analyzed. Financial stress is measured through the financial stress index (FSI). This FSI is a compressive stress measure based on different financial variables. It is derived from the dynamic conditional correlation-generalized autoregressive conditional heteroscedasticity (DCC-GARCH) method (see, Holló et al. 2012). The obtained FSI is used in the TVAR estimation as the threshold variable that endogenizes the regime-switching to study the asymmetric effects of monetary policy in different stress periods.

3.2 Review of Literature

Early literature has addressed the link between the financial sector, the real economy, and the transmission of monetary policy shocks (Friedman and Schwartz 1963; Brunner 1968). Subsequently, many studies empirically examine the effect of monetary policy on the real economy (Peersman and Smets 2001; Smets and Wouters 2002; Friedman and Kuttner 1990, 1992; Kashyap et al. 2016; Ramey 1993). These studies mainly explored the linear relationship. The literature also emphasizes that monetary authorities should act swiftly when financial stress is high, possibly before it becomes a full-blown economic crisis (Baxa et al., 2013). Several empirical studies have stressed this issue and developed the Financial Stress Index (FSI) to measure the development of financial stress in the system (see Brave and Butters 2011; Hakkio and Keeton 2009; Holló et al. 2012; Illing and Liu 2006). However, most research in this area has focused on investigating the effect of financial stress on the macroeconomy using linear models (see, for example, Hakkio and Keeton 2009; Cevik et al. 2013; Park and Mercado 2013; Mallick and Sousa 2013). These studies ignored regime-switching and the nonlinear effect of monetary policy shock. Some studies explored nonlinear interactions between economic activity, monetary policy, and financial stress (Balke, 2000; Calza and Sousa, 2005; Li and St-Amant, 2010; Evgenidis and Tsagkanos, 2017). These studies provide evidence of the asymmetric effects of monetary policy on the economy.

The literature covering the asymmetries in this relationship is scarce but growing. In an early contribution, Bernanke and Gertler (1989) present the role of the borrower's balance sheet in economic fluctuations where adverse shocks have a larger impact than positive shocks. Azariadis and Smith (1998) construct a model in which the economy can switch endogenously between financially constrained and unconstrained regimes, and these regime transitions display asymmetric responses to shocks.

Empirical studies have also corroborated the results derived from the theoretical models. Among them, Alessandri and Mumtaz (2017) compare linear and nonlinear VAR models and find that regime-switching models outperform linear models. Regarding methodological frameworks, regime-switching models have become an increasingly popular tool. Li and St-Amant (2010) used the TVAR model to study the propagation of monetary shocks using Canadian data. The analysis reveals an asymmetric effect on output where expansionary shocks have a larger effect on output in high-stress than low-stress regimes. Likewise, Fry-mckibbin and Zheng (2016) find similar financial regime-dependent results when they examine the impact of monetary policy in the US.

The empirical research emphasizes the importance of interest rates in propagating monetary policy shocks to the economy. In this regard, Garcia and Schaller (2002) and Kaufmann (2002) suggest that monetary policy shocks during financially stressful times disproportionately reduce consumption, investment, and thereby economic output.

In the Indian context, the focus of the related literature is confined to linear relationships to examine the propagation of monetary policy shocks in the real economy. For instance, Khundrakpam (2011) and Pandit and Vashisht (2011) analyze the operation of the credit channel of policy transmission and find it to be an important countercyclical tool to boost the economy. Patra and Kapur (2012), Khundrakpam (2012), and Mohanty (2012) investigate the interest rate channel and find it to have a significant negative impact on output growth, whereas Aleem (2010) and Bhaumik et al. (2011) find credit to be the relevant channel. This bulk of the research fails to capture the asymmetries involved during bouts of higher financial stress and the varied effect of monetary policy shocks on the real economy, which is different from the normal period.

3.3 Methodology

3.3.1 Data

The dataset is collected from the Reserve Bank of India (RBI) database and the Center for Monitoring the Indian Economy (CMIE) economic outlook database. The details about data sources are given in Appendix I. The sample consists of monthly data spanning from January 2001 to June 2021. This sample period includes high-financial stress periods like the Global Financial Crisis of 2008 and the European Debt Crisis of 2010. The variables included in the study are as follows: Industrial Production Index (IIP) as a measure of real economic activity;

Consumer Price Index (CPI) as a measure of inflation; Weighted Average Call Rate (WACR) as a proxy for policy rate; Financial Stress Index (FSI) as a measure of financial stress. The Financial Stress Index (FSI) employed is computed using the DCC-GARCH method. All variables in the estimations are log-transformed except WACR and FSI.

3.3.2 TVAR model specification and estimation

The asymmetric effects of monetary policy shocks in the low and high financial stress regimes are assessed by a structural threshold vector autoregression (TVAR) model. Among the class of nonlinear models, Markov switching models impose a Markov chain in regime-switching; therefore, the state variable is not directly observable. These models restrict the regime-switching to be exogenous. Another alternative is a nonlinear logistic smooth transition VAR, where the regimes are not necessarily determined by the switching variable itself but rather by the asymmetric interactions among the variables (Evgenidis and Tsagkanos, 2017; Fry-Mckibbin and Zheng, 2016). To overcome these limitations, we select the TVAR model as it allows an endogenous variable to switch regimes due to shocks to other variables and itself. Secondly, it is simple to model nonlinearities like asymmetry, regime-switching, and the existence of multiple equilibria (Balke 2000). We specify FSI as a nonlinear propagator of shocks modeled using TVAR:

$$Y_t = A^1 Y_t + B^1(L)Y_{t-1} + (A^2 Y_t + B^2(L)Y_{t-1})I(c_{t-d} > \gamma) + \varepsilon_t \qquad (3.1)$$

where Y_t is a vector containing endogenous variables, $B^1(L)$ and $B^2(L)$ are lag polynomial matrices and ε_t is disturbances. c_{t-d} is the threshold variable (i.e., FSI) that determines the regime of the system depending on threshold value γ. $I(c_{t-d} > \gamma)$ is an indicator function that equals 1 if $c_{t-d} > \gamma$ and otherwise 0. The time lag d is set to 1. The TVAR model reports the evolution of both Y_t and financial stress regimes as c_{t-d} is a function of the financial stress index and also an element in Y_t. It signifies that shocks to IIP, henceforth output, CPI, henceforth inflation, policy rate, and financial stress index can determine if the economy moves to a high financial stress regime. In addition to $B^1(L)$ and $B^2(L)$ changing across regimes, the structural contemporaneous relationships between variables, i.e., A^1 and A^2 can also change. A^1 and A^2 are assumed to have a recursive structure with casual ordering: output (y), inflation (π), policy rate (i), and financial stress index (f).

In the TVAR model, the Y_t a vector containing endogenous variables is given by $Y_t = [y_t\ \pi_t\ i_t\ f_t]$ representing the interest rate channel. This recursive ordering is in line with the VAR literature, implying that monetary shocks are shocks to the policy rate that affect output and inflation after a lag. It also signifies that these shocks affect the financial stress index contemporaneously. The lag length of the endogenous variables is determined using the Bayesian Information Criterion (BIC) and is set to one.

We test the significance of the estimated TVAR model relative to a linear VAR model. This test procedure is by Hansen (1999), where a Likelihood Ratio (LR) test compares the covariance matrix of each computed model.

$$LR_{ij} = T[\ln(\det \hat{\Sigma}_i) - \ln(\det \hat{\Sigma}_j)] \tag{3.2}$$

where $\hat{\Sigma}_i$ is the estimated covariance matrix with i regimes and i-1 thresholds.

Table 3.1 displays tests of a linear VAR against a TVAR model. The test presents p-values and critical values. As can be seen, the results reveal strong evidence against linear VAR and support in favor of the existence of a threshold for FSI.

A TVAR model is estimated by least squares (LS). These estimators jointly minimize the sum of squared errors. γ is assumed to be in the set $\tau = [\gamma_1, \gamma_2]$, where τ covers the sample range of the threshold variable. The concentrated sum of squared residuals is a function of γ, $\hat{\gamma}$ minimizes $S_n(\gamma)$, and is identified as:

$$\hat{\gamma} = argmin_{\gamma \epsilon \tau} S_n(\gamma) \qquad (3.3)$$

The estimated threshold value decides the state of the economy. When FSI is higher than this threshold value, the economy is in a high financial stress regime; when FSI is lower than the threshold value, the economy is in a low financial stress regime. The estimated threshold value for FSI is 0.097. Figure 3.1 plots the FSI and its estimated threshold value. It can be seen that all major stress events are found above the threshold value. This threshold value clearly distinguishes high-stress periods like the Global Financial Crisis of 2008-09, the European Debt Crisis of 2010 and its re-emergence in 2012, the Demonetization in November 2016, and the outbreak of the Covid-19 pandemic in April 2020. Therefore, this threshold value is useful in identifying high-stress periods and enables us to examine the monetary policy effect on the real economy in different regimes.

3.3.3 Nonlinear impulse response function

To gain insight into the asymmetric reactions to monetary policy shocks in low and high financial stress regimes, we compute nonlinear impulse response functions (Balke 2000; Koop et al. 1996). Here, the system can switch regimes and are history-dependent. A shock to the policy rate generates changes in the threshold variable, i.e., FSI, inducing regime-switching over the forecast horizon. This regime-switching makes the impulse response functions sensitive to the initial condition and nature of the shock, such as its size and sign.

The nonlinear impulse response function for a pre-specified forecast horizon k is the change in the conditional expectation of Y_{t+k} due to an exogenous shock ε_t and the past information set Ω_{t-1}, represented as:

$$E[Y_{t+k}|\Omega_{t-1}, \varepsilon_t] - E[Y_{t+k}|\Omega_{t-1}] \qquad (3.4)$$

In equation (3.4), the first term specifies that the conditional expectation of Y_{t+k} is dependent on the past information set Ω_{t-1} and an exogenous shock ε_t. The second term shows the conditional expectation of Y_{t+k} is independent of the exogenous shock ε_t. Also, at a time, single exogenous shock effects are examined, and the value of an i^{th} element in ε_t i.e., ε_t^i is set to a specific value. ε_t^i can trigger regime switch conditional on the past information, size, and direction of the shock. The conditional expectations $E[Y_{t+k}|\Omega_{t-1}, \varepsilon_t]$ and $E[Y_{t+k}|\Omega_{t-1}]$ are simulated by randomly drawing residuals, ε_{t+j}, $j = 1$ to k of the estimated TVAR. The simulation is conditional on the initial state, Ω_{t-1} and sequence of shocks ε_t. It is repeated 500 times to eliminate asymmetry due to sampling variation in the drawing ε_{t+j} and the average gives an impulse response function.

3.4 Results and discussion

3.4.1 Monetary policy practice in India

The primary objective of the Reserve Bank of India (RBI) is to maintain price stability along with the objective of economic growth. The changing domestic and global environment made RBI operationalize the Liquidity Adjustment Facility (LAF) in June 2000. In this system, the repo rate served as an instrument to inject liquidity, while the reverse repo served to absorb liquidity. It efficiently enabled RBI to stabilize money markets. Under this system, the overnight call money rate is a principal instrument to covey the monetary policy stance. Later, in 2016, RBI adopted an inflation-targeting monetary policy framework. In this, a Monetary Policy Committee (MPC) is constituted to determine the policy rate (repo rate) required to contain inflation within the tolerance band. The operating procedure of monetary policy continues to be liquidity management, and WACR remains the operating target. The committee announces the repo rate, and WACR is anchored around it through liquidity management.

In the following sections, we analyze nonlinear impulse response analysis obtained from the estimation of the TVAR model. These responses are used to examine the effects of contractionary and expansionary monetary policy shocks in the low and high-financial stress regimes. The regime-switching responses correspond to policy rate (WACR) shocks with one and two standard deviations and positive and negative signs. The positive sign shocks are related to contractionary shocks, and the negative sign shocks are related to expansionary shocks.

We also compare the magnitude of the effect between responses of large (two SD) and small (one SD) monetary policy shocks in both regimes. The comparison is made by scaling down the impulse response functions of large shocks by a factor of two. The following subsection discusses the results of monetary policy shocks.

3.4.2 Monetary policy shocks

Figure 3.2 presents the monetary policy transmission in the low and high financial stress regimes. It shows the nonlinear impulse responses of inflation and output to a one-time policy rate shock over a twelve-month horizon. The impulse response of output to policy rate shocks is heavily regime-dependent and noticeably larger in the high financial stress regime. Furthermore, two standard deviations (SD) contractionary shock reduces output by 2.2% in the high financial stress regime and 1.1% in the low financial stress regime. A two-SD expansionary shock increases output by 0.23% and 1% in the fourth month in the low and high financial stress regimes, respectively. In response to a rise in policy rates, inflation reduces insignificantly (0.06%) in the low financial stress regime. However, it reduces by 0.5% in the high financial stress regime, which is persistent even in the twelfth month.

It is also observed that the magnitude of the impulse responses of large (two SD) and small (one SD) monetary policy shocks in both regimes are not significantly different.

3.4.3 Financial accelerator effect

The financial accelerator effect described by Bernanke and Gertler (1989) and Bernanke et al. (1996) suggests that during the heightened stress period, the borrowers' net worth is low, and the external finance premium (EFP) is high. An expansionary monetary policy at this time results in a significant increase in asset prices that translate into higher borrower net worth, lower EFP, and amplified output. To validate this financial accelerator effect, we examine the impulse response of EFP to one SD shock to the policy rate. The EFP is the spread between the bank lending rate and the 3-month T-bill rate. This spread measures the premium that borrowers have to pay when they raise funds from the banking system (see Bernanke et al. 1999).

Figure 3.3 presents the impulse response of EFP to an expansionary policy shock. The results clearly show that an expansionary policy shock of one SD reduces EFP significantly. Strikingly, the EFP reacts so much that a decline in EFP in a high financial stress period is about ten times more than a reduction in a low financial stress regime. Thus, it confirms the existence of the financial accelerator effect, due to which output response to an expansionary policy shock is more pronounced in high financial stress periods.

Overall, the above results provide evidence of asymmetric effects of monetary policy shocks between low and high financial stress regimes, summarized as follows:

i. A contractionary monetary policy shock reduces output to a larger extent in the high financial stress regime than in the low financial stress regime. This finding is consistent with Blinder (1987) that tightening monetary policy during a credit constraint regime may substantially affect output but a weak effect when credit is abundant.
ii. An expansionary monetary policy shock increases output in both regimes but is higher in the high-financial stress regime. This observation is consistent with the emergence

of a stronger financial accelerator effect during heightened financial stress periods (Bernanke and Gertler, 1989; Bernanke et al., 1996).

3.4.4 Robustness checks

Several alternative specifications are estimated to check the robustness of the results. First, a TVAR model is estimated by changing the ordering of the variables. The policy rate WACR is ordered first in the vector of endogenous variables. By doing so, we imply that in the post-crisis period, the policy rate is unlikely to respond to macroeconomic or financial conditions contemporaneously. Second, a TVAR model is estimated using an alternative financial stress index for India using an exponentially weighted moving average (EWMA) method. The main results of these analyses are robust to the above cases. The obtained robustness results after changing the ordering of the variables and results using alternative EWMA-based FSI are reported in Figures 3.4 and 3.5, respectively. It is observed that a contractionary monetary policy shock reduces output to a larger extent in the high financial stress regime than in the low financial stress regime. An expansionary monetary policy shock increases output in both regimes but is higher in the high-financial stress regime. Moreover, inflation has a muted response in the low financial stress regime but is persistent in the high financial stress regime.

3.5 Conclusion

This chapter examines the asymmetric effects of monetary policy during low and high-financial stress regimes and its impact on the Indian economy. A TVAR model with FSI as a threshold variable is estimated to capture the nonlinear impulse responses of the model to monetary policy shocks. This exercise obtained substantial evidence of threshold effects related to financial stress conditions in the economy, implying that linear models may not appropriately record the effect of monetary policy shocks on the real economy. Consistent with this finding, the empirical results establish asymmetric effects of monetary policy with switching financial stress regimes. The obtained results are robust to changing the ordering of the variables and using an alternative FSI index in the TVAR estimations.

More specifically, contractionary and expansionary monetary policy shocks have a stronger effect on output in the high financial stress regime than in the low financial stress regime. These results provide strong evidence of the propagation of the financial accelerator mechanism being pronounced during a high financial stress regime. The financial accelerator effects are validated using a proxy variable for external finance premium. It considerably reduces to an expansionary policy shock in the high financial stress regime than in the low financial stress regime. Furthermore, inflation has a muted response in the low financial stress regime but is persistent in the high financial stress regime. Further, a different magnitude of shocks is found to have proportional effects on the real economy.

Table 3.1: Test for Threshold VAR

Test	74.39619
p-value	0.01000

Figure 3.1: Financial Stress Index and Its Estimated Threshold Value (0.097)

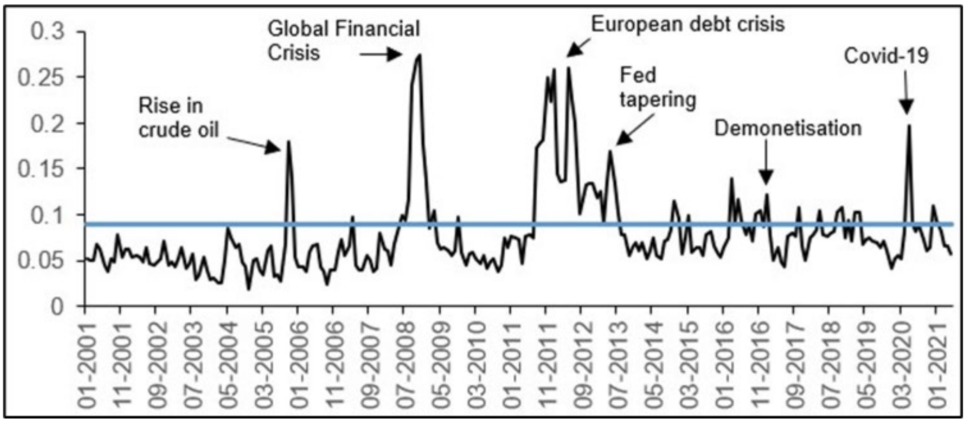


Figure 3.2: The Non-Linear Impulse Responses to Monetary Policy Shocks

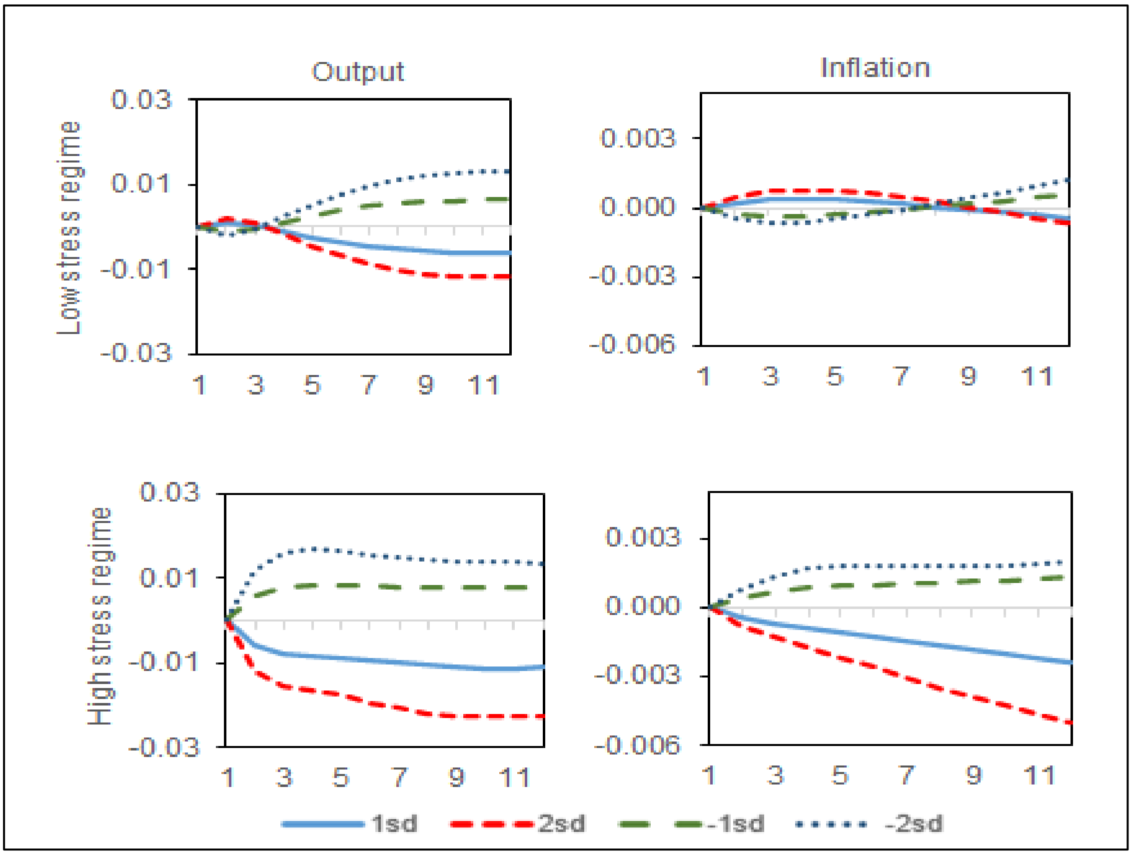


Figure 3.3: The Nonlinear Impulse Responses of External Finance Premium: Financial Accelerator Effects

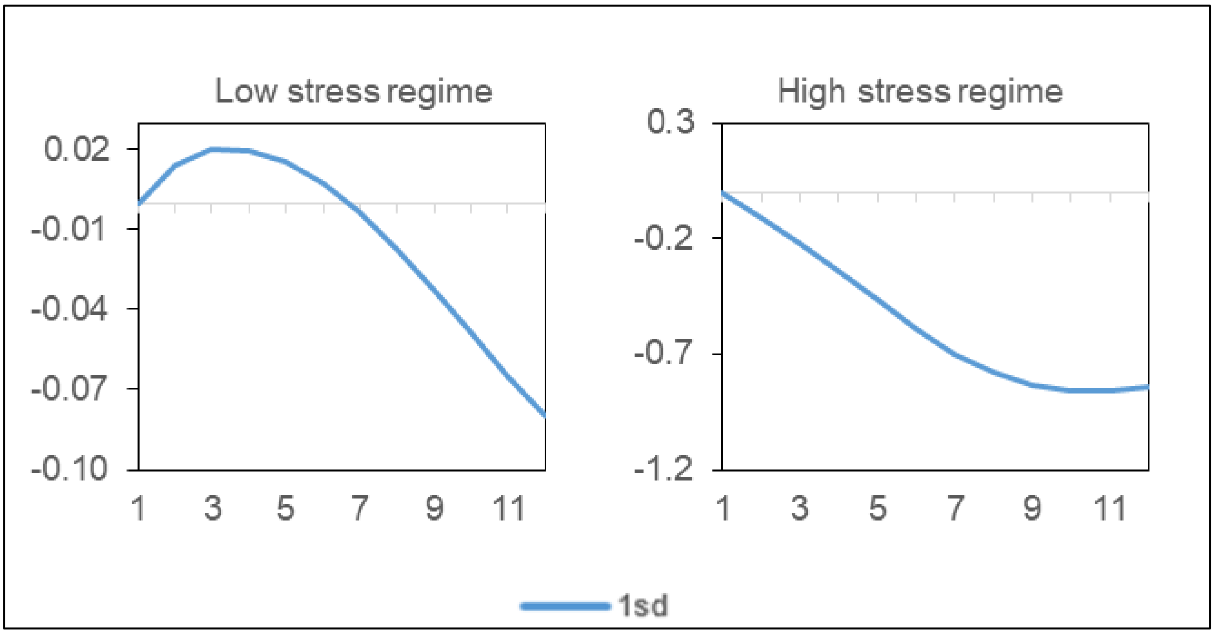


Figure 3.4: The Nonlinear Impulse Responses to Monetary Policy Shocks: Robustness Results After Changing the Ordering of The Variables

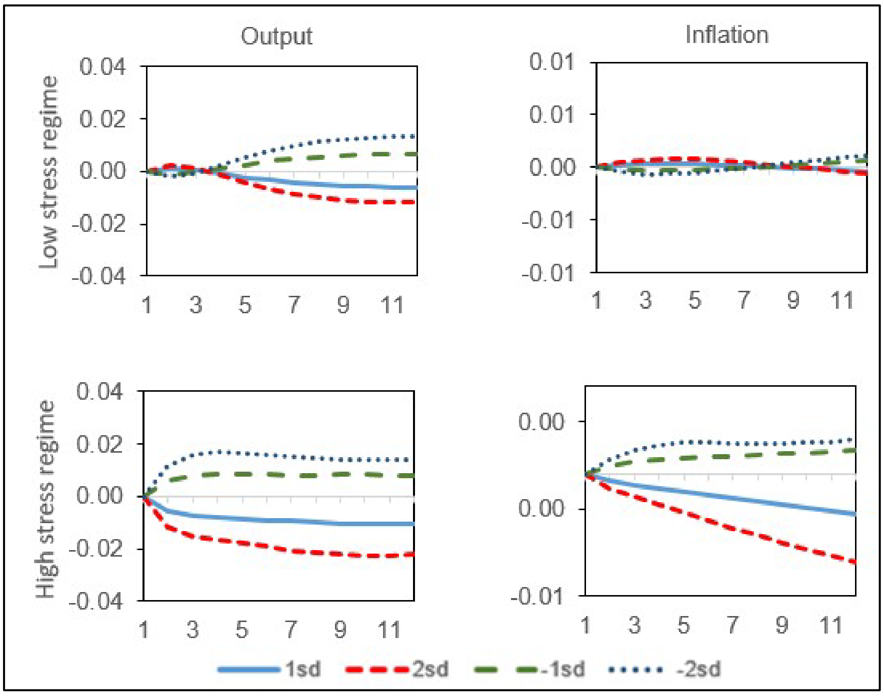
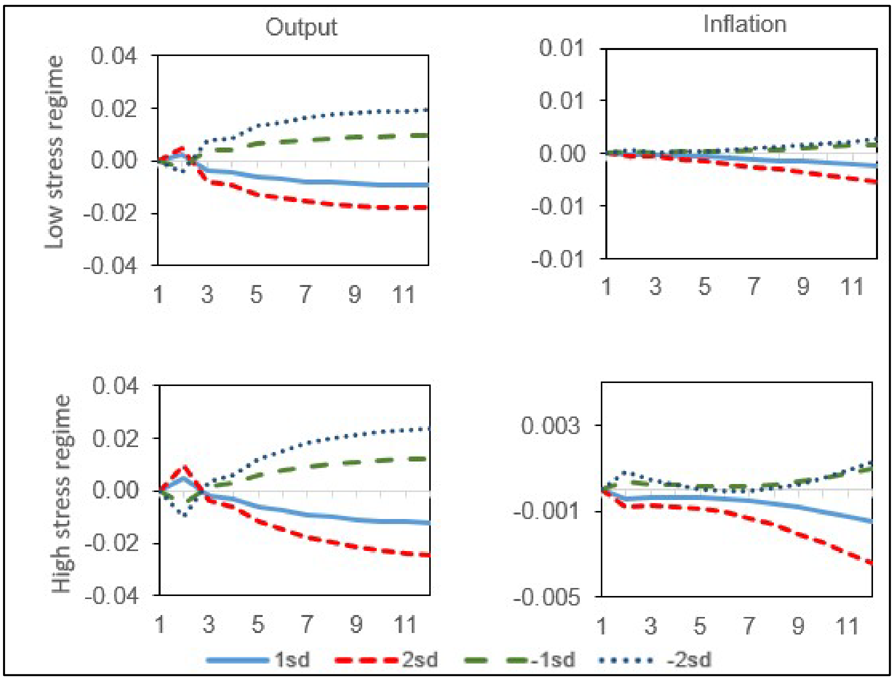


Figure 3.5: The Nonlinear Impulse Responses to Monetary Policy Shocks: Robustness Results Using Alternative EWMA Based FSI



CHAPTER 4

THE TRANSMISSION OF FINANCIAL STRESS FROM TRADING PARTNERS COUNTRIES TO INDIA

4.1 Introduction

The present chapter aims to measure macroeconomic interdependence through trade relations and financial linkages using FSI from India's top five trading partners: the United States, China, Singapore, Hong Kong, and the United Kingdom. To address this, we first understand the meaning of spillover. There are multiple notions of financial spillover in the literature. Some scholars define spillovers as cross-market movements in asset prices (Dornbusch et al. 2000), while others define cross-market linkage due to past shocks (Dungey and Martin 2007).

The chapter builds on the existing empirical literature in many aspects. Most of the literature focuses on a single or bivariate asset class and ignores multiple asset classes in the transmission of financial stress spillovers. Foremost, it uses a composite FSI estimate of financial stress covering several market segments. This enables to capture of financial stress contemporaneously and more accurately. Second, the study assesses the spillover effects of the financial stress of the trading partners on India's capital flows and trade flow. Third, it provides evidence of how emerging market economies (EMEs) like India are vulnerable to financial shocks that originated elsewhere. Also, literature on measuring spillovers effects focuses mainly on the sectors of financial markets; it largely ignores trade and financial channels that exist across countries. We attempt to fill these gaps in the case of an emerging economy, India. To study the spillovers effects, we estimate the Diebold and Yilmaz (2012) proposed VAR model of variance decomposition using country-specific FSIs.

4.2 Review of Literature

The literature defines fundamentals-based spillovers as global or local shocks transmitted across market economies through trade and financial linkages (Calvo and Reinhart 1996). There is extensive literature that investigates the factors that may explain stress spillovers. A fundamental cause is direct trade links. The crisis-hit country experiences a downturn in economic activity, causing a reduction in income and imports. The major trading partners bear the brunt of depressed exports and deteriorating trade balance (see, Caramazza et al. 2000; Claessens and Forbes 2004; Dornbusch et al. 2000). Likewise, Eichengreen et al. (1996) cover 20 industrial countries and find evidence of contagious currency crises spreading because of trade linkages rather than macroeconomic similarities. Similarly, Glick & Rose (1999) find the existence of trade linkages consistently explaining five episodes of currency crises in 161 countries between 1971 and 1997. Gelos and Sahay (2001) show the presence of direct trade links in the propagation of crises in transition economies. Gerlach and Smets (1995) explain that stronger trade integration is responsible for recurrent foreign exchange crises in Europe and has spillover effects. However, Fink and Schüler (2015) do not find evidence supporting bilateral trade driving spillovers.

Financial linkages also occupy a vital part in the transmission of spillovers. Claessens and Forbes (2004) and Dornbusch et al. (2000) find that countries suffering from the crisis have repercussions on capital flows abroad. Also, investors rebalance their portfolios to mitigate risk, thereby increasing the country’s financial vulnerability and transmitting the shock abroad by global diversification to minimize macroeconomic risks (see, Schinasi and Smith 1999; Broner et al. 2006). For instance, to reduce the increased risk subjection, investors sell assets that fluctuate or move in tandem with the assets of a crisis-hit country. G. Kaminsky et al. (2004) point towards the practice of portfolio investors selling assets from a country when prices fall in some other country. Froot et al. (2001) discuss institutional investor direct funds where prices increase and withdraw where prices reduce, acting as a shock transmission channel. Goldfajn and Valdes (1997) study the effects of a steady increase of capital inflows before the crisis and drowning out during the crisis. These findings suggest that countries are susceptible to capital outflows independent of their macroeconomic fundamentals. Caramazza et al. (2004) and Van Rijckeghem and Weder (2001) furnish empirical validation that financial linkages and capital flows amplified spillovers during the Mexican peso, Asian financial, and Russian crises. Frankel and Schmukler (2005) show Mexican crisis spread indirectly through New York financial markets to East Asian countries.

Park and Song (1999) test volatility spillovers in the currency market during the East Asian crisis and claim both trade links and institutional investor behavior in propagating the Thai crisis. Fratzscher (2003) blames a high degree of financial interdependence and real integration at the core of magnifying emerging market crises. All the above studies conclude that trade and financial link drives strong spillover.

Another body of literature finds that the US is at the epicenter of global shock transmission but remains insulated from elsewhere shocks (Antonakakis et al., 2015; Miescu, 2019). In this line, Fink and Schüler (2015) show that shocks emanating from the US cause more decline in real economic activity in emerging economies than in the US itself. In addition, Azis et al. (2020) show that the spillovers transmit rapidly to emerging countries in Asia within days.

The analysis in the literature shows that fundamental weaknesses like overvalued real exchange rates, low foreign exchange reserves, and lending booms are necessary conditions for the crisis. Further, the theoretical literature on financial crisis also emphasizes linkages among multiple asset markets, yet empirical work is directed toward modeling only one asset market at a time. Most of the empirical work is concentrated on equity markets. Balli et al. (2015), Miescu (2019), Yunus (2013), Dungey and Gajurel (2014), Dewandaru et al. (2015), and Białkowski et al. (2006) are some of the research where the financial aspect of global connectedness includes only equity market. Studies such as Eichengreen et al. (1996), Frankel and Rose (1996), Sachs et al. (1996), and Caramazza et al. (2004) involve currency crises.

Some studies investigate the bivariate relationship between two different markets. Hartmann et al. (2004) and Forbes and Chinn (2004) explore the relationship between stock and bond markets, whereas Frank and Hesse (2009) and Kal et al. (2015) explore the relationship between stock and foreign exchange markets. Alternatively, studies such as Ehrmann et al. (2011) consider multiple markets and estimate the cross-market spillovers between equity, bond, exchange, and money market within and between USA and Euro areas. Likewise, Apostolakis and Papadopoulos (2014) utilize FSI to examine financial stress spillover effects among banking, securities, and exchange markets across G7 countries. Apostolakis (2016) find significant cross-country stress spillover among Asian countries and China as the dominant stress transmitter. However, little research has been devoted to measuring spillover in various asset classes around the globe. The literature is concentrated either on different asset classes domestically or a single asset class across countries. Moreover, the literature on measuring spillovers is replete with work on financial markets. It largely ignores the linkages between real and financial sides within and across countries.

Diebold and Yilmaz (2009) provide a method for measuring return and volatility spillovers among asset markets. They provide a quantitative measure of interdependence called the spillovers index. In a subsequent paper, Diebold and Yilmaz (2012) advance this method to provide the measures of total, gross directional and net volatility spillovers. They show that cross-market volatility spillovers among US equity, foreign exchange, bond, and commodity markets and has intensified during GFC. This spillovers methodology has garnered widespread attention. Subsequently, several studies have applied this methodology to decipher various connectedness. For instance, Antonakakis et al. (2015), Miescu (2019), and Cotter et al. (2017) explored the dynamic interactions between financial and real sectors. Chow (2017), Tsai

(2014), and Yilmaz (2010) studied the equity markets, Antonakakis and Vergos (2013) for the bond market, Bubák et al. (2011), and McMillan and Speight (2010) for the foreign exchange market, Chevallier and Ielpo (2013) and Kang et al. (2017) for the commodity market and Cronin (2014) and Ribeiro and Curto (2017) for the money market.

4.3 Data and methodology

4.3.1 Data

The study selects India's five non-oil trading partners to study spillovers effects using monthly data from January 2001 to January 2018. The top trading countries in order of importance are the United States, China, Singapore, Hong Kong, and the United Kingdom. The most important trading partner is the United States, whose relative importance is unchanged in the sample period. The next major trading partner after UAE is China[6], whose position has also not changed. We compute the FSI of each trading partner's country to measure the financial stress and consider India's exports and net Foreign Institutional Investors (FIIs) to measure trade spillovers and financial spillovers, respectively. The relevant data for all sample countries are collected from Thomson Reuters Eikon, International Financial Statistics (IFS), and the Center for Monitoring the Indian Economy (CMIE). The details about the sources of data are given in Appendix I.

4.3.2 Measuring financial stress

For computing FSI, we use the variance equal weights[7] method used extensively in the research by Illing and Liu (2006), Duca and Peltonen (2011), Hanschel and Monnin (2005), and

[6] We exclude the UAE because its trade relation with India is mainly confined to the import of oils and the unavailability of data.

[7] Due to unavailability of data, we choose variance equal method as it can be applied to a small set of variables.

Cardarelli et al. (2011). This method gives equal importance to each variable. We use monthly data of five variables from each country's equity, bond, and foreign exchange markets. These variables are standardized in order to express them in the same units. It is done by deducting the mean from each variable and dividing it by its standard deviation. FSIs are then computed by taking an average of these standardized variables, hence the name variance equal weights. The selected five different variables to measure FSI are as follows.

i) The equity market consists of two variables, namely equity returns and volatility. The returns are calculated as the inverse of the year-on-year change in the equity market, and volatility is obtained by GARCH (1,1). We take the following index for equity markets: The Financial Times Stock Exchange 100 Index (FTSE 100) for the UK, S&P 500 for the US, Shanghai Stock Exchange Index (SSE) for China, Straits Times Index (SSI) for Singapore and Hang Seng Index (HSI) for Hong Kong.

ii) The bond market comprises the bond volatility of the 10-year government bond yield estimated by GARCH (1,1).

iii) The foreign exchange market comprises two variables, the exchange rate volatility estimated by GARCH (1,1) and changes in international reserves.

The FSI is then measured as:

$$FSI_t = \sum_{i=1}^{n} \omega_i \frac{x_{i,t} - \bar{x}_i}{\sigma_i} \tag{4.1}$$

where n is the number of variables in the index, ω_i is the weight of each variable, $\bar{x}_i$ is the mean of each variable and σ_i is its standard deviation.

4.3.3 Measuring financial stress spillovers effects

This study uses the methodology presented by Diebold and Yilmaz (2012), which is a generalized VAR framework of Koop et al. (1996) and Pesaran and Shin (1998), to assess the effects of spillovers. In this framework, the generalized forecast error variance decompositions are constant to variable ordering. The spillovers index represents the degree of cross-variance spillovers. It is computed as the proportion of spillovers across all asset markets to the total forecast-error variance. They also measure gross and net directional spillovers received by a specific asset market and transmitted by a specific asset market, enabling to determine the recipients and transmitters of spillovers. We estimate the VAR model for seven variables to assess the spillover effects: five FSIs of India's trading partner countries, India's exports, and net foreign institutional investors (FIIs). The estimated standard covariance stationary N-variable VAR(p) model can be represented as

$$x_t = \sum_{m=1}^{p} \emptyset_i X_{t-m} + \varepsilon_t \tag{4.2}$$

where $\varepsilon \sim (0, \Sigma)$ is a vector of independently and identically distributed disturbances. The moving average is given by

$$X_t = \sum_{m=0}^{\infty} S_m \, \varepsilon_{t-m} \tag{4.3}$$

where $S_m = \emptyset_1 S_{m-1} + \emptyset_2 S_{m-2} + \cdots + \emptyset_p S_{m-p}$ and S_0 is $N \times N$ identity matrix where $S_m = 0$ for $m < 0$.

The variance decomposition enables to forecast the proportion of the B-step-ahead error variances X_m that occur as a result of the shocks to X_m itself, where $m = 1,2 \ldots, N$. These are called own variance spillovers. Alternatively, forecasting the proportions of the B-step-ahead error variances X_m that occur because of shocks to X_n, where $m, n = 1,2 \ldots, N$, and $m \neq n$ are called cross variance spillovers. We estimate seven variables, two lags VAR model, i.e., $p = 2$, and 10-step-ahead forecasts, i.e., $B = 10$. The B-step-ahead forecast error variance decomposition, $\theta_{mn}^{c}(B)$ is given as:

$$\theta_{mn}^{c}(B) = \frac{\sigma_{nn}^{-1} \sum_{b=0}^{B-1} \left(e_m' S_b \Sigma e_n\right)^2}{\sum_{b=0}^{B-1} \left(e_m' S_b \Sigma S_b' e_n\right)} \tag{4.4}$$

where the summation is the variance decomposition matrix for the error vector ε, σ_{nn} represents the standard deviation of ε for the n^{th} equation and e_m is the selection vector taking 1 as m^{th} element or else null. It follows that the sum of the elements in each row of the $\Sigma \neq 1$ such that, $\sum_{n=1}^{N} \tilde{\theta}_{mn}^{c}(B) \neq 1$. Each entry in Σ is then standardized by the row sum as:

$$\tilde{\theta}_{mn}^{c}(B) = \frac{\theta_{mn}^{c}(B)}{\sum_{n=1}^{N} \theta_{mn}^{c}(B)} \tag{4.5}$$

It follows, $\sum_{n=1}^{N} \tilde{\theta}_{mn}^{c}(B) = 1$ and $\sum_{m,n=1}^{N} \tilde{\theta}_{mn}^{c}(B) = N$

From Σ, the total spillovers index, $V^{c}(B)$ is computed as the proportion of spillovers across variables to $\theta_{mn}^{c}(B)$, the total forecast error variance as:

$$V^{c}(B) = \frac{\sum_{\substack{m,n=1 \\ m\neq n}}^{N} \tilde{\theta}_{mn}^{c}(B)}{\sum_{m,n=1}^{N} \tilde{\theta}_{mn}^{c}(B)} \times 100 = \frac{\sum_{\substack{m,n=1 \\ m\neq n}}^{N} \tilde{\theta}_{mn}^{c}(B)}{N} \times 100 \tag{4.6}$$

The gross directional spillovers received by variable m from all other variables n, i.e., $S_{m\leftarrow}^{c}(B)$ as:

$$V_{m\leftarrow}^{c}(B) = \frac{\sum_{\substack{n=1 \\ n\neq m}}^{N} \tilde{\theta}_{mn}^{c}(B)}{\sum_{m,n=1}^{N} \tilde{\theta}_{mn}^{c}(B)} \times 100 = \frac{\sum_{\substack{n=1 \\ n\neq m}}^{N} \tilde{\theta}_{mn}^{c}(B)}{N} \times 100 \tag{4.7}$$

Likewise, the gross directional spillovers transmitted by variable m to all other variables n, i.e., $V_{\rightarrow m}^{c}(B)$ as:

$$V_{\rightarrow m}^{c}(B) = \frac{\sum_{\substack{n=1 \\ n\neq m}}^{N} \tilde{\theta}_{nm}^{c}(B)}{\sum_{n,m=1}^{N} \tilde{\theta}_{nm}^{c}(B)} \times 100 = \frac{\sum_{\substack{n=1 \\ n\neq m}}^{N} \tilde{\theta}_{nm}^{c}(B)}{N} \times 100 \tag{4.8}$$

The net directional spillovers, $V_{m}^{c}(B)$ is obtained as the deduction between gross directional spillovers transmitted to all other variables and received from all other variables as:

$$V_{m}^{c}(B) = V_{\rightarrow m}^{c}(B) - V_{m\leftarrow}^{c}(B) \tag{4.9}$$

Also, the net pairwise directional spillovers, $V_{mn}^{c}(B)$ is obtained as the deduction between the gross directional spillovers transmitted from variable m to variable n and from n to m, which is given by

$$V_{mn}^{c}(B) = \left(\frac{\tilde{\theta}_{nm}^{c}(B)}{\sum_{m,k=1}^{N}\tilde{\theta}_{mk}^{c}(B)} - \frac{\tilde{\theta}_{nm}^{c}(B)}{\sum_{n,k=1}^{N}\tilde{\theta}_{nk}^{c}(B)}\right) \times 100 = \left(\frac{\tilde{\theta}_{nm}^{c}(B) - \tilde{\theta}_{mn}^{c}(B)}{N}\right) \times 100 \qquad (4.10)$$

4.4 Empirical Analysis

4.4.1 Preliminary statistics

At the outset, we compute the summary statistics for FSIs presented in Table 4.1. The maximum stress level value of 3.32 is observed for the US, followed by 2.55 for China. Whereas the US, UK, and Singapore display the largest volatility of financial stress. FII is also found to be volatile. All the series follow a normal distribution. The Augmented Dickey-Fuller (ADF) test suggests that all the country-specific FSIs, exports, and FII series are stationary. Figure 4.1 presents the evolution of financial stress, and it is evident that the sharpest spike in the FSIs of all the countries was seen in 2008, during Global Financial Crisis. The FSIs thus identify the most stressful period, with higher values indicating increased financial stress.

4.4.2 Full sample volatility spillovers

The spillovers table represents the decomposition of the total financial stress spillovers index. It is derived from equation 4.6 and presented in Table 4.2. The mn^{th} element in Table 4.2 gives the computed proportion of the forecast error variance of variable m due to innovations to variable n. Hence, the diagonal elements ($m = n$) estimate the variance spillovers, and the off-diagonal elements ($m \neq n$) estimate cross-variance spillovers. The summation of the off-diagonal row is named "FROM" others and gives the directional spillovers received by a variable from all other variables. The summation of the off-diagonal column is named "TO" others and gives the directional spillovers transmitted by a variable to all other variables. The difference between "FROM" and "TO" gives the net volatility spillovers. Moreover, the total spillovers index appearing at the lower right corner is the grand off-diagonal column or row sum relative to the grand column or row sum, including diagonals, expressed as a percentage.

The own stress spillovers fluctuate between 33.03 percent for Singapore and 86.25 percent for exports and describe the largest share of forecast error variance. The cross-stress spillover is lower in magnitude than the own stress spillovers. For instance, shocks emanating from the US contribute 16.30 percent of the error variance in the 10-month-ahead forecasts of the UK. Likewise, shocks from China, Hong Kong, and the UK financial markets are responsible for 3.78 percent, 2.98 percent, and 1.87 percent of the error variance in exports. Similarly, Singapore, China, and the US financial markets are responsible for 9.5 percent, 7.18 percent, and 5.06 percent of the error variance in FIIs.

Now consider gross and net directional financial stress spillovers. The "directional from others" column signifies that the exports receive 13.75 percent of the forecast error variance from others, and FII receives 31.91 percent. The "directional to others" row shows that exports and FII transmit 18.04 percent and 17.13 percent of the forecast error variance to others. The net directional financial stress spillovers from exports to others are 18.04 -13.75 = 4.29 percent, and from others to FIIs is 17.13-31.91= -14.78 percent.

4.4.3 The rolling sample gross directional volatility spillovers

The full-sample financial stress spillovers table summarizes the average spillovers nature, although it misses important cyclical movements in spillovers. To study the progression of the financial stress spillovers from India's trading partners, we analyze the model with a rolling sample to capture time-variation in the financial stress spillovers indices. Accordingly, we compute financial stress spillovers using a 50-month rolling window and graphically evaluate the behavior of the time-varying financial stress spillovers using the corresponding time series of spillovers.

Figure 4.2 displays the gross directional financial stress spillovers *from* the others to exports and FII (representing the "Directional FROM others" column derived from equation 7). The financial stress spillovers differ substantially over time. The spillovers *from* trading partners to exports are below 7% during tranquil times but increase close to 13% during turbulent times (Figure 4.2(a)). A similar pattern is observed for FIIs, below 8% during calm periods and close to 14% during the volatile period (Figure 4.2(b)). The spillovers from each trading partner to exports are presented in Figure 4.3. These increased in all the countries except Singapore during Global Financial Crisis in 2007. Moreover, Singapore appears low throughout the sample period, while China displays considerable variation. Also, spillovers from the US increased at the beginning of 2011 due to the European debt crisis and then from both US and UK in 2012-13 (Figure 4.3(a) and (b)). The spillovers from the US to FII increased during the Global Financial Crisis, the Eurozone crisis, and unexpected US presidential election results at the end of 2016 (Figure 4.4(a)). The spillovers increased from the UK during 2017 on account of negotiations surrounding Brexit; Singapore transmitted it throughout the analysis period, from Hong Kong from 2008 to 2010 and China from 2011 to 2020 (Figure 4.4(b) to 4e)).

Interestingly, Figure 4.5 and Figure 4.6 present the directional financial stress spillovers from the US and China during turbulent periods and show that the spillovers to exports and FII is more prominent than in other countries. Figure 4.5 display that the spillovers from the US hovered around 20% during three phases of turmoil. The initial major phase occurred during the worst financial crisis of 2008 when exports received the largest spillovers, followed by FIIs. The year 2009 witnessed a similar trend, and the pattern reversed at the beginning of 2010 when FIIs were at the receiving end. Next, during the European debt crisis in 2010-11, exports and FIIs received most of the spillovers. The third episode occurred around November 2016, marked by unexpected US presidential election results when FIIs received significant spillovers.

This work identifies four episodes of significant financial stress spillovers from China. The first episode is when China announced the adoption of a managed floating exchange rate regime and a revaluation of the Renminbi (RMB) in 2005. Here, the FIIs were the worst hit, and exports bore the brunt. The next episode was during Global Financial Crisis when spillovers to exports jumped to 25%, and exports kept receiving massive spillovers. Again, exports received heavy spillovers throughout the Eurozone crisis from late 2010 to mid-2012. The FIIs, too, received significant volatility in the first half of 2012. The third bout of big spillovers was seen exceptionally in exports and FII from late 2013 to mid-2014 due to the slowdown in China. China recorded the lowest growth rate of 7.8% since 1999. The last episode, where the spillovers increased more than 20%, is attributable to US-China trade tension and further deceleration in China's economic growth.

We now discuss net directional financial stress spillovers and present these plots in Figure 4.7. It is derived from (equation (4.9)), which is obtained by deducting the summation of “directional spillovers from” column and the summation of “directional spillovers to” row. We also estimate net pairwise spillovers (equation. (4.10)) of trading partners with exports and FII and present them in Figure 4.8 and Figure 4.9.

A detailed analysis of net stress spillovers between trading partners and exports is provided using Figure 4.7. It is evident that the net export spillovers have been negative for the majority period, which signifies that exports have been at the receiving end (Figure 4.7(a)). From 2005 to 2020, the net volatility spillovers can be dissected into the following episodes (Figure 4.7(a)): October 2008 to February 2009, the last six months of 2010, the last six months of 2012 to early 2013, late 2014 to 2015, mid-2017 and mid-2019. The first bout of financial spillovers was witnessed during Global Financial Crisis. Until 2008, net directional spillovers never exceeded the four percent mark, but in late 2008 it reached nine percent with the failure of Lehman Brothers (Figure 4.7(a)). At this time, the bulk of the spillovers was received from the US, the UK, and Hong Kong (Figure 4.8(a), (b), and (d)).

The subsequent two periods when exports were net receivers are related to the 2010 Eurozone crisis and its re-emergence in 2012. Moreover, a slowdown in the economic recovery of the US and other advanced economies was coupled with grim global growth, RBI (2010-11, Q2). Again, the exports received net spillovers of nine percent in 2010, mainly from the US (Figure 4.8(a)). Then in 2012, the sovereign debt overhang continued to increase stress in the financial markets with the deepening crisis in Greece and Spain. Further, the LIBOR-fixing case demonstrated the vulnerabilities of the financial markets, RBI (2012-13, Q1). This time the UK was the main transmitter, and the highest spillovers from the UK were received during this period (Figure 4.8(b)).

From October 2014 to 2015, exports were net transmitters of spillovers to the US, UK, and Singapore (Figure 4.8(a), (b), and (c)). The spillovers reach the eight percent mark (Figure 4.7(a)) on account of the brewing crisis in Greece, the normalization of US monetary policy, and oil prices falling below US$ 30 per barrel, reaching a 12-year low. The bursting of the equity bubble in China led to RMB devaluation, downslides, a slump in investment, a decline in manufacturing, weak external demand, and high debt levels, which manifested a more profound weakness in the Chinese economy. This significant devaluation in RMB resulted in increased unremunerated terms of trade, RBI (September 2015).

In mid-2017, exports received five percent net spillovers due to the first round of Brexit negotiations. Figure 4.8(b) shows that most stress spillovers were received from the UK alone.

The mounting stress spillovers in mid-2019 rose from trade disputes combined with tumultuous geopolitical developments. An escalation of trade tension between the US and China, protectionist trends along with lingering uncertainty surrounding Brexit, political unrest in Hong Kong, an attack on Saudi Arabian oil facilities disrupting global supply, a sharper than-anticipated slowdown in the US and Chinese economies, and uncertainty of the monetary policy decision in the US, RBI (October 2019) resulted in exports receiving close to eight percent net stress spillovers (Figure 4.7(a)). Here, the UK, Singapore, and Hong Kong were the main transmitters (Figure 4.8(b), 4.8(c), 4.8(d)). This episode marks the highest net stress spillovers from Singapore and Hong Kong in the sample period.

The net FII spillovers plot is presented in Figure 4.7(b)). We identify four episodes of heightened spillovers to FIIs: mid-2008, 2009-2010, December-2016, and 2017 to 2019. It is evident that the net spillovers hovered around the three percent mark and jumped to fifteen percent in 2008. Here, the FIIs were the main transmitters of spillovers to the trading partners (Figure 4.9), whereas in 2009-2010, the majority of spillovers were received by FIIs from the US, Singapore, and Hong Kong. In December-2016, the net spillovers jumped close to eight percent in the wake of demonetization in India and unanticipated US presidential election results. At this time, FIIs received spillovers from the US, UK, and China. Moreover, we also find FIIs receiving spillovers from Singapore and China from mid-2019 (Figure 4.9(c), (d)). Also, FIIs were net transmitters to Hong Kong from late 2016, which peaked in August 2017 with massive pro-democracy protests.

4.5. Conclusion

This chapter investigates the transmission of financial stress spillovers from India's main trading partners through bilateral trade relations and financial linkages. We discuss two main transmission channels: a decline in export demand and capital flows. The results show that stress spillovers increase during turmoil, mainly US and China, which are key contributors. We also find evidence that exports are net receivers of financial stress spillovers throughout the analysis period. These spillovers are most significant during crisis events like GFC and European Debt Crisis. On the other hand, during GFC, FIIs are found to be net transmitters, higher in magnitude than what is received through exports. However, FIIs are net receivers during the European Debt Crisis and other episodes.

Former studies suggested that financial shocks transmitted from advanced to emerging market economies. While corroborating the prior findings, the current research finds bilateral trade relations to drive financial stress spillovers in emerging markets like India. In contrast, it also finds that capital flows exert significant spillovers and spillbacks. This indicates global financial market interdependence as emerging markets develop and demonstrate greater financial integration with developed markets.

The markets of emerging economies are highly susceptible to both upside and downside volatilities. Such a high degree of volatility exposes these markets to shocks and crises. The disruption is manifold in the presence of bilateral trade and financial globalization. The inevitable inference is that while the global economy has come a long way, it is still not sufficiently shielded against the adverse fallout of either decline in trade flow or 'sudden stops'- a sudden reversal of capital flows. To overcome this, emerging economies should strengthen their resilience by implementing macro-prudential regulations. This also calls for increased international macroprudential policy coordination to strengthen the financial system and macroeconomic stability.

Table 4.1: Descriptive Statistics

	US	UK	Singapore	HK	China	Exports	FII
Mean	0.000	0.000	0.000	0.000	-0.024	0.009	994.258
Median	-0.148	-0.115	-0.126	-0.081	-0.106	0.006	450
Max.	3.320	2.527	2.189	1.926	2.556	0.269	28630
Min.	-0.858	-1.038	-1.157	-1.002	-0.934	-0.339	-19921
Std. Dev.	0.610	0.576	0.575	0.446	0.446	0.114	3628.118
Skewness	2.404	1.721	1.235	1.161	1.131	-0.252	1.214
Kurtosis	8.300	4.044	1.897	2.448	3.749	0.367	18.306
Jarque-Bera	952.48***	291.46***	99.913***	118.32***	200.57***	4.334***	3551.9***
ADF	-3.547**	-3.504**	-3.465**	-3.651**	-3.861**	-5.450***	-5.375***

Note: ADF denotes the Augmented Dickey-Fuller test. The sample size is 229 monthly observations spanning from 01-01-2001 to 01-01-2020.
*** Significance at 1% level
** Significance at 5% level

Table 4.2: Volatility Spillovers

	US	UK	Singapore	HK	China	Exports	FII	Directional FROM others
US	33.64	17.75	15.16	12.75	13.25	4.77	2.68	66.36
UK	16.30	33.83	15.53	11.05	14.10	5.43	3.76	66.17
Singapore	19.00	8.88	33.03	22.24	9.39	3.59	3.88	66.98
HK	12.73	5.71	17.03	50.83	10.37	0.91	2.42	49.17
China	9.89	9.17	13.00	15.55	46.99	2.62	2.78	53.01
Exports	1.74	1.87	1.77	2.98	3.78	86.25	1.61	13.75
FII	5.06	4.66	9.50	4.79	7.18	0.72	68.10	31.91
Directional TO others	64.72	48.04	71.99	69.36	58.07	18.04	17.13	347.3
Directional including own	98.36	81.87	105.02	120.19	105.06	104.29	85.23	
Net spillovers	-1.64	-18.13	5.01	20.19	5.06	4.29	-14.78	(347.3/700) =49.62%

Figure 4.1: Financial Stress Indices

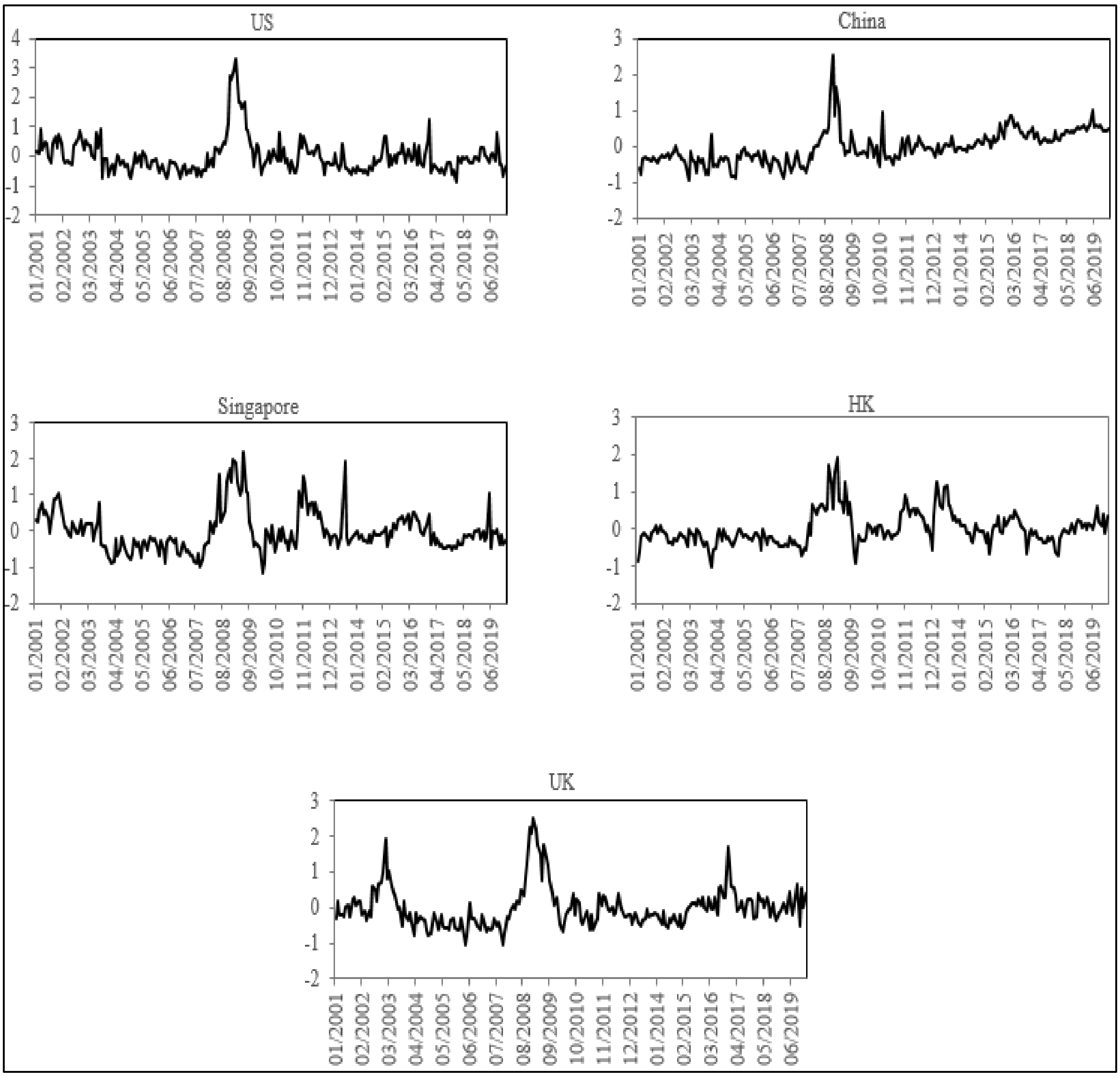


Figure 4.2: Directional Financial Stress Spillovers, FROM Trading Partners to Exports and FII

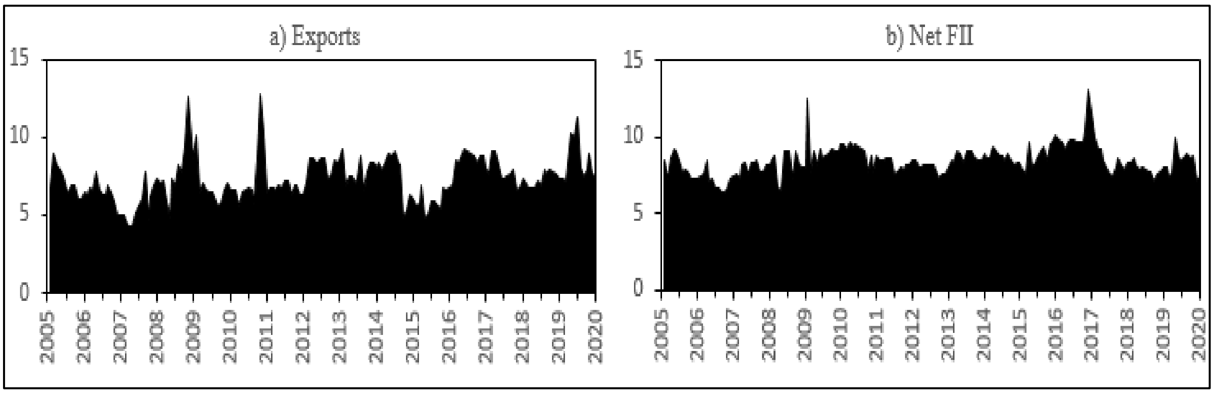


Figure 4.3: Directional Financial Stress Spillovers, FROM Each Trading Partner to Exports

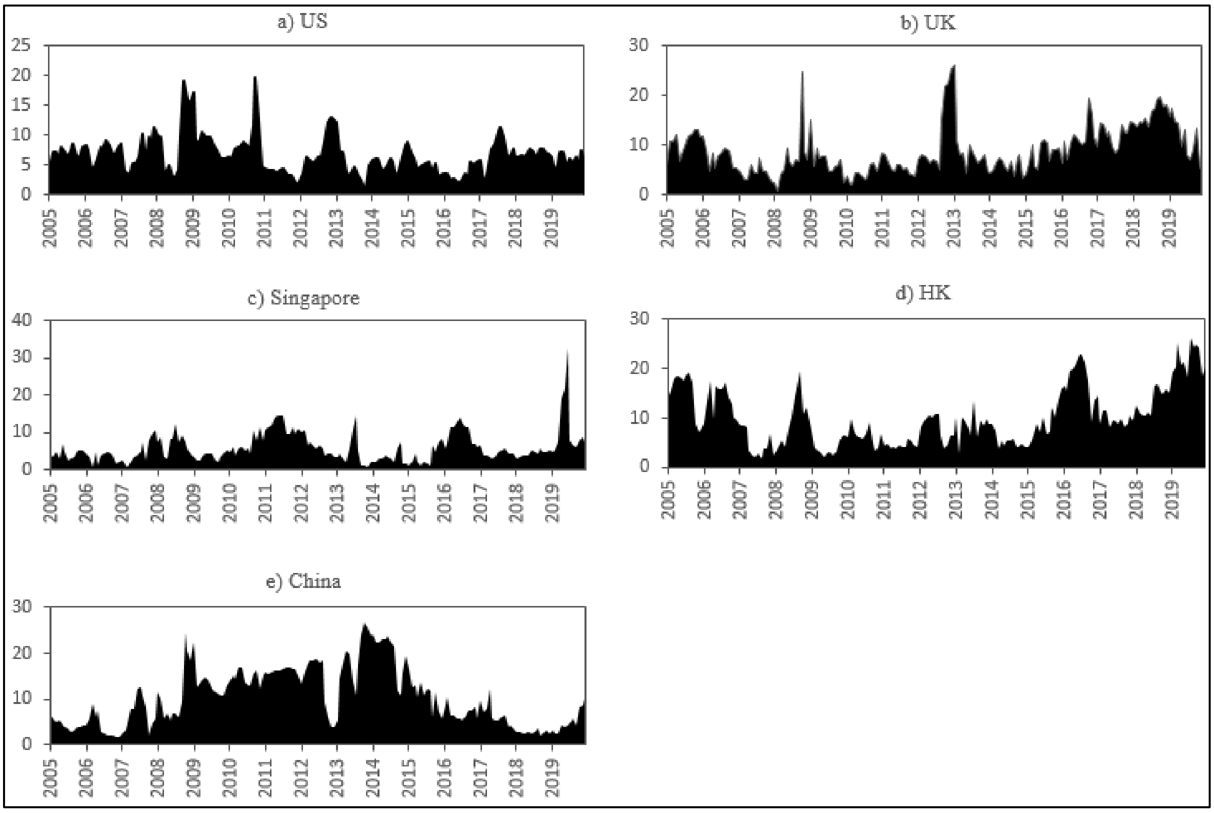


Figure 4.4: Directional Financial Stress Spillovers, FROM Each Trading Partner to FII

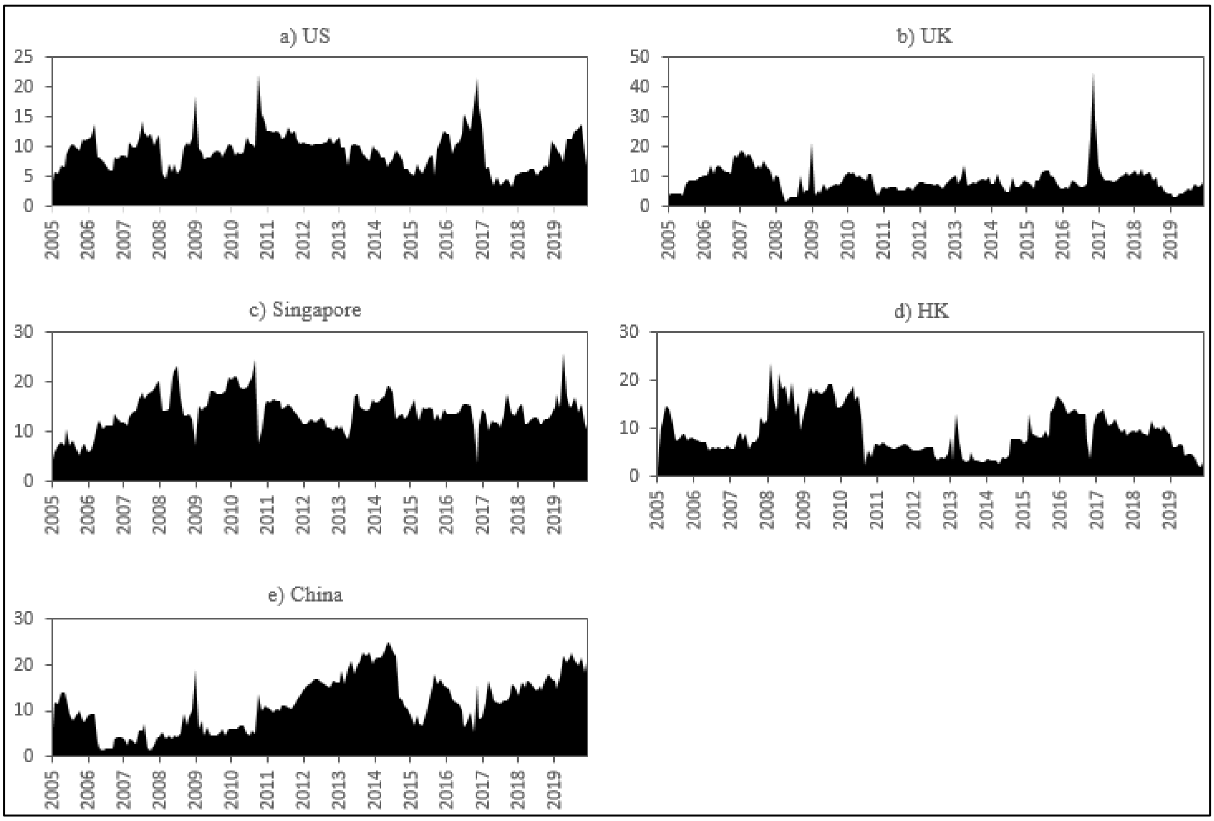


Figure 4.5: Directional Financial Stress Spillovers from the US During Turmoil Periods

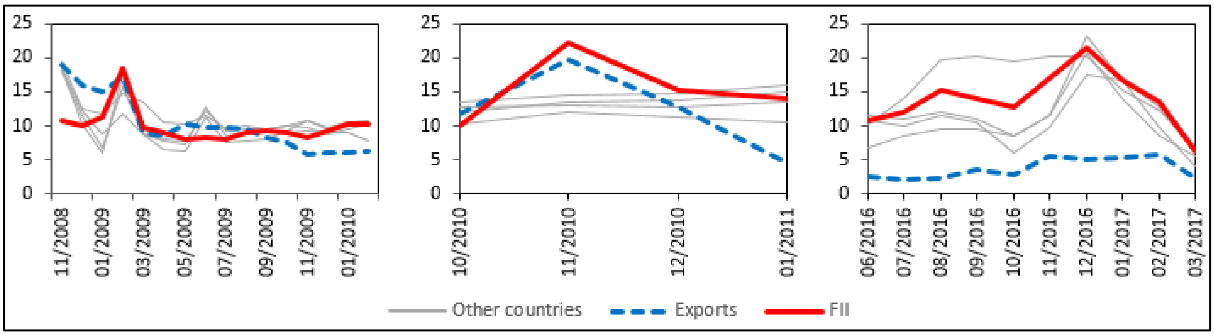


Figure 4.6: Directional Financial Stress Spillovers from China During Turmoil Periods

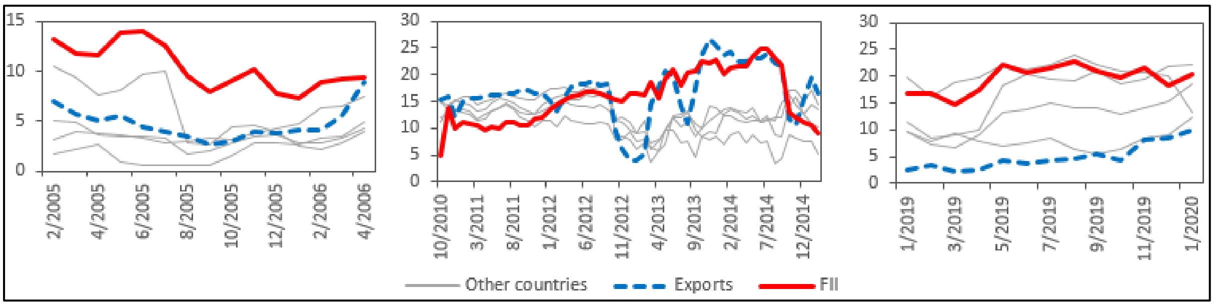


Figure 4.7: Net Directional Financial Stress Spillovers

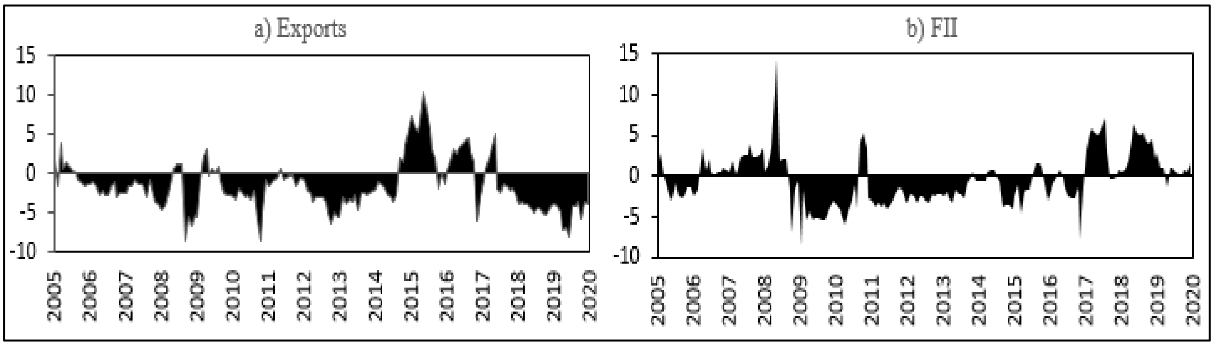


Figure 4.8: Net Exports-Pairwise Directional Financial Stress Spillovers

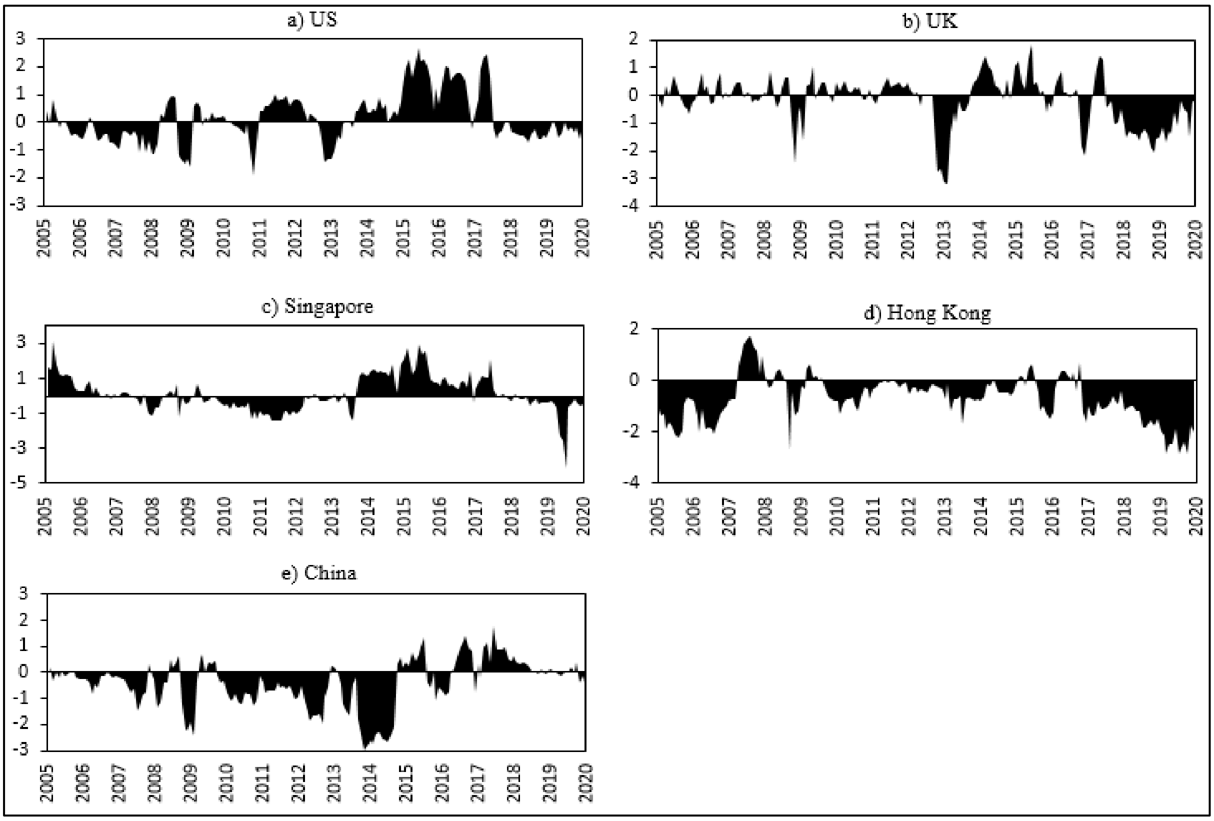
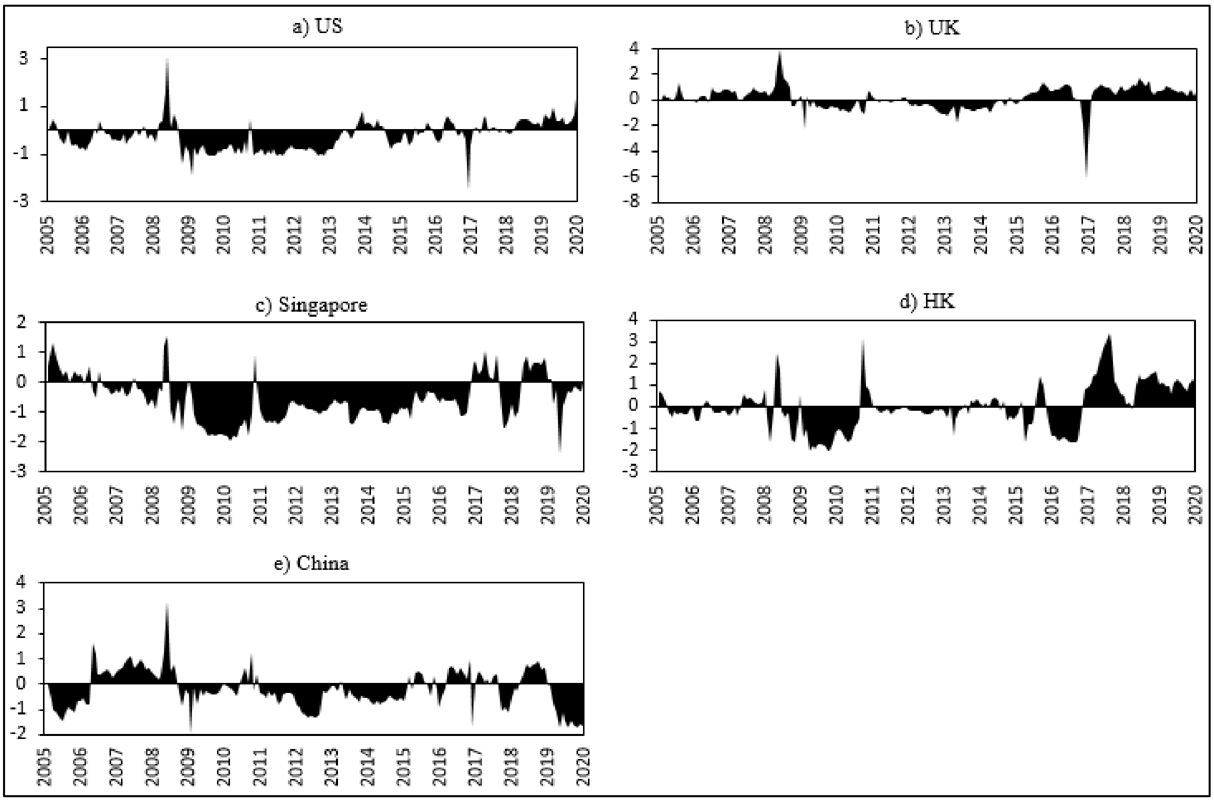


Figure 4.9: Net FII-Pairwise Directional Financial Stress Spillovers



CHAPTER 5

FINANCIAL CYCLE CO-MOVEMENT WITH MONETARY AND MACROPRUDENTIAL POLICIES

5.1 Introduction

The goal of achieving long-term financial stability prompted evaluating the build-up of cyclical financial risks and the subsequent financial crises. It has developed an increasing interest in financial cycles and their characteristics (BIS 2014). The empirical literature represents the financial cycle as a procyclical cumulative build-up of financial imbalances that cause financial booms and busts (Borio 2014). It has also been found to be a good predictor of financial crises (Alessi and Detken 2009; Borio and Drehmann 2009; Drehmann and Juselius 2013; Schuler et al. 2020; Voutilainen 2017).

The central banks began to incorporate financial stability into their monetary policy decisions. However, monetary policy alone has proved insufficient in maintaining financial stability. This prompted policymakers to renew discussions on addressing financial instability, and a consensus emerged on the need to introduce a macroprudential policy to safeguard financial stability. Macroprudential policies restrict the accumulation phase of financial imbalances and strengthen the adaptability of the financial sector to withstand crisis and their unwinding. The new paradigm aims at using both monetary and macroprudential policies for countercyclical management (Silvo 2018). The limited research on the coordination between monetary policy and macroprudential policy advocates optimum economic outcomes when these policies are co-ordinated. This makes it necessary to inspect the behavior of monetary, macroprudential policies with the financial cycle.

This chapter aims to assess the co-movement of monetary policy and macroprudential policy stance toward the financial cycle phases in India. It analyses co-movement between short-term interest rate changes, changes in time-varying risk weights, and provisioning norms of certain sectors and financial cycle phases. It also computes procyclicality ratios to analyze the negative effects of monetary and macroprudential policies, i.e., expansionary policies in the upswing phase or contractionary policies in the downturn phase.

5.2 Review of literature

The literature on the financial cycle remains considerably less explored. This literature lacks consensus on characterizing financial cycles, their definition, choice of variables, and the methods employed in construction. ~~For instance,~~ Borio et al. (2001) and Brunnermeier et al. (2009) describe the financial cycle as an enormous expansion in credit and asset prices along with liberal access to funding followed by the crisis-bearing consequences on the real economy. Another definition is from Adrian and Shin (2010) and Borio (2014a), who define the financial cycle as changing perceptions in the price of risk with a sequence of booms and busts which translate into wide financial distress, thus requiring the usage of macroprudential policies (Schuler et al. 2015). The sophistication of financial interlinkages, evolving financial system and the time lags for the crisis to become evident have made the researchers identify a set of variables. Claessens et al. (2011), Dutra (2022), and Drehmann et al. (2012) consider combinations of credit, property, and stock prices as representative variables for financial cycles.

Apart from the choice of the variable, the approach to measuring the financial cycle is also important. A sizeable literature separates trends and cycles underlying the financial cycle. The widely used methods are turning point analysis (Claessens et al. 2011), frequency-based filters (Aikman et al. 2015), and model-based filters (Galati et al. 2016; Winter et al. 2022). The main drawback of these methods is that they require an a priori presumption of the length of the financial cycle. The shortcomings of these methods have been discussed and criticized by Hamilton (2018) and Schuler et al. (2020). In recent years, spectral and wavelet analysis has increasingly become popular in economics and financial research (Crowley 2007; Mandler and Scharnagl 2022). This method overcomes the drawbacks of the above methods by capturing the time and frequency feature of the financial cycle more comprehensively and accurately (Strohsal et al. 2019; Verona 2016). It also avoids making assumptions about the length of the financial cycle.

The existing literature that characterizes financial cycles finds financial cycle variables more volatile than the traditional business cycle variables (Hiebert et al. 2014). In addition, financial cycles evolve over the medium term and are deeper, longer, and more severe than business cycles (Aikman et al., 2015). The duration and amplitude of financial cycles depend on the state of the financial sector, monetary regimes, and real economic conditions. Since mid-1980, the length and amplitude of the financial cycle have lengthened, averaging around sixteen years. It also detects the build-up of risk of a financial crisis with a lead in real-time (Borio 2014a; Drehmann et al. 2012).

The recent literature on monetary policy emphasizes the impact of monetary policy transmission channels on financial stability and the financial cycle. These channels include balance sheet and profitability, asset prices, banking liquidity, bank capital, and risk-taking channels (Beyer et al. 2017). Taylor (2007) shows that monetary policy instruments, such as low-interest rates, caused a boom followed by a bust in asset values between 2001 to 2005. Studies show that prolonged expansionary monetary policy leads to higher bank leverage and induces risk-taking behavior (Gersl et al. 2015). This is seen especially in small banks and cooperative banks. They provide loans to riskier borrowers with worse credit histories. It also encourages borrowers to take large uncollateralized loans (Ioannidou et al. 2015; Jimenez et al. 2014), resulting in rapid growth in household indebtedness (Persson 2009). Further, low-interest rates promote the search for yield making risky investments with short-term horizons attractive (Nicolo et al., 2010). The interest rates are raised only when signs of financial cycle peaks emerge (Ajello et al. 2019). Kurowski and Smaga (2018) and Smaga (2021) explore the procyclical behavior of monetary policy during different phases of the financial cycle. These studies shed light on how monetary policy decisions might lead to the accumulation of the financial cycle, stressing the need to mitigate the degree of procyclicality of the financial cycle.

This further reinforces the demand for synchronization between monetary and macroprudential decisions to manage crises. According to Igan et al. (2011), monetary policy alone is ineffective in controlling asset price boom. Similarly, Greenwood-Nimmo and Tarassow (2016) advocate that while contractionary monetary policy exacerbates financial fragility, the effect of macroprudential policy alone is ambiguous, but a coordinated approach might be effective. In this context, Aikman et al. (2015), Bean (2009), Borio (2014b), and Smets (2014) discuss the importance of macroprudential and monetary policies in managing the financial cycle and strengthening the financial sector. Moderating the financial cycle can ensure financial stability and an effective monetary policy transmission process. For this purpose, it becomes essential to address the procyclicality of the financial cycle. A number of policy options and appropriate tools have been identified, such as capital and liquidity standards, provisions, collateral and margining practices, and loan-to-value ratios (Borio 2014b; Borio and White 2004; Maddaloni and Peydro 2013). RBI (2021) documents the effectiveness of such tools in dampening credit growth in sensitive sectors in India.

5.3 Data and methodology

The dataset is collected from the Reserve Bank of India (RBI) database, the Center for Monitoring the Indian Economy (CMIE) economic outlook database, Thomson Reuters, and the Bank for International Settlements database. The details about data sources are given in Appendix I. The sample consists of quarterly data spanning over the period starting from 1990Q1-2021Q4. The variables included in the study are as follows: non-food bank credit, BSE Sensex, Weighted Average Call Rate (WACR) and time-varying risk weights and provisioning norms on the capital market, housing, consumer loans, commercial real estate and non-deposit taking systematically important NBFCs. The credit and equity variables are real-log transformed and seasonalised using the X13 method. These variables are then standardized using mean $\bar{x}$ and standard deviation σ as follows:

$$y_t = \frac{(x_t - \overline{x})}{\sigma} \tag{5.1}$$

In The literature, Hakkio and Keeton (2009) use weights from the Principal Component Analysis (PCA) to integrate variables into a composite index. We follow this method and combine the credit and equity variables of India to derive a single index. We then apply wavelet analysis on this index to compute the financial cycle for India (Aravalath 2020).

Wavelet analysis has increasingly become a popular method in economics and financial research as it provides advantages in analyzing time-varying characteristics (Gencay 2001; Ramsey 2002; Ramsey and Lampart 1998). It efficiently captures characteristics that are in the time domain and frequency domain. This time-frequency representation in wavelet analysis captures attributes over a broad horizon of frequencies like low and high frequencies (Daubechius 1992). A wavelet is a function of different scale components, which is reciprocal to the frequency parameter. Suppose the scale component expands; the wavelet stretches across the time domain, reduces the frequency component, and moves towards lower frequency. The wavelet analysis is suitable for studying a broad spectrum of time series as it allows us to assess episodes in both time and scale.

The Maximal Overlap Discrete Wavelet Transform (MODWT) method was proposed by Gencay (2001) and Percival and Walden (2000). This method can be applied to a sample size N and remains constant to alterations in the original time series. Let x be length N size. The vector of MODWT coefficients is:

$$\tilde{\omega} = [\tilde{\omega}_1, \tilde{\omega}_2, \dots, \tilde{\omega}_J, \tilde{\upsilon}_J]^T \tag{5.2}$$

Where wavelet coefficient $\tilde{\omega}_j$ is a length $N/2^j$ with a scale of length $\lambda_j = 2^{j-1}$ and scale coefficient $\tilde{\upsilon}_J$ is a length $N/2^J$ with a scale of length $2^J = 2\lambda_J$. The wavelet coefficient generates the high-frequency component called the cyclical component of the series that fluctuate around the trend. The scaling coefficient generates the low-frequency component. It represents the longest component, called the trend.

The wavelet filter is defined as:

$$\tilde{h}_j = h_j/2^j \tag{5.3}$$

The scaling filter is defined as:

$$\tilde{g}_J = g_J/2^J \tag{5.4}$$

A pyramid algorithm by Mallat (1989) is employed to compute the MODWT. The first iteration of the algorithm filters data with $\tilde{h}_1$ and $\tilde{g}_1$ to generate wavelet and scaling coefficients:

$$\tilde{\omega}_{1,t} = \sum_{l=0}^{L-1} \tilde{h}_l x_{t-lmodN} \text{ and } \tilde{\upsilon}_{1,t} = \sum_{l=0}^{L-1} \tilde{g}_l x_{t-lmodN} \tag{5.5}$$

where $t = 0,1,\dots,N-1$.

The next step of the algorithm defines the data to be the scaling coefficients $\tilde{\upsilon}_1$ from the previous step and implement the filtering operations like above to generate the next wavelet and scaling coefficients:

$$\tilde{\omega}_{2,t} = \sum_{l=0}^{L-1} \tilde{h}_l \tilde{\upsilon}_{1,t-lmodN} \text{ and } \tilde{\upsilon}_{2,t} = \sum_{l=0}^{L-1} \tilde{g}_l \tilde{\upsilon}_{1,t-lmodN}, \tag{5.6}$$

This procedure is replicated J times where $J = \log_2(N)$ and gives MODWT coefficients like equation 5.2.

Next, the study assesses the behavior of domestic policies, such as monetary policy and macroprudential policy, toward the financial cycle according to the research approach of Claessens et al. (2011) and Kurowski and Smaga (2018). They proposed to measure cycle synchronization based on changes in the levels of variables. For this purpose, expansive monetary policy when interest rates decrease. Restrictive monetary policy is when interest rates rise. An expansive macroprudential policy is defined as a period when macroprudential measures such as time-varying risk weights and provisioning norms on the capital market, housing, consumer loans, commercial real estate, and non-deposit taking systematically important NBFCs are relaxed. Restrictive macroprudential policy is the period when these measures are introduced or tightened.

The study follows Kurowski and Smaga (2018) to assess the behaviour of monetary policy and macroprudential policy toward the financial cycle. It calculates the number of observations when each policy stance (expansive or restrictive) behaves in the respective financial cycle phase (upswing or downturn).

$$PA_{s,f} = \frac{p_{s,f}}{n},$$

where PA is the policy approach in the financial cycle phase, $p_{s,f}$ represents the number of periods with policy stance 's' in financial cycle phase f, and n represents the number of periods. This exercise is carried out considering the number of periods in the financial cycle phase and the whole sample.

The study also assumes that it cannot assess the behavior of these policies toward the financial cycle along its equilibrium (trend). When the financial cycle gap is small and close to 0, it does not cause any immediate threat to financial stability. Thus, we consider financial cycle gaps that are significant and exclude the gaps within the equilibrium range. The equilibrium range consists of 30% of the minimum financial gap and 30% of the maximum financial gap in each financial cycle phase. This range is excluded from further analysis.

Additionally, as seen in Table 5.1, an expansive policy is procyclical when financial cycle gaps are positive and countercyclical when financial cycle gaps are negative. When financial cycle gaps are positive, the interest rate cut or the loosening of macroprudential policies results in the build-up of financial imbalances. When this gap is negative, expansive policy dampens imbalances, thus stimulating the financial cycle. A similar case involves when the policy is restrictive and financial gaps are positive. When the financial cycle gap is negative, the restrictive policy is procyclical.

5.4 Empirical analysis

This study defines the characteristics of a financial cycle as in Claessens et al. (2011). The main characteristics are the duration and amplitude of the financial cycle. They define the duration of an upswing, D_e, as the number of quarters, k, the financial cycle f_t takes to reach its peak after the trough. Similarly, the duration of the downturn, D_c, is the number of quarters, k, between a peak and the next trough. The amplitude of an upswing, A_e, is measured as the change in f_t from a trough (f_k) to the next peak(f_p), $A_c = f_p - f_k$. Likewise, the amplitude of a downturn, A_c, is measured as the change in f_t from a peak (f_p) to the next trough (f_k),$A_c = f_k - f_p$. The duration of the full financial cycle is measured from peak to peak. Table 5.2 provides the characteristics of the financial cycle in India. It can be seen that the average duration of the upswing is 20 quarters, and the average duration of the downturn is slightly higher at 23 quarters. The average length of the financial cycle is found to be 47 quarters. The amplitude of the downturn phase is much smaller than the upswing phase signifying that the depth of the downturn phase is smaller in India.

The chapter assesses the monetary policy and macroprudential policy stance with the financial cycle phases in two steps. First, it compares expansive/restrictive policy with the upswing/downturn phase of the financial cycle to assess the procyclical or countercyclical outcomes, as in Table 5.1. It defines monetary policy as procyclical when the expansionary stance of the policy stimulates the current upswing in the financial cycle, or the restrictive stance deepens the downturn in the financial cycle. Similarly, it defines macroprudential policy as procyclical when time-varying risk weights and provisioning norms on specific sectors are relaxed during the upswing phase of the cycle or when these measures are tightened during the downturn phase of the cycle. This leads to the build-up of cyclical imbalances in the system. Alternatively, monetary policy is countercyclical if the stance is restrictive during the financial cycle upswing or expansionary during the downturn phase of the cycle. Similarly, macroprudential policy works counter-cyclically when time-varying risk weights and provisioning norms on specific sectors are tightened in the upswing phase of the cycle or loosened in the downturn phase. This leads to the reduction of cyclical imbalances in the financial system. The monetary policy stance is observed in changes in the short-term (WACR). The macroprudential policy stance is observed in changes in time-varying risk weights and provisioning norms on the capital market, housing, consumer loans, commercial real estate, and non-deposit systematically important NBFCs.

This research provides evidence that monetary policy is, on average expansive in 70% of the financial cycle upswing phase. As can be seen from Table 5.3, the procyclicality of the policies is dominant during the upswing phase of the financial cycle. It is less visible during the cyclical downturn phase. The countercyclical policies exist during the financial cycle downturn phase than the upswing phase. On average, the procyclical stance is lower than the countercyclical stance. It may be because India is predominantly a bank-based economy with efficient monetary policy transmission. This suggests the effectiveness of monetary and macroprudential policies in shaping the financial cycle (Bauer et al., 2016).

Several conclusions can be drawn from Figure 5.1. The monetary policy stance from 1997 to 2008 is mostly procyclical. Since 1997, the monetary policy stance ensured softening of the interest rate regime with greater flexibility in the medium term. This was signaled through successive interest rate cuts in all segments of the market spectrum. For instance, the repo rate was brought down from 8.0 per cent in March 1999 to 4.5 per cent in August 2003 (RBI 2002-03). This ensured sufficient liquidity in the economy to meet additional credit requirements of the growing economy and support investment demand. From 1999 to 2005, the bank credit to the commercial sector increased from 14.5 to 27.0 percent, and scheduled commercial banks' non-food credit rose from 16.5 to 31.8 percent. The personal loans absorbed 24 percent of the additional non-food credit, and the portion of housing loans in personal loans increased to 49.4 percent. The unusual credit growth to the commercial real estate sector accelerated sharply, more than 100 percent in 2005-06 and above 50 percent till mid-2007. This has resulted in an increase in asset prices, especially real estate prices. This induced higher bank leverage and increased the risk exposure of the banking sector. Then in 2006, RBI explicitly indicated decelerating the non-food credit growth to 20 percent. The monetary tightening measures were initiated in September 2004 and continued till 2008. The repo rate was hiked to 9 per cent (RBI 2007-08).

In order to protect the bank's balance sheet, risk weights, and provisioning norms were tightened in specific sectors beginning in December 2004 to ensure asset quality (Table 4). Beginning commercial real estate was increased from 100 percent to 150 percent in May 2006, capital markets to 125 percent, and housing loans (LTV>75 percent) were hiked to 100 percent. The provisioning requirements on assets in the real estate sector, personal loans, credit card receivables, capital market exposure, and NBFCs were tightened in November 2005, May

2006, and January 2007. Simultaneously, banks were also encouraged to evaluate sectoral credit growth, especially in the above sectors. These measures made credit costlier to targeted sectors, and thus credit growth in the commercial real estate sector decelerated from 150 percent in 2005 to 50 percent by 2008. The monetary policy and macroprudential policy co-ordinated each other because the monetary tightening helped contain credit growth while macroprudential norms moderated credit growth in specific sectors.

The last quarter of 2008 to early 2012 depicts the countercyclical stance of the policies with the financial cycle phases. The transmission of the global financial crisis required policy actions to ensure the normal functioning of financial sectors, maintain financial stability, and support economic growth. The non-food credit growth shrank from 29.4 percent in October 2008 to 12.7 percent in September 2009. Bank credit to the commercial sector expanded by only 16.8 percent in March 2009. During this period, the repo rate was cut to 4.75 per cent. The countercyclical prudential measures were employed to stimulate bank lending. The provision norms and risk weights on standard assets were reduced in November 2008. Further, the real estate prices corrected lower than anticipated with potential financial stability concerns; the provision norm on the real estate sector was tightened in November 2009 from 0.4 percent to 1.0 percent. The housing prices accelerated sharply, and banks introduced new teaser loan schemes. To mitigate asset quality concerns, in November 2010, RBI increased the provision norm on standard teaser housing to 2 percent, and in December 2010, introduced a ceiling on the LTV ratio and tightened risk weight on housing loans to 125 percent. Because of supply shocks, RBI aggressively raised the repo rate, which reached 8.0 per cent by August 2011 (RBI 2011-12).

The policy stance from late 2013 to early 2016 is found to be procyclical with the financial cycle phase. This can be attributed to accommodative monetary policy to boost fragile economic activity. Moreover, a correction in the real estate sector due to subdued demand prompted authorities to reduce risk weight and provisional requirements on housing loans and commercial real estate in June 2013 and October 2015.

The policy stance turned countercyclical with financial cycle phases from 2016 to 2020. During this period, reviving bank credit and investments remained a challenge. The effects of 2016 demonetization were seen in non-food credit growth decelerating to 5.8 percent in March 2017, the lowest since 1995. Bank credit to the commercial sector also touched a significant low of 3.7 percent. The declining momentum in the real sector added to the mounting pressure of unsold house inventories. In this context, the repo rate steadily reached 6.25 per cent in June 2017, the lowest since November 2010. In June 2017 and September 2019, the risk weights and provision norms on housing and retail loans were reduced. This made banks shift loan portfolio allocations and expanded personal loan exposure. The outbreak of the COVID-19 pandemic in 2020 had an unprecedented adverse impact on the economy. Monetary policy stance continued to be accommodative to aid economic recovery, which was continuously slowing down for eight quarters. The repo rates were cumulatively brought down by 250 basis points to a significant low of 4.0 per cent in May 2020 (RBI 2019-20). The year 2021 is seen to be procyclical as RBI maintained an accommodative policy stance, and the risk weight on retail loans was reduced further. It is evident from Figure 5.1 that the monetary policy and macroprudential policy moved together throughout the sample period.

5.5 Conclusion

This chapter assesses the co-movement of monetary, macroprudential policies stance towards financial cycle phases in India from 1990-2021. For this purpose, it uses credit and equity prices to generate a financial cycle derived from the low-frequency component of wavelet analysis. The study finds that the amplitude of the downturn phase is much smaller than the upswing phase signifying that the downturn phase is milder in India.

The study assesses the co-movement of monetary and macroprudential policy stances by comparing the phases of the financial cycle with interest rate changes and changes in risk weights and provisioning norms of certain sectors. We found that the procyclicality of both policies is dominant during the upswing phase of the financial cycle. This behavior can amplify the accumulation of cyclical imbalances in the financial sector. The monetary policy and macroprudential policy coordinated each other throughout the sample period. The efficacy of macroprudential policy in the Indian financial system indicates that it is a valuable additional tool other than monetary policy in dampening the financial cycle.

Table 5.1 Monetary, Macroprudential Policy, and Financial Cycle Gap

Domestic Policy/Gap	Positive Financial Cycle gap in period *i* (Upswing phase)		Negative Financial Cycle gap in period *i* (Downturn phase)	
	Non-equilibrium range	Equilibrium range	Non-equilibrium range	Equilibrium range
Expansive in period *i*	Procyclical (accumulation of financial imbalances)	Indeterminate	Countercyclical (easing of financial imbalances)	Indeterminate
Restrictive in period *i*	Countercyclical (easing of financial imbalances)	Indeterminate	Procyclical (accumulation of financial imbalances)	Indeterminate

Source: Own work based on Kurowski and Smaga (2018)

Table 5.2 Characteristics of the Financial Cycle in India

Amplitude		Duration		
Upswing	Downturn	Upswing	Downturn	Cycle
In percent		Number of quarters		
57	-13	20	23	47

Table 5.3 Monetary and Macroprudential Policy Stance in Financial Cycle Phases

Instrument	Policy Stance	1 or 2#	Upswing	Downturn
Monetary policy	Expansive	1	0.636	0.648
		2	0.286	0.357
	Restrictive	1	0.432	0.352
		2	0.194	0.194
Macroprudential measures	Expansive	1	0.571	0.743
		2	0.214	0.464
	Restrictive	1	0.714	0.457
		2	0.268	0.286

#1: number of periods to total periods in the financial cycle phase
2: number of periods to total periods in the sample

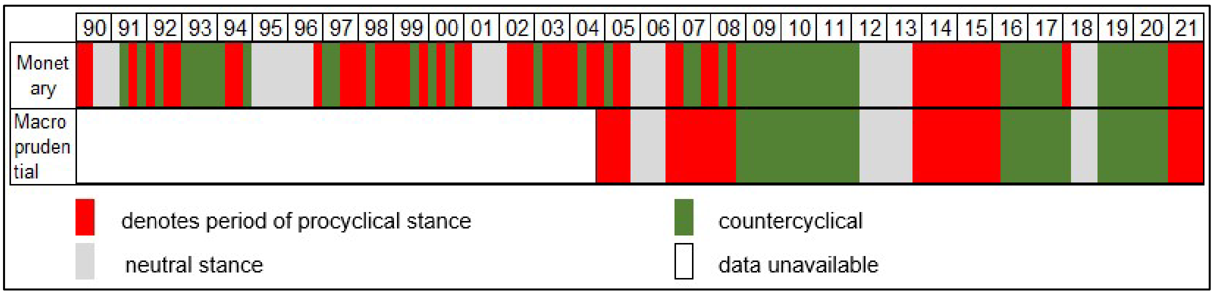
Table 5.4 Macroprudential Regulation: Variations in Risk Weights and Provisioning Norms

Date	Capital Market		Housing		Other Retail		Commercial real estate		Non-Deposit taking Systematically Important NBFCs	
	Risk Weight	Provisions	Risk Weight	Provisions	Risk Weight	Provisions	Risk Weight	Provisions	Risk Weight	Provisions
Dec-04	100.0	0.25	75.0	0.25	125.0	0.25	100.0	0.25	100.0	0.25
July-05	125.0	0.25	75.0	0.25	125.0	0.25	125.0	0.25	100.0	0.25
Nov-05	125.0	0.4	75.0	0.4	125.0	0.40	125.0	0.40	100.0	0.4
May-06	125.0	1.0	75.0	1.00	125.0	1.0	150.0	1.0	100.0	0.4
Jan-07	125.0	2.0	75.0	1.00	125.0	2.0	150.0	2.0	125.0	2.0
May-07	125.0	2.0	50.0-75.0*	1.00	125.0	2.0	150.0	2.0	125.0	2.0
May-08	125.0	2.0	50.0-100.0*	1.00	125.0	2.0	150.0	2.0	125.0	2.0
Nov-08	125.0	0.4	50.0-100.0*	0.4	125.0	0.4	100.0	0.4	100.0	0.4

Nov-09	125.0	0.4	50.0-100.0*	0.4	125.0	0.4	100.0	1.0	100.0	0.4
Dec-10	125.0	0.4	50.0-125.0*	0.4-2.0#	125.0	0.4	100.0	1.0	100.0	0.4
June-13	125.0	0.4	50.0-75.0*	0.4-2.0#	125.0	0.4	75.0@	0.75@	100.0	0.4
Oct-15	125.0	0.4	35.0-75.0*	0.4-2.0#	125.0	0.4	75.0@	0.75@	100.0	0.4
June-17	125.0	0.4	35.0-50.0*	0.25	125.0	0.4	75.0@	0.75@	100.0	0.4
Sept-2019	125.0	0.4	35.0-50.0*	0.25	100.0	0.4	75.0@	0.75@	100.0	0.4
Jan-21	125.0	0.4	35.0-50.0*	0.25	75.0	0.4	75.0@	0.75@	100.0	0.4

*: Residential Housing.
#: Increased to 2.0% in December 2010 and remained the same in June 2013 and October 2015.
@: Depends on LTV.
Source: Reserve Bank of India and Sinha (2011).

Figure 5.1 Heatmap of Monetary and Macroprudential Procyclicality



CHAPTER 6

SUMMARY AND CONCLUSION

6.1 Summary of the study

An attempt has been made in this study to examine issues relating to financial stress. The first is to construct financial stress indicators for India, the second is to measure the financial stress spillover to India, and the third is to study the behavior of the financial cycle*. For this purpose, the study outlined four objectives, constituting four empirical chapters of the thesis. We briefly summarise each chapter of the thesis below.

To fulfill the objectives, we first gained knowledge of the various aspects of financial stress. Since there is no agreed single definition or method to measure financial stress in the literature, this gives rise to different problems in measuring financial stress. It includes the selection of variables, frequency of data, aggregation scheme, and evaluation criteria to pin down a particular measure of financial stress. This complicates the task of measuring the financial stress. Thus, in Chapter 2, we comprehensively evaluate the systemic nature of financial stress for India by computing systemic stress indices and their usefulness in real-time assessment from an emerging country perspective. For this, we first identify several representative variables covering all four financial market segments, namely, banking, equity, foreign exchange, and bond market. We then use four methods to construct FSI, including frequently applied methods like equal-variance weighting and principal component analysis (PCA). We follow Hollo et al. (2012) and compute the time-varying cross-correlation matrix of sub-markets derived from the exponential-weighted moving average (EWMA) method. A drawback of this method is the usage of arbitrarily assigned smoothing parameters. To overcome this drawback, a dynamic conditional correlation (DCC)-GARCH approach is used, as employed by Polat and Ozkan (2019). The derived indices are evaluated in terms of tracing known periods of stress events. The results suggest that the derived FSI indices, mainly the DCC-GARCH FSI, locate all the major and minor events efficiently. It also detects the evolution of stress and revision to normal periods correctly, which other alternative indices do not demonstrate.

In Chapter 3, we analyze the impact of monetary policy during low and high financial stress regimes in India. The vast literature covering the linkages between the financial sector, real economy, and monetary policy transmission assumes a linear relationship. On the contrary, we measure the asymmetric effects of monetary policy during low and high financial stress. Using a threshold vector autoregression (TVAR) model, the study analyses the effects of expansionary and contractionary monetary policy shocks and the magnitude of such shocks in low and high financial stress regimes. The DCC-GARCH based FSI is used in the TVAR estimations as the threshold variable that endogenizes the regime-switching to study the asymmetric effects of monetary policy in different stress periods. The results provide evidence of threshold effects related to financial stress conditions in the Indian economy, signifying that linear models may not be suitable to analyze the impact of monetary policy in different financial stress regimes. The TVAR model consists of endogenous variables, output, inflation, call money rate, and FSI.

The results indicate that a contractionary monetary policy shock has a stronger effect on output in the high financial stress regime than in the low financial stress regime. Also, an expansionary monetary policy shock has a larger effect on output in a high-financial stress regime. This nonlinear effect of monetary policy indicates the existence of the financial accelerator effect: in high-stress times, expansionary monetary policy results in a significant increase in asset prices, translating into higher borrower net worth leading to lower external finance premium, resulting in amplified output. The study explores this effect using proxy variables for external finance premium. The results confirm that an expansionary monetary policy shock significantly reduces external finance premium. In the case of inflation, the response to monetary policy shocks is small and short-lived in the low financial stress regime but large and persistent in the high financial stress regime. Further, different magnitudes of shocks are found to have proportional effects on the real economy. These results are robust to changing the ordering of the variables and using an alternative FSI index in the TVAR estimations. Overall, this chapter provides empirical evidence on the asymmetric effects of monetary policy and the existence of financial accelerators that have significant policy implications for monetary policy conduct in India.

Toward the third objective, Chapter 4 measures financial stress spillovers from the top five trading partners to India. The nascent literature on financial stress spillovers identifies bilateral trade and financial linkages as the main transmission channels that transmit crises to other countries. To this end, this chapter analyses the transmission of financial stress spillovers from India's main trading partners through bilateral trade relations and financial linkages. The trading partners include the United States, China, Singapore, Hong Kong, and the United Kingdom. It discusses two main transmission channels: a decline in export demand and capital flows. For this purpose, the FSIs are constructed for each trading partner using five variables from equity, bond, and foreign exchange markets. The variance equal method is applied to these variables to generate a composite FSI index. Then, the framework presented by Diebold and Yilmaz (2012) is used to assess the financial stress spillovers effects. This method is a generalized vector autoregressions (VARs) where variance decomposition is constant to the ordering of variables. The estimation produces spillovers index, directional spillovers, and net directional spillovers from a particular market and to a particular market, enabling us to determine the recipients and transmitters of spillovers.

The results indicate that financial stress spillovers increase in magnitude during turmoil periods of the Global Financial Crisis, the Eurozone crisis, and other events. The spillovers to India's exports are highest from China and lowest from Singapore. While FIIs receive more significant spillovers from the US, China, and Singapore. Also, during the peak of crisis episodes, the US and China transmit more significant spillovers to exports and FIIs than other countries. This aspect demonstrates EME's strong vulnerability to shocks to the two largest economies. Lastly, exports turn out to be net receivers of spillovers, whereas FIIs transmit and receive them. This signifies that trade relations are a major determinant in explaining the transmission of shocks.

In Chapter 5, the study aims to assess the co-movement of monetary policy and macroprudential policy stance toward financial cycle phases in India. This is done in two stages. First, it computes procyclicality ratios to analyze the negative effects of monetary and macroprudential policies, i.e., expansionary policies in the upswing phase or contractionary policies in the downturn phase. Second, it analyses the co-movement of monetary policy stance by comparing interest rate changes with financial cycle phases. It also analyses the co-movement of macroprudential policy stance focusing on changes in time-varying risk weights and provisioning norms on the capital market, housing, consumer loans, commercial real estate, and non-deposit systematically important NBFCs with the financial cycle phases.

For this purpose, we use credit and equity prices to generate a financial cycle derived from the low-frequency component of wavelet analysis. The study finds that the amplitude of the downturn phase is much smaller than the upswing phase, signifying that the downturn phase is milder in India. It also finds that the procyclicality of monetary and macroprudential policies dominates during the upswing phase of the financial cycle. The monetary policy and macroprudential policy coordinated each other throughout the sample period.

6.2 Policy implications

The findings of the study have some important policy implications, which are as follows:

- The study found that the DCC-FSI index can be a useful indicator for policymakers to monitor financial conditions regularly and fragility in the financial system by tracking the development of stress. The source of financial stress can be traced by the relative contribution of each financial indicator to the overall stress of the index and helps formulate the policy responses accordingly.
- Considering the asymmetric responses of monetary policy during low and high financial stress on the economy, monetary authorities must act swiftly when financial stress is high, possibly before it becomes a full-blown economic crisis.
- This study provide evidence that the vulnerability of an emerging economy like India to shocks originating elsewhere due to financial stress spillovers. It finds trade relations to be a major determinant in explaining the transmission of shocks as exports turn out to be net receivers of spillovers, whereas FIIs transmit and receive them. The evidence suggests that spillovers have become bidirectional, threatening global financial stability. The study provides insights to policymakers to strengthen the resilience of economies in a financially interconnected global economy. From the perspective of an individual country, macroprudential regulation can lead to more resilience toward global financial shocks. Other economies may benefit from greater financial stability due to less volatility in trade and financial flows with that country.
- Based on assessing financial cycle behavior, it is critically important to detect cyclical imbalances and to identify signs of financial instability. Often a crisis episode renders financial institutions vulnerable to a common shock. Therefore, macroprudential measures can achieve financial stability.

6.3 Conclusion

This study develops a Financial Stress Index for India that can locate the major and the minor events and accurately revert to normal periods. This index provides insight into fluctuating stress levels. It is thus useful in assessing financial instability and can be fed into policy decisions to flux out the stress before it blows out on the full scale. It is also seen that monetary policy decisions have asymmetric effects during low and high-financial stress regimes, warranting suitable policy actions. The study also indicates global financial market interdependence as emerging markets develop and demonstrate greater financial integration with developed markets. Additionally, it finds monetary policy and macroprudential policy to be coordinated. The effectiveness of macroprudential policy in the Indian financial system suggests that it can be used as a valuable additional tool other than monetary policy in stabilizing the financial cycle.

Appendix:

Appendix I: Data Sources

Variable Name	Data Source
1. Bank beta 2. Nifty bank index, Nifty 50 index	Authors calculation CMIE
3. Change in bank credit	CMIE
4. Spread between Certificate of Deposit and 15-91days T-bills 5. Certificate of Deposit 6. 15-91days T-bills	Authors calculation CMIE RBI
7. Equity volatility 8. Nifty 50 index	Authors calculation CMIE
9. Stock bond correlation 10. 10 year Indian government bond return 11. Nifty 50 return	Authors calculation RBI CMIE
12. Exchange rate CMAX 13. INR/US dollar rate	Authors calculation CMIE
14. Change in international reserves	CMIE
15. Inverted term spread 16. 10 year Indian government bond yield, 15-91days T-bill	Authors calculation RBI
17. Spread between commercial paper rate and treasury bill rate 18. Commercial paper rate 19. 15-91days T-bill	Authors calculation CMIE RBI
20. IIP	CMIE
21. CPI	RBI
22. WACR	RBI
23. S&P 500, SSE, HSI, FTSE 100	Thomson Reuters Eikon
24. STI	Yahoo Finance
25. 10-year government bond yield	International Financial Statistics
26. Exchange rate	International Financial Statistics
27. International reserves minus gold	International Financial Statistics
28. Exports	CMIE
29. Net. FIIs	CMIE
30. Non-food bank credit	CMIE
31. BSE Sensex	CMIE
32. Risk weights and provisioning norms	RBI and Sinha (2011)

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