# Essays on Jump Risk in The Indian Financial Market

**Mohammad Abu Sayeed**

(MBus, MBA, BBA)

Tasmanian School of Economics and Business

University of Tasmania

This dissertation is submitted in fullfilment of the requirment for the degree of Doctor of Philosophy

November 2017

# Declaration of Originality

I hereby declare that this dissertation is composed of my original work, and contains no material which has been previously published in a thesis, dissertation submitted for a degree or diploma by the University or any other institution. I alone remain responsible for the content of the following, including any errors or ommissions which may unwittingly remain.

Mohammad Abu Sayeed

Hobart, Tasmania

November 9, 2017

# Preface

The essays in this dissertation represent collaborative efforts with my suppervisors. Chapter 2 and 3 are joint work with Professor Mardi Dungey and Dr. Wenying Yao, Chapter 4 is with Dr. Wenying Yao and Chapter 5 is with Professor Mardi Dungey and Dr. Vladimir Volkov.

# Acknowledgements

Firstly, I would like to express my sincere gratitude to my primary supervisor Professor Mardi Dungey for her continuous support of my PhD study and related research, for her patience, motivation, and immense knowledge. Her guidance helps me in all the time of research and writing of this thesis. I could not have imagined having a better advisor and mentor for my PhD study.

I would also like to thank the rest of my supervisory committee: Dr. Wenying Yao and Dr. Vladimir Volkov for their insightful comments and encouragements and also hard questions. I received enormous support from Dr Wenying from idea generation to Matlab coding for the first three papers and received the same support from Dr Vladimir in the fourth paper. I must acknowledge the support of John Harvey here in developing codes for the fourth paper. I am also grateful to Dr. Vitali Alexeev and Dr. Marius Matei for being in the supervisory team at different times and being helpful whenever needed.

I thank my fellow PhD colleagues in TSBE: Biplob Chowdhury and Dr Dinesh Gajurel for the stimulating discussions and advices. I especially received great help from them in completing the rigorous documentations with the Graduate Research Office. I also acknowledge the great company and mental support I received from Monoj Kumar Mojumder, Moses Kangogo, Richard Ahadzie, Faisal Khan, Mizuki Yamasaki, Sahar Siami and other TSBE PhD candidates.

Last but not the least, I would like to thank my family members for all their sacrifices and spiritual support throughout the PhD period.

## Abstract

The dissertation consists of four independent but related studies on jump risk and the systemic risk of Indian banking stocks. Jumps are defined as abnormal stock price movements in terms of a local volatility. We provide evidence of the existence of jumps in the Indian market and banking sector and show that jump systematic risks (or jump betas) are priced differently from continuous systematic risks (or continuous betas). These jump occurrences can be explained partly by market liquidity conditions in addition to news arrivals. We finally show that banks with higher jump and continuous betas are also more active in propagating systemic risk.

In the first study, we use high-frequency stock returns of 41 Indian banks and find that the beta on jump movements of these stocks substantially exceeds that on the continuous components, and that the majority of the information content for returns lies with the jump beta. The predictability of stock returns from the traditional CAPM beta mainly comes from the jump beta. In this study, we contribute to the debate on strategies to decrease systematic risk, showing that increased bank capital and reduced leverage reduce both jump and continuous beta – with slightly stronger effects for capital on continuous beta and stronger effects for leverage on jump beta. However, changes in these firm characteristics need to be large to create an economically meaningful change in beta.

The second study examines the jump risks for banking sector represented by 41 banking stocks and non-banking financial sector comprises 55 financial Institutions (FI) all

listed on the National Stock Exchange of India (NSE). Using intra-day high frequency data we apply several widely-used jump tests to the price series of the financial institutions of India. We observe wide variation in jump detection rates across different methods. Our test results show that the banking industry is associated with a higher degree of jump risk compared with the market whereas the result is opposite for the FI industry. Results from a probit regression indicate that jumps in the market increase the likelihood of jump occurrence in the financial sectors in the next period. The intra-day jump test results of Indian financial stocks reveal the existence of intra-day and weekly seasonality in jump patterns in contrast with the general description of jump occurrences in early literature as a Poisson distribution.

The third study seeks to understand the relationship of liquidity variables with jump movements based on emerging market stocks. We use 15-minute return data from ten of the largest Indian banking stocks and implement an event study method to examine the behaviour of liquidity variables around the jump times. We find notable variations in the liquidity measures around the jump occurrences in the stocks. Liquidity characterized by market spread, trading quantity and immediacy do improve around jumps. The results indicate that the demand of immediacy of traders may cause jumps in stock returns. The Mann-Whitney test results also confirm the significant changes in the liquidity variable during the jump intervals from the non-jump intervals. Our probit and logit estimations show that the liquidity variables have more explanatory power in determining the probability of negative jump occurrences than that of positive ones. We do not observe substantial changes in the results by dividing our sample into pre-crisis,

crisis and post crisis periods, indicating that the effects of liquidity variables are general on jump occurrences. Finally, several liquidity variables are shown to contribute to price discovery although the post jump price discovery process does not seem strongly related with these variables.

In the fourth paper we measure the Indian banks' systemic risk which can be defined as the likelihood of propagating financial adversity such as illiquidity. We use stock returns of 40 listed commercial banks of India for the period of 2011 to 2015. First we apply a multivariate Granger causality test to establish statistically significant connections between each pair of banks. To measure the strength of each of the links we measure the weight of the link by applying a variance decomposition method. Finally, we derive the network of banks where only the statistically significant links with their respective weights are retained and from this network matrix we identify the most systemically active banks in India. An analysis on the daily rolling window of the network measures shows that the overall network strength increases during our sample period. Our analysis shows that market liquidity and volatility are related to the network connectivities. Decrease in liquidity and increase in volatility heighten the connectivity of networks. In addition, the systematically risky banks in terms of both jump and continuous beta are found also to be the more active banks in strengthening network connectivities.

# Contents

# List of Tables

# List of Figures

# 1 Introduction

## 1.1. Motivation

The asset price process is known to be a combination of drift, continuous movement and jumps. While asset and derivative pricing models have been formed primarily on the basis of a continuous-time diffusion process, practical implications of those models become limited as these models do not fit well with the discrete nature of financial data. Recent literature incorporates random walk behaviour, market microstructure effects, stochastic volatility and jumps into asset pricing models which can be classified as arbitrage free Itô semi-martingale (Merton (1976),Andersen et al., 2007b and Evans, 2011). These processes are combinations of a continuous diffusive Brownian component and a discontinuous jump component in addition to drifts. Decomposing these different parts is important as they represent fundamentally different risks for the investors (Aït-Sahalia, 2004). Investors can improve decisions on option pricing (Cox and Ross, 1976; Duffie and Pan, 2001; Merton, 1976), risk management (Bakshi and Panayotov, 2010; Duffie and Pan, 2001), and asset allocation (Jarrow and Rosenfeld, 1984; Liu et al., 2003) by acknowledging both the continuous and jump parts. In portfolio allocation one can optimize the demand for assets subject to both types to risks; in risk management, we can manage continuous risk using Gaussian tools and the jump risks, focusing only on large fluctuations; in option pricing, we can consider different hedging requirements conditioning on the existence of both components(Aït-Sahalia, 2004). This dissertation examines the impacts of jumps on the market, the influence of market factors on jump occurrences and individual stocks' reaction to market jumps.

We observe an increasing interest in dealing with jump processes in recent literature. Aït-Sahalia (2004) divided these studies into three broad directions: estimating financial models incorporating jumps, testing for the detection of jumps from discrete data and examining the characteristics of different variables such as quadratic variation in the presence of jumps. A number of studies attempt to identify what causes the jumps in asset returns such as news arrival and market liquidity. However, these studies are largely concentrated on the U.S. and other developed economies. We do not know whether the findings of these studies hold for emerging economies which are heading towards becoming the driving forces of world economy in near future. Our effort is to bolster the jump literature by extending different branches of jump studies to an important emerging market, India.

The availability of high-frequency observations is one of the factors contributing to the expansion of the jump literature (Aït-Sahalia et al., 2009) The use of high-frequency data in the research of financial economics has become popular in recent years. The rapid development and automation of financial markets and transactions around the world contribute to this development. It is hypothesized that the use of high-frequency data can increase the accuracy of various financial estimates such as volatility (Fleming et al., 2003) and covariances (Barndorff-Nielsen and Shephard, 2005). By not using high-frequency data we discard a vast amount data and lose important information (Aït-Sahalia et al., 2005). The use of high and ultra-high frequency data in empirical studies enables us to adhere more closely to the models developed based on continuous time series data. We use intra-day stock price and market index data to detect jumps in the market and individual stocks. This dissertation concentrates on the banking and financial sector of India. The banking stocks are large capitalized stocks which are followed by a large number of individual and institutional investors ensuring high frequency trading of these stocks. As a result, these stocks, in a setting of emerging market where capital markets are not yet as liquid as the developed markets, are suited to study in high frequency data. The other reason for choosing the banking sector is its vulnerability towards shocks (for example see Laeven and Valencia, 2013) and propensity for propagating shocks to other sectors of the economy (for example see Jermann and Quadrini, 2012 and Meh and Moran, 2010). Thus it is important to examine how sensitive the banking stocks are to shocks in the market reflected by market jumps and also how strong is the network of bank in spreading idiosyncratic shocks from one bank to others. This dissertation has four main chapters each covering an independent study on the Indian banking sector related to different aspects of jump detection and/or systemic risk.

## 1.2. Research questions and outline of this thesis

It is now documented in the literature, based mainly on developed economies, that markets and individual stocks experience infrequent jumps. Following Christensen et al. (2014), the effort of separating the jump components can be divided into three phases. The first phase noticeably begins after the work of Press (1967) in his jump diffusion models. After that, a number of authors up to Jorion (1988) used different jump-diffusion models and reported over 20% jump variations in total returns. The jump diffusion models used in this phase tend to overestimate jump occurrences as it does not account for the contribution of stochastic volatility in fat tail measures of return distribution (Christensen et al., 2014). After 1990, the jump diffusion papers such as Andersen et al. (2002) and Bollerslev and Zhou (2002) include one or more stochastic volatility factors and report that the jump components constitute 5% - 10% of the whole process. The most recent trend is to apply non-parametric models based on high-frequency data inspired by the work of Barndorff-Nielsen and Shephard (2006) and strengthened by Lee and Mykland (2008) Aït-Sahalia et al. (2009), Andersen et al. (2012), Corsi et al. (2010). Studies based on these model free methods report around 10% jump on stock returns in USA and confirm that the non-trivial jump proportions deserve consideration in relevant decision makings.

Because of the dearth of studies on the emerging markets we do not know the extent of jump existence in these markets and how they behave. Among these markets only China has attracted the attention of a few researchers, however, another fast growing

Asian economy, India is still largely under-researched. A recent study, Sen and Mehrotra (2016) shows that jumps exist in the Indian market but does not report the intensity and other dynamics of jump occurrences in this market. The Indian market which is broker dominated, may not be as efficient as the US and other developed and liquid markets. Thus our first research question is:

*Research Question 1: Do jumps exist in emerging market like India? If they do, to what extent, and what are the characteristics of those jump occurrences?*

We examine these questions partly in Chapter 2 and more thoroughly in Chapter 3. Given that jumps exist, how do investors react to those jumps? From the Capital Asset Pricing model (CAPM) proposed by Sharpe (1964) and Lintner (1965) we know that individual stocks react when the whole market moves. This co-movement of individual stocks with the market, known as beta is an important measure of systematic risk and the highly cited study of Fama and MacBeth (1973) and subsequent plethora of studies show that investors price beta. If the movements of the market comprises irregular jumps, which may result from news arrival, along with regular continuous movements then investors may react differently to those jumps (Todorov and Bollerslev, 2010, Bollerslev et al., 2016,Alexeev et al., 2017) . Thus our second research question is:

*Research Question 2: Do investors price jump risk differently than non jump market movements?*

We address this research question in Chapter 2. Since the recent global financial crisis another risk has drawn the attention of researchers as well as regulators. Systemic risk is loosely defined as the likelihood of propagating shocks from individual entities to the greater market. If there is any relationship between the systematic risk and systemic risk, then understanding the relationship will enable us to formulate an comprehensive strategy to mitigate these risks. Firms with higher beta or systematic risk are clearly the firms which are more active against market shocks and news arrivals. It is thus more likely that these banks will also be active in propagating systemic risks. Therefore, a related research question is

*Research Question 2a: Are the banks with higher systematic jump and continuous risk also active in propagating risks in systemic nature?*

We address this question in Chapter 5 of our thesis. A network analysis of banks enable us determining the systemic risk of Indian banks and examine the relationship between systemic and systematic risks.

Arrival of news has been attributed as the single most important factor causing jumps in stocks and the overall market (Dungey et al., 2009b, Lahaye et al., 2011, Patton and Verardo, 2012). However, not all the jumps are related to news - Boudt and Petitjean (2014) report that a one third of the jumps are related to macroeconomic news and 5% from firm specific news. Not many studies are directed in exploring the non-news related instigators of jumps. Two studies, Jiang et al. (2011) and Boudt and Petitjean (2014), examine the interaction between liquidity and jumps and found significant relationships between these variables. Findings of these papers are again based on markets with high liquidity and efficiency where news spread in the market rapidly. In a market like India where news may not spread as fast as the US market, liquidity and market conditions may pay a higher role in jump occurrences as opposed to news arrival. Thus our third research question is:

*Research question 3: What liquidity and market condition variables cause jumps other than news arrival?*

Chapter 4 is dedicated to examining this question where the dynamics between liquidity and jumps of the the ten largest Indian banks are analysed.

## 1.3. Key contributions

In examining the research questions outlined in Section 1.2, this thesis contributes by exploring the jump risk of the Indian financial market by using high frequency data. The specific contributions are as follows:

1) Based on recently developed methods, we confirm the existence of jumps in the Indian market and show that the sensitivities of individual stocks towards the market jump are substantially different from continuous market movements. The difference in such sensitivities are higher than what is reported in literature for the developed markets. Our results show that the price discovery of beta is mainly derived from its jump component rather than the continuous component. This finding underpins the importance of considering the jump beta in investment and portfolio decisions.

2) We show a wide variation of results from different jump detection methods in an emerging market setting. While doing the analysis, we show the optimal frequency of intra-day return we may use for a country like India. We find seasonality and clustering behaviour of jumps in our results, corroborating with recent findings that jump occurrences do not follow a Poisson distribution as described in the early literature.

3) The relationship between the liquidity and jumps has rarely been studied before in an emerging market context. Our paper is the first attempt in this direction. Our work provides the narration of similarities and differences of the interaction of liquidity variables around the jump with the US based findings reported in Jiang et al. (2011) and Boudt and Petitjean (2014).

4) We apply a recently developed network model to the Indian market in assessing systemic risk using stock returns. Our results show that systematic risk and systemic risk have a relationship that is not properly investigated in the literature so far. Another important result from our study is that we find significant effects of liquidity and volatility on the different aspect of network connectivity measures that may provide a new perspective to the systemic risk researchers and regulators.

## 1.4. A brief history of the Indian banking sector

All of the individual papers incorporated in this thesis are conducted on the Indian banking sector. A short history of Indian banking sector is presented below.

India has a long history of banking and finance although there is lack of coherent commentaries of historical sequence in the literature. For instance, there is lack of consensus regarding the first Indian bank and its year of establishment. However, there is consensus among authors (Gauba, 2012; Ratti, 2012) that an indigenous banking system existed in India from the ancient past. Although the formal banking system was established in the hands of British traders in the 18th century an indigenous payment and lending system existed in India from the ancient past (RBI, 1998[1]).

After the invasion of India, English traders began banking businesses to facilitate their trading business. Although an indigenous banking system was in existence in India language difference motivated English traders to start their own banking institutes established by the English agency houses. The first few banks were set up in Calcutta and Bombay. These agency houses were mainly established by people who were retired from civil and military services and worked as managing agencies for establishing business houses. They were involved in financing movement of crops, issuing paper money and establishing joint stock banks. The such recorded first bank in India was Hindoostan Bank which started operation in 1770. However, some authors claim that, the General bank of India, established in 1786, was the first bank of India. Both these banks are defunct now. The oldest bank in existence is the State Bank of India which originated as the Bank of Calcutta in 1806 and later converted into Bank of Bengal. This bank along with two other banks, Bank of Bombay and Bank of Madras, known as the Presidency banks were established under charter from the British East India Company. These three banks worked as quasi-central banks and subsequently merged into one bank named the Imperial Bank of India in 1925. After the independence of India the same bank became the State Bank of India which is the biggest bank still today. Few foreign banks opened branches in Calcutta in the 1860s. The Comptoire d' Escompte de Paris and HSBC are the first two foreign banks with a presence in India, more particularly Calcutta which became the banking centre being the most active trading port of the country.

[1]RBI. (1998). Evolution of Payment Systems in India. Retrieved from http://www.rbi.org.in/scripts/PublicationsView.aspx?id=155.

The first local bank was Union Bank of India, established by Indian merchants in 1839 but this institution failed during the financial crisis of 1848-49. Allahabad Bank established in 1865 is the oldest bank to be still functioning in India today. It was established amid a boom of local joint stock companies. The boom was instigated by the civil war of USA that cut off supply of cotton in England causing an uprise of India's cotton trade in England. The first joint stock bank was Bank of Upper India (1863) and the first entirely Indian joint stock bank was the Oudh Commercial Bank established in 1881. None of these banks survive but the next bank, Punjab National Bank established in 1895 still exists and is now one of the largest banks in the country. At the beginning of the 20th century when Indian economic conditions were stabilizing, small banks were established by Indians which served particular ethnic and religious communities. But it was the presidency banks which dominated the industry. Some joint stock banks were established in this period by mostly the Europeans and were involved mainly in financing foreign trade. The period of between 1906 to 1911 is denoted as Swadeshi (Self independent) movement in India led by Mahatma Gandhi. A number of banks were established by local businessmen and politicians who were inspired by this movement. Some of the surviving banks today such as Bank of India, Corporation Bank, Indian Bank, Bank of Baroda, Canara Bank and Central Bank of India were established at that time.

The period from 1914 to 1945 (From first world war to the second world war) Indian banks faced a turbulent period. A total of 94 banks collapsed during only the First World War (1914 - 1918) as a result of war-related economic downturn. However, the

Indian economy as whole was boosted after the war by the recovery activities.

The independence of India in 1947 was coupled with dividing it into two independent countries, India and Pakistan. The impact of partition adversely impacted the economy of India and its banking sector. The government of India adopted a policy of having a greater role in economy ending the laissez – fair era for Indian Banking sector. The Reserve Bank of India (RBI), which was established in 1935, was nationalized on January 1, 1949 according to the Reserve Bank of India Act, 1948. The RBI was empowered to approve new banks or branches of an existing bank, regulate, control and inspect the banks in India under the Banking Regulation Act enacted in 1949. The act also prohibits any two banks having common directors.

The banking sector still owned and managed by the private sector gained strength to facilitate economic development. The government led by Indira Gandhi decided to nationalize the banking sector and issued an ordinance known as Banking Companies (Acquisition and Transfer of Undertakings) Ordinance, 1969. Under this ordinance the government nationalized the 14 largest commercial banks representing 85% of the country's bank deposits, on 19 July 1969.

Through the second phase of nationalization, which took place in 1980, the government took control of 91% of the banking business of the country. The number of nationalized banks grew to 20. However, after a merger of 'New Bank of India' with 'Punjab National Bank' the number was reduced to 19, a number which remains the same until the current period.

The government of India decided to liberalize the economy in the early 1990s and undertook a number of steps – reducing required regulatory reserve on deposits, relaxing rules for entry and exit of private sector banks, allowing public sector banks to collect capital from the capital market, liberalizing fixed interest rate system, easing up branch licensing policies, strengthening bank supervision by RBI etc. Thus there has been a structural change in Indian Banking sector reform after 1990 (Mor et al., 2006). The sector which was under state ownership was opened to a large extent by allowing entry of a number of private banks. These banks include Trust bank which later amalgamated with Oriental Bank of Commerce, UTI bank which is renamed as Axis Bank, ICICI Bank and HDFC Bank. These banks are known as new generation of tech savvy banks. The entry requirement of foreign banks was also liberalized, and the ownership of the public banks was made diversified. As a result of these developments the banking sector of India has become more competitive (Prasad et al., 2007).

The government also relaxed the restriction on foreign direct investment by withdrawing voting rights of foreign investors in banks. Adoption of IT infrastructure had modernized the banking service to a great extent. Most of the banks both in private and public sector are now using online banking to differing degrees. The liberalization of policy and modernization of banking operation led a boom in retail banking, mortgage and investment services. The high growth of Indian economy coupled with the policy reform has reinvigorated the banking sector which is experiencing a rapid growth rate in last two decades.

# 2 High Frequency Characterization of Indian Banking Stocks

## 2.1. Introduction

The risk of an investment is typically divided into two parts: idiosyncratic risk and systematic risk which results from exposure to overall market shocks and is often represented as beta in a CAPM framework. CAPM typically quantifies the co-movement of returns in an individual asset (or portfolio) with the market. However, the price process is also known to be a combination of continuous and jump components; see Merton (1976) and plentiful references since. Jumps are a means by which new information may be incorporated into the market, and there is an emerging literature hypothesising that the CAPM beta for the jump and continuous components of the price process may differ. For example, Patton and Verardo (2012) provide a learning argument and empirical evidence for increased beta around the release of earnings information on individual stocks, and Todorov and Bollerslev (2010) provide evidence for 40 US stocks.

This chapter estimates continuous and jump betas for equities in the Indian banking sector using recent developments in high frequency financial econometrics by Todorov and Bollerslev (2010). The application to individual stock prices in emerging market equities is novel, there is little literature on the high frequency behaviour of emerging markets (the exceptions are for market indices in Chinese markets (Liao et al., 2010; Zhou and Zhu, 2012), and in Eastern European markets in Hanousek and Novotný (2012)) and nothing on individual stocks in the financial sector. Yet the emerging markets are critically important to the future of the world economy, and their financial sectors drive that development. Emerging economies, termed "the world economy's $21^{st}$ century sprinters" by *"The Economist"* leapt to producing over half of world output in the first decade of this century. India is one of the major drivers of this growth, with a large aggregate output, a vast young population and underutilized resources. The market for the Indian rupee has grown from 0.1% of global turnover in 1998 to 1% in 2013 (BIS, 2013), and in 2012 was amongst the top 10 global equity markets by market capitalisation. Indian markets have a number of important advantages over those of other BRIC economies with strong institutional structure, unburdened with the non-performing assets and ageing population structure of China, the Russian exposure to the Chinese slowdown, or the high inflation of Brazil.

The Indian banking sector follows the British structure of banking, India is one of the English common law countries (Buchanan et al., 2011), and listed banks are not only under the purview of the Reserve Bank of India but also the Securities and Exchange Board of India which ensures strong information disclosure to investors. Rathinam and Raja (2010) attribute the phenomenal growth in the Indian financial sector to legal development, improvements in property rights protection and contract enforcement and positive changes in the regulatory environment. The banking sector (commercial banks, regional rural banks, rural and urban co-operative banks) accounted for 63% of India's financial assets in the 2012-13 financial year, with the remainder shared between insurance companies (19%), non banking financial institutions (8%), mutual funds (6%) and provident and pension funds (4%). The 89 commercial banks operating in India in 2012-13, consisted of 43 foreign banks, 20 local privately-owned banks and 26 nationalised banks. The market is distinguished by significant government ownership in a number of banks, exposing 73% of total banking sector assets to some degree of government investment. However, the sector is well dispersed with a 5 bank concentration ratio of 38% in 2012-13 and only one bank, the State Bank of India, with a significant dominance (17% of 2012-13). The total deposit of the banking sector was 74.29 trillion Indian rupee representing 73.46% of GDP at the end of 2012-13 financial year, employing over one million employees across 92 thousand bank branches/offices[1].

We initially confirm the existence of jumps in the 5-minute stock returns for 41 banks listed on the National Stock Exchange of India over 2004 to 2015, providing the motivation for our estimation of separate continuous and jump betas. The estimated jump beta is generally higher than the corresponding continuous beta, supporting the hypothesis that stocks behave differently in response to jumps than continuous market movements. When testing the validity of the disentangled betas against the CAPM standard beta, we find that it is the jump beta rather than the continuous beta which has explanatory

[1] The exchange rate was US$1=59.5260 Indian rupee as of 30/06/2013.

power over the variation in stock returns, leading to the conclusion that the predictive power of CAPM beta comes mainly from the jump component.

We relate the variation in betas to firm characteristics and find that financial leverage, capital adequacy, and firm size have significant impacts on each of the jump and continuous beta estimates. These relationships are informative for the debate about reducing systemic risk via options to constrain leverage or increase the capital base of the banking sector. We show that financial leverage has a positive effect on beta, indicating that a more heavily leveraged firm is more exposed to market movements, although we demonstrate that the impact of changes in leverage are economically very small. Greater capital adequacy reduces both jump and continuous beta, but again requires relatively large changes to have a substantial economic effect. Thus, our results support the direction of the impact of policies to decrease leverage and increase the capital base on reducing systematic risk, but throw some doubt on the size of the changes needed to obtain an effective impact in reducing risk in the financial sector.

Competing hypotheses on firm size suggest that either larger firms are more stable and able to weather market shocks more easily, or that as they are a substantial part of the market they are more exposed to market shocks. Our results support the hypothesis that larger firms are more exposed with higher beta, but this effect is more evident for continuous movements; the effects for jump beta are statistically significant but smaller. Our estimates also find that price volatility is a contributing factor for higher continuous beta, but not jump beta, and that more profitable firms have lower continuous and jump beta although the relationships are not statistically significant in contrast with the hypothesis that these firms may be taking more risk to achieve these profits.

The paper has two major contributions. First of all, it is the first paper to extend the exercise of decomposing CAPM beta to an emerging market where market characteristics differ from the US market in terms of liquidity and information efficiency. Second, it is in our knowledge one of the the first papers to show that the price discovery of systematic risk is derived mainly from the jump beta rather than the continuous beta. Thus, it underpin the importance of detecting and incorporating jumps for the market participants.

The rest of the chapter is organized as follows. Section 2.2 reviews the literature related to the decomposition of CAPM and Section 2.3 elaborates the methodology employed for jump detection and beta estimation. We outline data collection and the cleaning process along with choices of calibrated parameter value in Section 2.4. Section 2.5 discusses the results of the empirical analysis and Section 2.6 concludes.

## 2.2. The CAPM and decomposition of beta

The capital asset pricing model (CAPM) (Sharpe, 1964 and Lintner, 1965), models the return on an asset (or portfolio of assets) as a linear combination of return on the risk free asset and a market risk premium multiplied by the associated beta. The CAPM beta itself is estimated as the covariance between the asset return and market return, standardized by the variance of market return. A subsequent large literature of empirical studies shows mixed results on the effectiveness of beta in explaining the variation of stock returns. A number of alternatives have been proposed to improve empirical CAPM including multi-factor models, such as the three factor model of Fama and French (1993), arbitrage pricing theory by Ross (1976), incorporating higher order co-moments (Kraus and Litzenberger, 1976; Friend and Westerfield, 1980; Faff et al., 1998; Harvey and Siddique, 2000) , CAPM conditional on market conditions (such as Fabozzi and Francis, 1978), and CAPM with time varying beta (such as Bollerslev et al., 1988; Fraser et al., 2000).

This study takes the approach of decomposing the price process into a continuous and jump component consistent with recent evidence (see Andersen et al., 2007a; Barndorff-Nielsen and Shephard, 2004b, 2006; Huang and Tauchen, 2005; Dungey et al., 2009b; Aït-Sahalia and Jacod, 2012), and consequently estimating betas on the two components using the method developed in Todorov and Bollerslev (2010).

The standard one factor CAPM relates the return of individual stocks to the return of the benchmark market portfolio as follows:

$$r_i = \alpha_i + \beta_i r_0 + \varepsilon_i, \quad \text{for} \quad i = 1, \ldots, N, \tag{2.1}$$

where $r_i$ is the return of the $i^{th}$ asset, and $r_0$ denotes the return of the market portfolio which represents the systematic risk factor. The $\beta_i$ coefficient quantifies the sensitivity of the asset return to the movement of the market return.

Decomposing the market return into continuous and jump components suggests the following form:

$$r_i = \alpha_i + \beta_i^c r_0^c + \beta_i^d r_0^d + \varepsilon_i, \quad \text{for} \quad i = 1, \ldots, N, \tag{2.2}$$

where the market return $r_0$ is decomposed into the continuous market return, $r_0^c$, and the discontinuous (or jump) market return, $r_0^d$. Correspondingly, the systematic risk also comprises two components, continuous beta $\beta_i^c$, and jump beta $\beta_i^d$, which represent the sensitivities of the $i^{th}$ asset return to $r_0^c$ and $r_0^d$, respectively. Using high frequency data, which has already been shown to increase the predictive power of estimates of beta (Andersen et al., 2005; Bollerslev and Zhang, 2003; Barndorff-Nielsen and Shephard, 2004a; Patton and Verardo, 2012), allows estimation of $\beta_i^c$, and jump beta $\beta_i^d$ using the methods proposed in Todorov and Bollerslev (2010).

## 2.3. Jump detection and beta estimation

The calculation of jump beta is motivated by the fact that the price process of any asset is a combination of a Brownian semi-martingale plus jumps. Denoting the return of an asset as $dp_t$, where $p_t$ is the log-price series, the continuous-time model for the asset return is

$$dp_t = \mu_t dt + \sigma_t dW_t + \kappa_t dq_t, \qquad 0 \leq t \leq T, \tag{2.3}$$

where $\mu_t$ is the drift term, $\sigma_t$ represents the spot volatility, and $W_t$ is a standard Brownian motion. The third term, $\kappa_t dq_t$ captures the jumps in the price process, where $q_t$ is a counting process with $dq_t = 1$ if there is a jump occurred at time $t$, and 0 otherwise. $\kappa_t$ is the size of the jump at time $t$. The quadratic variation for the process in (2.3) is defined as

$$QV^{[0,T]} = \int_0^T \sigma_s^2 \mathrm{d}s + \sum_{0<s\leq T} \kappa_s^2. \tag{2.4}$$

In practice, we can only observe the asset price at discrete time intervals, say, every $\Delta^n$ interval. Hence, the observed return series becomes $\Delta_j^n p = p_j - p_{j-1}$, $j = 1, 2, \ldots, [T/\Delta^n]$. As $\Delta^n \to 0$, a consistent estimator of $QV^{[0,T]}$ is the realized variation popularized by Andersen and Bollerslev (1998),

$$RV^{[0,T]} = \sum_{j=1}^{[T/\Delta^n]} |\Delta_j^n p|^2 \xrightarrow{p} QV^{[0,T]} \quad \text{as} \quad \Delta^n \to 0. \tag{2.5}$$

Barndorff-Nielsen and Shephard (2004b) introduce an alternative measure, realized bipower variation, defined as

$$BV^{[0,T]} = \mu^{-2} \sum_{j=2}^{[T/\Delta^n - 1]} |\Delta_j^n p||\Delta_{j+1}^n p|, \tag{2.6}$$

where $\mu = \sqrt{2/\pi} = \mathbb{E}(|\mathbb{Z}|)$ represents the mean of absolute value of a standard normal random variable $\mathbb{Z}$. As $\Delta^n \to 0$, $BV^{[0,T]}$ converges to the contribution to $QV^{[0,T]}$ from the Brownian component, $\int_0^T \sigma_s^2 \mathrm{d}s$ in probability, even in the presence of jumps. Hence, the contribution from the jump component to $QV^{[0,T]}$ can be estimated consistently by taking the difference of $RV^{[0,T]}$ and $BV^{[0,T]}$, that is,

$$RV^{[0,T]} - BV^{[0,T]} \xrightarrow{p} \sum_{0<s\leq T} \kappa_s^2 \quad \text{as} \quad \Delta^n \to 0. \tag{2.7}$$

As first proposed by Barndorff-Nielsen and Shephard (2006) (BNS henceforth), the discrepancy between $RV^{[0,T]}$ and $BV^{[0,T]}$ is utilized to detect the presence of jumps. We apply their adjusted ratio test statistic. The feasible test statistic of jump detection is given by

$$\hat{\mathcal{J}} = \frac{1}{\sqrt{\Delta^n}} \cdot \frac{1}{\sqrt{\theta \cdot \max(1/T, DV^{[0,T]}/(BV^{[0,T]})^2)}} \cdot \left( \frac{BV^{[0,T]}}{RV^{[0,T]}} - 1 \right), \tag{2.8}$$

where $DV^{[0,T]} = \sum_{j=1}^{[T/\Delta_n - 3]} |\Delta_j^n p||\Delta_{j+1}^n p||\Delta_{j+2}^n p||\Delta_{j+3}^n p|$ and $\theta = \frac{\pi^2}{4} + \pi - 5$. In the absence of jumps, the test statistic $\hat{\mathcal{J}}$ given in (2.8) follows a standard normal distribution asymptotically. Therefore, under the null of no jumps,

$$\hat{\mathcal{J}} \xrightarrow{L} \mathcal{N}(0,1) \quad \text{as} \quad \Delta^n \to 0. \tag{2.9}$$

We reject the null hypothesis of no jumps if the test statistic is significantly negative.

The detection of jumps paves the way to separately estimate continuous and jump beta. Todorov and Bollerslev (2010) derive the nonparametric estimates of both $\beta_i^c$ and $\beta_i^d$ in (2.2). By expressing the co-variation between the continuous components of $p_i$ and $p_0$ as $[p_i^c, p_0^c]_{(0,T]} = \beta_i^c \int_0^T \sigma_{0,s}^2 ds$, and the variance of the continuous component of $p_0$ as $[p_0^c, p_0^c]_{(0,T]} = \int_0^T \sigma_{0,s}^2 ds$ in the continuous-time model, they show that the continuous beta of the $i^{th}$ asset, $\beta_i^c$ can be expressed as

$$\beta_i^c = \frac{[p_i^c, p_0^c]_{(0,T]}}{[p_0^c, p_0^c]_{(0,T]}}, \qquad i = 1, \ldots, N. \tag{2.10}$$

In reality observing price data on continuous basis is not possible. Therefore, the estimator $\hat{\beta}_i^c$ takes the following form in the discrete-time setting

$$\hat{\beta}_i^c = \frac{\sum_{j=1}^{[T/\Delta^n]} \Delta_j^n p_i \Delta_j^n p_0 \mathbb{1}_{\{|\Delta_j^n p| \leq u_n\}}}{\sum_{j=1}^{[T/\Delta^n]} (\Delta_j^n p_0)^2 \mathbb{1}_{\{|\Delta_j^n p| \leq u_n\}}}, \quad i = 1, \ldots, N, \tag{2.11}$$

where $\mathbb{1}\{\cdot\}$ is the indicator function. Here, we require a truncation threshold that will identify the continuous price movement from the whole price process. In our empirical analysis, the continuous price movement corresponds to those observations that satisfy $|\Delta_j^n p| \leq u_n$. The truncation threshold, $u_n$ is set to be an $(N+1) \times 1$ vector, where $N$ is the number of assets, and $u_n = (\alpha_0 \Delta_n^\omega, \alpha_1 \Delta_n^\omega, \ldots, \alpha_n \Delta_N^\omega)'$, where $\omega \in (0, \frac{1}{2})$, and $\alpha_i \geq 0,\ i = 0, \ldots, N$. Therefore, values of the truncation thresholds across different assets depend on the different values of $\alpha_i$.

For the discontinuous price movement, Todorov and Bollerslev (2010) show that the jump beta of the $i^{th}$ asset, $\beta_i^d$ based on a continuous-time basis is

$$\begin{aligned} \beta_i^d = \operatorname{sign} & \left\{ \sum_{s \leq T} \operatorname{sign}\{\Delta p_i \Delta p_{0,s}\} |\Delta p_{i,s} \Delta p_{0,s}|^\tau \right\} \\ & \times \left( \frac{|\sum_{s \leq T} \operatorname{sign}\{\Delta p_{i,s} \Delta p_{0,s}\} |\Delta p_{i,s} \Delta p_{i,s}|^\tau|}{\sum_{s \leq T} |\Delta p_{0,s}|^{2\tau}} \right)^{\frac{1}{\tau}}. \end{aligned} \tag{2.12}$$

The discrete time estimator $\hat{\beta}_i^d$ as derived by Todorov and Bollerslev (2010) is

$$\hat{\beta}_i^d = \text{sign}\left\{\sum_{j=1}^{[T/\Delta^n]} \text{sign}\{\Delta_j^n p_i \Delta_j^n p_0\}|\Delta_j^n p_i \Delta_j^n p_0|^\tau\right\} \\ \times \left(\frac{|\sum_{j=1}^{[T/\Delta^n]} \text{sign}\{\Delta_j^n p_{i,s} \Delta_j^n p_0\}|\Delta_j^n p_i \Delta_j^n p_0|^\tau|}{\sum_{j=1}^{[T/\Delta^n]} |\Delta_j^n p_0|^{2\tau}}\right)^{\frac{1}{\tau}}, \qquad (2.13)$$

where $i = 1, \ldots, N$, and the power $\tau$ is restricted to be $\tau \geq 2$, so that the presence of continuous price movements becomes negligible asymptotically, and only the discontinuous movements matter. Todorov and Bollerslev (2010) show that $\hat{\beta}_i^c \xrightarrow{p} \beta_i^c$ as $\Delta^n \to 0$, and $\hat{\beta}_i^d \xrightarrow{p} \beta_i^d$ on $\Omega^{(0)}$, when $\Omega^{(0)}$ is the set where there is at least one systematic jump on $[0, T]$. Further, they show that both beta estimates have an asymptotic normal distribution, and provide consistent estimators for the variances of $\hat{\beta}_i^c$ and $\hat{\beta}_i^d$.

## 2.4. Data and parameter values

The high frequency stock price data are extracted from the Thompson Reuters Tick History (TRTH) database provided by SIRCA for the sample period from January 1, 2004 to December 31, 2015. The quality of data before 2004 is not satisfactory as it contains excessive missing observations that may bias the jump-robust volatility estimates. Thus, our sample period does not include any period before January 1, 2004. We collate data on 5-minute stock returns for 41 commercial banks listed on the National Stock Exchange of India (NSE) shown in Table 2.1. The NSE was established in 1990 and soon became an important exchange by providing a fully automated screen-based trading system. It is now the largest stock exchange in India in terms of daily turnover and number of trades, and ranks second in terms of total market turnover, behind the Bombay Stock Exchange, with turnover in July 2013 of USD $0.99 billion.

The sampling frequency of 5 minutes is relatively standard in the high frequency literature. It provides a reasonable compromise between the need to sample at very high frequencies in order to resemble the continuous price process (Andersen et al., 2001), and possible contamination from micro-structure noise. The literature developing optimal sampling frequency for the analysis of multiple assets, with or without noise, is ongoing[2].

We use the last price recorded in each of the 5-minute intervals from 9:15am to 3:30pm. Missing data are filled with the price of the previous interval which assumes that the price remains unchanged during a non-trading interval. We drop the first 15 minutes of each day to avoid noise associated with market opening. Hence, the first 5-minute intervals is 9.30 am to 9.35 am and we capture 72 price observations on each trading day. We use the CNX500 index as the benchmark market portfolio, which represents 96.76% of the free float market capitalization of stocks listed on the NSE. Among the indexes of NSE available in TRTH database CNX500 offers the broadest coverage of the stocks listed on the exchange, hence we choose this index to represent the market.

We apply the calibrated parameter values implemented by Todorov and Bollerslev (2010) and Alexeev et al. (2017). Following those authors we estimate both daily and

[2]In the third chapter, we conducted the signature plot analysis showing that 15-minute data is optimal for this market and all of our subsequent high-frequency analyses are conducted based on this sampling interval.

monthly betas, so that $T = 1$ represents one day in the first case and one month in the second. As $\Delta^n$ is the reciprocal of the number of observations during a given period, it equals 1/72 for daily estimation but varies from month to month; for example, $\Delta^n$ equals to 1/1584 in a month with 22 trading days. The threshold values, $u_n$ are chosen by taking $\omega = 0.49$. We implement $\alpha_i^c = 3\sqrt{BV^{[0,T]}}$ for $\hat{\beta}_i^c$, and $\alpha_i^d = \sqrt{BV_i^{[0,T]}}$ for $\hat{\beta}_i^d$, where $BV_i^{[0,T]}$ is the bi-power variation of the $i^{th}$ stock over the time interval $[0, T]$ ,$i = 0, \ldots, N$. The value of $\tau = 2$ in equation (2.12) follows Todorov and Bollerslev (2010).

## 2.5. Empirical analysis

The first step in the empirical analysis is to determine the existence of jumps in the Indian market. Table 2.2 reports the descriptive statistics of the two daily volatility measures $RV$ and $BV$ of the CNX500 and Figure 2.1 depicts the occurrence of jump days detected using the BNS test in the market index throughout the sample period 2004 – 2015.

Within our sample period from 2004 to 2015, we find 136 jump days out of 2,904 trading days in the market index, that is in 4.68% of our sampled trading days. This percentage is lower than the percentage reported by Todorov and Bollerslev (2010) for the US market using a test statistic based on the difference between RV and BV (106 out of 1241 days or 8.54%). However, our percentage is higher than the reported proportion of Alexeev et al. (2017) who apply the same test statistic in (2.8) to the US market. We cannot verify our results with any literature on Indian market as this is the first study of jump detection for this market. However, the proportion of jump days reported by Zhou and Zhu (2012) for China, is similar to our results. Applying the same methodology, they report 2.25% jump days for the SSE A Share Index, and 5.75% jump days for the SSE B Share Index. Of the 144 months in our sample, 87 months have at least one jump day.

The number of jump days in the CNX500 index decreases gradually from 2004 (22 days) to 2008 (4 days), then increases in 2009 (13 days), and remains stable afterwards; see Figure 2.1 for a depiction. During the global financial crisis (GFC), there is no evidence of a notable increase in the number of jump days. In fact, during 2008, when the GFC was at its nadir, the Indian market experiences a lower number of jumps than the adjacent years. This result may indicate the resilience of Indian market against global shocks, although Bianconi et al. (2011) and Mensi et al. (2014) show that the US and global crisis spread through the BRIC countries including India. However, a number of studies show similar reductions in the number of jumps detected during the crisis period compared with the prior tranquil period; Barada and Yasuda (2012) and Chowdhury (2014) for the Japanese market, Novotný et al. (2013) for six mature and three emerging stock market indices, Black et al. (2012) and Alexeev et al. (2017) for the US stock market. An alternative explanation, supported by these studies, is that during the crisis period the threshold of jump identification increases with the overall market volatility and some price discontinuities that may be classified as jumps during the tranquil period may be classified as continuous movements during the crisis period.

### 2.5.1. Betas for the Indian banks

The summary statistics of monthly continuous and jump betas of the sample banking stocks are reported in Table 2.3. The mean values of jump betas (1.42) are 89.33 per cent larger than the mean values of continuous betas. That indicates that the sensitivity of banking stocks towards the market is much higher against the market jumps than the calm market conditions. The lower standard deviation of jump average jump betas shows that the behaviour across banking stocks behave more homogeneously in the face of market jumps or shocks. Table 2.4 shows reiterates that for each of the banks the monthly average estimated jump beta, $\hat{\beta}_i^d$, is higher than the average estimated continuous beta, $\hat{\beta}_i^c$, indicating that banks respond more strongly to systematic risk via the discontinuous market movements (or jumps).[3] The average continuous beta is generally smaller than one, which implies that in response to the continuous market movements, the returns of banking stocks move less than the market return for the wider variety of stocks contained in the CNX500 index. Only 16 banks, ALBK, AXBK, BOB, BOI, CNBK, DCBA, DENA, ICBK, IDBI, ORBC, PNBK, SBI, SBNK, UCBK, UNBK and YESB have an average estimated continuous beta that is higher than one. These banks do not exhibit any obvious uniform firm characteristics with respect to ownership, market capitalization, profitability or leverage. None of the banks have a negative average $\hat{\beta}_i^c$, and the lowest sensitivity to continuous market movement is evident for Standard Chartered Bank (STNCy) with an average continuous beta of 0.04.

[3] Although we have calculated both daily and monthly time varying betas, in common with Todorov and Bollerslev (2010) and Alexeev et al. (2017) we find that the volatility in the daily beta estimates favours the use of the monthly betas for analysis.

Standard Chartered Bank is the only foreign bank in our data set, which may be why it is more resilient to movements in the domestic Indian market.[4]

Of the 41 banks in our sample, 38 have an average jump beta larger than one. This indicates that the returns of banking stocks move more than the return of the market itself when the market experiences jumps. DCBA is the bank with highest average jump beta (1.92) followed by IDBI (1.74). The bank with lowest average jump beta is STNCy (0.63), consistent with its very low continuous beta, followed by KARU (0.81).

The jump betas of all banks are on average 159% percent higher than their continuous betas, and the columns of average confidence intervals of continuous and jump betas in Table 2.4 show that there is no overlap between the confidence intervals of $\hat{\beta}_i^c$ and $\hat{\beta}_i^d$ for any bank. This supports the hypothesis that the continuous and jump betas in the augmented CAPM specification of equation (2.2) differ, and that a single factor CAPM model may miss information which is important for effective portfolio diversification and pricing. As an example, consider the confidence intervals for the average continuous and jump beta for all banks depicted in Figure 2.2, and for the State Bank of India, the largest Indian bank, in Figure 2.3. The figures show a volatile pattern of average betas for all banks and a stable level of continuous beta from January 2004 to December 2015 for SBI, while the jump beta has both higher values and relatively higher variability than the continuous beta in both figures.

We may expect changes in the beta estimates caused by the GFC since 2008. Hence

[4]Unfortunately access to the firm characteristic data for STNCy is limited, restricting subsequent analysis. Of the 108 months in our sample period, we have data for STNCy in 31 months, and hence estimate $\hat{\beta}^c$ for that subsample.

we divide our full sample into three sub-periods: pre-GFC (January, 2004 to August 2008), GFC (September, 2008 to March, 2010) and post-GFC (April, 2010 to December, 2015), and calculate the average beta estimates for the three sub-sample periods. The summary of the results are shown in Table 2.5. Both continuous and jumps betas are lower during the GFC period than their values in pre-GFC and post-GFC periods. The variations as indicated by the standard veviations of betas also did not increase during the GFC. We report the individual bank results in Table 2.6. The range of the beta estimates varies considerably for each individual bank. For example, the continuous beta for KARU during the GFC is as low as 0.19, while for DCBA and IDBI, the continuous beta estimates are consistently above unity in any sub-sample periods.

For most banks, the average continuous and average jump betas of banking stocks decrease during the GFC from the pre-GFC period. However, these betas increase after the GFC and rise above the pre-GFC level. This pattern of changes is more evident for jump beta than continuous beta. However, it contradicts what we would expect from the financial contagion literature, that co-movements among assets during crisis would become stronger. On the other hand, this phenomenon could be explained as a distinctive feature of an emerging market compared to well-developed financial markets. As the banking sector was hit particularly hard by the crisis, investors of these stocks may refrain from trading. Consequently, these stocks may become detached from the market resulting in lower betas.

### 2.5.2. Risk premia

The estimates of beta are now considered with respect to their explanatory power for observed stock returns (see, for example, Black et al., 1972; Fama and MacBeth, 1973). The usual approach regresses the standard CAPM beta on stock returns, using a pooled OLS approach, as follows

$$dp_{i,t} = \delta + \phi_h \hat{\beta}^h_{i,t} + v_{i,t}, \tag{2.14}$$

where $\hat{\beta}^h_{i,t}$ denotes the estimated single-factor CAPM beta. We extend this to incorporate the separation of market returns into continuous and jump components below:

$$dp_{i,t} = \delta + \phi_c \hat{\beta}^c_{i,t} + \phi_d \hat{\beta}^d_{i,t} + \omega_{i,t}, \tag{2.15}$$

where $dp_i$ indicates stock returns, and $\hat{\beta}^c_i$, and $\hat{\beta}^d_i$ denote the estimated continuous and jump betas, respectively. The models should produce a constant value, $\delta$, equal to the risk free rate, and the coefficients on the beta estimates, $\phi$'s, should indicate the relevant market risk premium which are expected to be significantly positive.

We first estimate monthly standard single factor CAPM beta in order to compare the results with the disentangled betas. The summary statistics of estimated standard CAPM betas $\hat{\beta}^h_{i,t}$ are reported in Table 2.7 while the average values these betas for each of the sample banks are shown in Table 2.8. The mean value of standard betas lies in-between the continuous and jump betas. It is an expected result given that continuous and jump betas are decomposed form of standard CAPM betas. For all banks, the standard CAPM beta has a value higher than the continuous beta and lower than the jump beta. Thus, it is clear that ignoring the source (continuous or jump) of change in the market return may lead to an over-estimate of systematic risk during continuous market movements, and under-estimate during discontinuous market movements. The average standard beta across all Indian banks is 0.96, while the average continuous beta is 0.75 and average jump beta is 1.42.

The results imply that the predictive power of CAPM beta is derived mainly from its jump component rather than the continuous component. The regression results for equations (2.14) and (2.15) are reported in Table 2.9 . We find positive and significant coefficients of only jump and CAPM betas but not for continuous beta in univariate regressions shown in models (1), (2) and (3). When we regress the stock returns on continuous and jump betas together as shown in model (4), jump beta remains significant, the continuous beta again does not have a significant coefficient.[5]. The random effect panel regression of the same model [6] shown in Table 2.10 provide us almost the same results. The continuous beta is significant now in model (1) in the univariate regression but still insignificant in model (4) thus reaffirming our finding that the jump beta has higher price discovery characteristic than the continuous beta.

[5]Extending the set of potential explanatory variables to include firm characteristics covered in the next section does not affect these conclusions. Results available from the authors on request.

[6]We choose random effect over fixed effect panel regression model as the Hausman Tests results fail to reject that the random effect models are misspecified.

### 2.5.3. The role of firm characteristics

There is substantial heterogeneity in the estimated continuous and discontinuous betas across the banks although they belong to the same industry. Patton and Verardo (2012) suggest that the variations in beta are associated with firm-specific news and stock fundamentals. We hypothesize that firm characteristics may contribute to the variations in the bank betas. The size of the banks, their profitability, leverage, capital stock against risky assets and ownership may contribute to the estimated differences.

The Basel regulatory framework advocates higher capital stock as a buffer against risky assets for banks implying that banks with higher capital adequacy ratios (CAR) should have lower chance of failure and hence be more resilient to risks arising from the market. Our first hypothesis is that CAR is negatively related to the systematic risk of banking firms.

Leverage, on the other hand, has been argued to increase systematic risk through correlation with business cycle conditions. Buiter and Rahbeir (2012) argue that leveraging is positively related to long-lived and costly systemic risk. Thus, our second hypothesis is that leverage is positively related to the systematic risk of banks.

Larger banks may be able to withstand market downturns via their ability to diversify and increased market power, and hence the third hypothesis is that larger firms have a lower beta. Profitable firms may exhibit stable price behaviour, stemming from the confidence that investors bestow on these stocks, making profitable firms less volatile than the market as a whole, leading to hypothesis four that higher profitability is negatively related to beta. Finally, we test whether similarly private versus government ownership reduces or increases the systematic risk of a bank, as investors may have different degrees of confidence on these two ownership modes.

Incorporating these firm characteristic factors, we estimate the following regression model:

$$\hat{\beta}_{i,t} = \alpha + \sum_{i=1}^{m} \gamma X_{i,t} + u_{i,t}, \tag{2.16}$$

for both jump beta and continuous beta separately, where $X_{i,t}$ are the firm characteristic variables of $i^{th}$ bank at time $t$. We collect data on the firm characteristics for 23 Indian banks from Datastream[7], and regress the jump beta or continuous beta on firm size, profitability, leverage, ownership and CAR separately. Firm size is represented by market capitalization in log form. Leverage is computed as the ratio of total debt to market capitalization. Profitability is measured in percentage of the return on assets (RoA), computed as earnings before interest tax and depreciation and amortization (EBITDA) divided by market value of assets. We use a dummy variable for nationalized versus private ownership of the banks and CAR is directly extracted from Datastream. The summary statistics for the firm characteristics are reported in Table 2.11.

In addition to firm characteristics, we consider the potential role of individual stock volatility. A firm that is highly volatile may show a greater reaction when the market moves. Alternatively, volatile stocks may be largely influenced by idiosyncratic factors rather than market conditions, and thus exhibit lower beta values. Thus our final form

[7] The macroeconomic data only for 23 of our sample banks are available in Datastream.

of equation (2.16) takes the following form:

$$\hat{\beta}_{i,t} = \alpha + \gamma_1 CAR_{i,t} + \gamma_2 Lev_{i,t} + \gamma_3 RoA_{i,t} + \gamma_4 Size_{i,t} + \gamma_5 Private_{i,t} + \gamma_6 RV_{i,t} + u_{i,t}, \quad (2.17)$$

incorporating capital assets ration (CAR), leverage (Lev), return on assets (RoA), size (Size) and $RV_{i,t}$ is realized variation for the $i^{th}$ bank at time $t$.

Table 2.12 reports the regression results on the relationship between betas and firm characteristics. The first column reports the results for continuous beta and the second column the results for jump beta. In the continuous beta specification we additionally include an AR(1) term to tackle the autocorrelation in the error term. The table reports White adjusted standard errors.

The results in Table 2.12 show that relationship between continuous beta and leverage is positive and significant, at the 1% significance level, while the relationship of continuous beta with CAR is negative and significant at the 5% level. A decrease of one unit in the leverage ratio is estimated to lead to a decrease of 0.03 in the continuous beta, assessed at the mean value of leverage, this is equivalent to a decrease in the leverage ratio for Indian banks from 2.05 to 1.85 resulting in a decrease in continuous beta of 0.006. It is immediately apparent that a large change in leverage would be required to alter beta to an economically meaningful extent. Similarly, although the relationship between continuous beta and CAR is statistically significant, and negative, the change required in CAR to obtain an economically meaningful reduction in beta is relatively large; an increase in CAR from its mean value of 9.52 to 10.52 results in a small 0.02

decrease in continuous beta.

Size and volatility have significant effects on continuous beta. The positive coefficient of market capitalization indicates that banks of larger size show higher sensitivities towards continuous market movements. The negative coefficient of profitability (RoA) indicate that less profitable banks have higher continuous systemic risk though the coefficient is not statistically significant. The volatility measure, $RV$, is a significant and positive factor for the continuous beta, indicating that higher price volatility results in higher continuous risk for these banks. Private versus government ownership (Private) has significant and negative relationship with continuous beta at the 10% significance level, implying that government owned banks are more sensitive than public sector banks towards continuous market movements.

Among the explanatory variables, leverage and size and ownership have significant effects on jump beta – CAR, RoA and volatility, however, do not. The signs are the same as those for the continuous beta estimates; thus decreased leverage and size and government ownership increase jump beta. The effects of CAR are smaller than in the continuous case and statistically insignificant, thus increasing bank capital has even lower impact here on reducing the reaction to market discontinuities than in the continuous case. The leverage effect is only slightly higher than in the continuous case. Although the coefficient on size almost halves for jump betas compared with continuous betas, in both cases larger firms have lower betas than their comparator firms, supporting the hypothesis that larger firms are less able to diversify away from the market. The insignificant coefficient of RoA in both case of betas fails to support the hypothesis that profits provide a buffer from unexpected market movements.

Our investigation quantifies the importance of the well-recognised decomposition of financial price movements into continuous and jump components. We test whether separating the beta estimates for these two components is warranted and unambiguously reject the hypothesis that the jump beta and continuous beta are the same using data for the Indian banking sector. The evidence strongly suggests that jump beta is higher than continuous beta, and that it has more explanatory power over returns, consistent with the view that discontinuities in financial prices are indicative of new information entering the market as in Patton and Verardo (2012) and the evidence for US markets in Todorov and Bollerslev (2010) and Alexeev et al. (2017).

We estimate the continuous and jump betas for an emerging market, and moreover, the banking sector of that market which bears a high responsibility for effectively funding future growth in India. Investigating the banking market specifically ties our results firmly to propositions for reducing systematic risk in that sector, with a view to reducing systemic risk in the economy as a whole. We find that recent proposals to reduce systemic risk via increasing capital requirements or reducing leverage in the banking sector would have the desired effect of reducing the systematic risk in the sector for both continuous and jump betas, but either the changes in capital or leverage required to produce economically meaningful results are very large or there is a substantial non-linearity in the relationship between these variables and systematic risk which is not captured by either this or other existing frameworks.

## 2.6. Conclusion

New tools allow the separate estimation of the beta on the continuous and jump component of the underlying price process which characterises financial market data. The existing literature for the US in Todorov and Bollerslev (2010) and Alexeev et al. (2017) estimate higher jump beta than continuous beta. This study produces a similar finding for Indian banking stocks. The focus on the Indian banking sector links the results to an important emerging economy with a high reliance on the banking sector for funding future growth, and contemporary issues concerning regulatory proposals for reducing systemic risk in international banking sectors.

Using 5-minute stock price data for 41 listed Indian banks for 2004-2015 we establish evidence of jumps in the Indian equity markets, consistent with existing evidence for developed markets and as yet a small range of equities in emerging market. The results show that the proportion of days containing a jump, at 4.68% of trading days, is not dissimilar to the evidence for developed economies – and that the proportion of jumps did not increase during the GFC, also consistent with the small existing literature concerning jump behaviour during crisis periods.

The estimates of separate continuous and jump betas for the Indian banks show that on average jump beta exceeds continuous beta by 159%, and the confidence band on these estimate rarely overlap for any of the individual stocks. We conclude that the reaction of individual stocks to discontinuities in the market indicator price is substantially higher than the reaction to continuous movements. This is consistent with the documented strong association of jumps with news events, particularly unanticipated news, and the learning model posited in Patton and Verardo (2012) which anticipates temporarily increased beta for stocks around the time of earnings announcements. Our study differs from theirs in that we condition the differing beta estimates on the existence of jumps, rather than on the existence of a news announcement (there is clearly overlap between these groups but it is by no means complete).

The estimated continuous and jump betas are related positively to firm size and leverage, and negatively to capital adequacy and profitability. Smaller profitable firms, with lower leverage and strong capital will have lower betas. However, the effect of size on beta is twice as large for continuous beta than jump beta, and the effect of profitability is twice as strong for jump beta than continuous beta. These findings have bearing on the debate concerning future regulatory practice for the banking sector in reducing systemic risk. Our results show that proposals to increase bank capital and decrease leverage will act to reduce the systematic risk in the Indian banking sector, with capital slightly more effective against continuous risk and leverage slightly more effective against jump risk, but the extent of the reduction in betas that can be produced in this manner are economically quite small. If the linear specification proposed in this study is correct the required reduction in leverage or increase in capital to produce an economically meaningful impact on jump or continuous beta is beyond the scope of current policy discussions. The behaviour of beta in response to leverage and capital would need to be highly non-linear to prompt the required regulatory response – the existence of such non-linearities is a scope for further research.

The results can be extended to other emerging economies to see whether the results are unique to the Indian market or can be generalized for all emerging markets. We include only banking stocks in this exercise. A comparison with other sectors would provide validity of the results and thus subject to future studies. We can also check whether the results stand when we use other jump tests available in the literature and use different sampling frequencies. We conduct different jump tests at different sampling frequencies on the Indian stocks in Chapter three.

Table 2.1: Banks listed on the NSE

*The table shows names and codes of 41 banks listed on the National Stock Exchange of India (NSE).*

| No. | Bank Name | Code | No. | Bank Name | Code |
|---|---|---|---|---|---|
| 1 | Andhra Bank | ADBK | 22 | Karur Vysya Bank | KARU |
| 2 | Allahabad Bank | ALBK | 23 | Karnataka Bank | KBNK |
| 3 | Axis Bank | AXBK | 24 | Kotak Mahindra Bank | KTKM |
| 4 | Bank Of Maharashtra | BMBK | 25 | Lakshmi Vilas Bank | LVLS |
| 5 | Bank Of Baroda | BOB | 26 | Oriental Bank Of Commerce | ORBC |
| 6 | Bank Of India | BOI | 27 | Punjab National Bank | PNBK |
| 7 | Central Bank Of India | CBI | 28 | Punjab & Sind Bank | PUNA |
| 8 | Canara Bank | CNBK | 29 | State Bank Of India | SBI |
| 9 | Corporation Bank | CRBK | 30 | State Bank Of Bikaner And Jaipur | SBKB |
| 10 | City Union Bank | CTBK | 31 | State Bank Of Mysore | SBKM |
| 11 | Development Credit Bank | DCBA | 32 | State Bank Of Travancore | SBKT |
| 12 | Dena Bank | DENA | 33 | Syndicate Bank | SBNK |
| 13 | Dhanlaxmi Bank Ltd | DNBK | 34 | South Indian Bank | SIBK |
| 14 | Federal Bank | FED | 35 | Standard Chartered Bank | STNCy |
| 15 | HDFC Bank | HDBK | 36 | United Bank Of India | UBOI |
| 16 | ICICI Bank | ICBK | 37 | UCO Bank | UCBK |
| 17 | IDBI Bank | IDBI | 38 | Union Bank Of India | UNBK |
| 18 | Indian Bank | INBA | 39 | Vijaya Bank | VJBK |
| 19 | Indusind Bank Limited | INBK | 40 | Ing Vysya Bank Ltd | VYSA |
| 20 | Indian Overseas Bank | IOBK | 41 | Yes Bank | YESB |
| 21 | Jammu And Kashmir Bank | JKBK | | | |

Table 2.2: Volatility measures for Indian market during the sample period 2004 − 2015

*The Table reports the descriptive statistics of the two daily volatility measures RV and BV of the CNX500. The square root version of the volatility measures are shown here. We report both daily and monthly measures of these variable.*

| Descriptive Statistics | Daily | | Monthly | |
|---|---|---|---|---|
| | $\sqrt{RV}$ | $\sqrt{BV}$ | $\sqrt{RV}$ | $\sqrt{BV}$ |
| Mean | 0.00760 | 0.00728 | 0.04273 | 0.04025 |
| Median | 0.00676 | 0.00642 | 0.03489 | 0.03352 |
| Std. Dev. | 0.00612 | 0.00577 | 0.02399 | 0.02040 |
| maximum | 0.09633 | 0.07384 | 0.16732 | 0.12823 |

Table 2.3: Summary statistics of continuous and jump betas

*The second column and third column show the summary statistics of continuous and jump betas of all sample banking stocks respectively.*

| Banks | BetaC | BetaD |
|---|---|---|
| Mean | 0.75 | 1.42 |
| Max | 1.26 | 1.85 |
| Min | 0.04 | 0.47 |
| Standard Dev | 0.36 | 0.32 |
| Skewness | -0.43 | -0.76 |
| Kurtosis | -1.27 | 0.36 |

Table 2.4: Average continuous and jump betas for listed Indian Banks

*We show bank names in the first column, average monthly continuous betas in the second column, the 95% confidence levels of continuous betas in column three and four, average monthly jump betas in column five, 95% confidence levels of jump betas in column six and seven and the differences between the two average beta values in column eight.*

| Banks | $\beta_i^c$ | | | $\beta_i^d$ | | | Difference (%) |
|---|---|---|---|---|---|---|---|
| ADBK | 0.98 | [0.90, | 1.06] | 1.48 | [1.46, | 1.49] | 51.02 |
| ALBK | 1.01 | [0.93, | 1.09 ] | 1.61 | [1.60, | 1.62 ] | 59.71 |
| AXBK | 1.09 | [1.01, | 1.16 ] | 1.56 | [1.54, | 1.57 ] | 43.29 |
| BMBK | 0.48 | [0.40, | 0.57 ] | 1.21 | [1.19, | 1.22 ] | 150.19 |
| BOB | 1.05 | [0.96, | 1.13 ] | 1.68 | [1.67, | 1.69 ] | 60.43 |
| BOI | 1.25 | [1.16, | 1.33 ] | 1.85 | [1.84, | 1.87 ] | 48.42 |
| CBI | 0.75 | [0.66, | 0.84 ] | 1.47 | [1.45, | 1.48 ] | 95.21 |
| CNBK | 1.12 | [1.04, | 1.21 ] | 1.74 | [1.73, | 1.76 ] | 55.08 |
| CRBK | 0.38 | [0.29, | 0.47 ] | 1.14 | [1.13, | 1.16 ] | 199.83 |
| CTBK | 0.32 | [0.23, | 0.41 ] | 1.03 | [1.01, | 1.05 ] | 218.91 |
| DCBA | 1.04 | [0.95, | 1.13 ] | 1.83 | [1.81, | 1.84 ] | 75.24 |
| DENA | 1.06 | [0.97, | 1.15 ] | 1.68 | [1.66, | 1.69 ] | 58.47 |
| DNBK | 0.49 | [0.39, | 0.60 ] | 1.16 | [1.14, | 1.19 ] | 134.59 |
| FED | 0.71 | [0.62, | 0.79 ] | 1.39 | [1.38, | 1.40 ] | 96.88 |
| HDBK | 0.69 | [0.61, | 0.76 ] | 1.19 | [1.19, | 1.20 ] | 73.92 |
| ICBK | 1.04 | [0.96, | 1.11 ] | 1.55 | [1.54, | 1.56 ] | 49.75 |
| IDBI | 1.26 | [1.18, | 1.34 ] | 1.82 | [1.81, | 1.84 ] | 44.58 |
| INBA | 0.63 | [0.54, | 0.72 ] | 1.41 | [1.39, | 1.42 ] | 122.86 |
| INBK | 0.98 | [0.89, | 1.06 ] | 1.71 | [1.69, | 1.72 ] | 75.26 |
| IOBK | 0.92 | [0.83, | 1.00 ] | 1.54 | [1.52, | 1.55 ] | 67.31 |
| JKBK | 0.27 | [0.19, | 0.36 ] | 1.04 | [1.03, | 1.06 ] | 282.08 |
| KARU | 0.24 | [0.16, | 0.32 ] | 0.82 | [0.80, | 0.83 ] | 244.32 |
| KBNK | 0.96 | [0.88, | 1.05 ] | 1.72 | [1.70, | 1.73 ] | 78.33 |
| KTKM | 0.87 | [0.79, | 0.96 ] | 1.42 | [1.40, | 1.43 ] | 62.19 |
| LVLS | 0.40 | [0.31, | 0.49 ] | 1.17 | [1.15, | 1.18 ] | 189.46 |
| ORBC | 1.07 | [0.98, | 1.15 ] | 1.74 | [1.73, | 1.76 ] | 63.58 |
| PNBK | 1.01 | [0.93, | 1.09 ] | 1.63 | [1.62, | 1.64 ] | 61.66 |
| PUNA | 0.38 | [0.29, | 0.47 ] | 1.36 | [1.35, | 1.36 ] | 259.62 |
| SBI | 1.03 | [0.96, | 1.10 ] | 1.50 | [1.49, | 1.51 ] | 45.27 |
| SBKB | 0.24 | [0.15, | 0.32 ] | 1.09 | [1.08, | 1.10 ] | 362.56 |
| SBKM | 0.14 | [0.05, | 0.24 ] | 0.96 | [0.96, | 0.97 ] | 570.01 |
| SBKT | 0.21 | [0.12, | 0.30 ] | 1.08 | [1.08, | 1.09 ] | 414.70 |
| SBNK | 1.11 | [1.03, | 1.20 ] | 1.83 | [1.82, | 1.84 ] | 64.39 |
| SIBK | 0.51 | [0.42, | 0.60 ] | 1.23 | [1.21, | 1.24 ] | 139.65 |
| STNCy | 0.04 | [-0.04, | 0.12 ] | 0.47 | [0.46, | 0.47 ] | 1144.74 |
| UBOI | 0.56 | [0.46, | 0.65 ] | 1.45 | [1.44, | 1.46 ] | 160.90 |
| UCBK | 1.15 | [1.07, | 1.24 ] | 1.82 | [1.81, | 1.83 ] | 58.06 |
| UNBK | 1.12 | [1.03, | 1.20 ] | 1.78 | [1.77, | 1.80 ] | 59.80 |
| VJBK | 0.97 | [0.89, | 1.05 ] | 1.56 | [1.55, | 1.57 ] | 61.01 |
| VYSA | 0.29 | [0.20, | 0.38 ] | 1.08 | [1.06, | 1.10 ] | 277.22 |
| YESB | 1.05 | [0.96, | 1.13 ] | 1.62 | [1.60, | 1.63 ] | 54.16 |

Table 2.5: Summary statistics of Indian Bank betas during pre-GFC, GFC and post-GFC periods

*The second, third and fourth columns show the summary statistics of continuous betas sample banking stocks in the pre-GFC, GFC and post-GFC periods. The same statistics for jump betas are shown in the fifth, sixth and seventh columns.*

| | BetaC | | | BetaC | | |
|---|---|---|---|---|---|---|
| | PreGFC | GFC | Post-GFC | PreGFC | GFC | Post-GFC |
| Mean | 0.73 | 0.68 | 0.96 | 1.40 | 1.13 | 1.63 |
| Max | 1.18 | 1.17 | 1.55 | 1.89 | 1.57 | 2.34 |
| Min | 0.20 | 0.18 | 0.25 | 0.72 | 0.71 | 0.84 |
| Std | 0.27 | 0.28 | 0.39 | 0.28 | 0.23 | 0.37 |
| Skewness | -0.42 | 0.17 | -0.57 | -0.38 | -0.01 | -0.43 |
| Kurtosis | -0.85 | -0.87 | -0.94 | -0.14 | -0.49 | -0.54 |

Table 2.6: Average continuous and jump betas during the pre-GFC, GFC and post-GFC periods for listed Indian Banks.

*The pre-GFC, GFC and post-GFC average monthly continuous betas are reported in column two, three and four, whereas the average monthly jump betas of these same time periods are reported in column five, six and seven.*

| Banks | BetaC | | | BetaD | | |
|---|---|---|---|---|---|---|
| | PreGFC | GFC | Post-GFC | PreGFC | GFC | Post-GFC |
| ADBK | 0.88 | 0.52 | 1.18 | 1.28 | 1.02 | 1.75 |
| ALBK | 0.74 | 0.63 | 1.33 | 1.36 | 1.11 | 1.95 |
| AXBK | 0.76 | 1.04 | 1.16 | 1.18 | 1.28 | 1.69 |
| BMBK | 0.51 | 0.44 | 0.47 | 1.33 | 0.94 | 1.16 |
| BOB | 1.08 | 0.74 | 1.11 | 1.62 | 1.05 | 1.87 |
| BOI | 1.18 | 0.91 | 1.40 | 1.80 | 1.19 | 2.04 |
| CBI | 0.63 | 0.57 | 0.82 | 1.14 | 1.18 | 1.59 |
| CNBK | 1.01 | 0.68 | 1.34 | 1.68 | 1.06 | 1.95 |
| CRBK | 0.45 | 0.30 | 0.34 | 1.33 | 0.71 | 1.07 |
| CTBK | 0.33 | 0.48 | 0.27 | 1.04 | 1.28 | 0.96 |
| DCBA | 1.00 | 1.12 | 1.03 | 1.89 | 1.56 | 1.86 |
| DENA | 0.85 | 0.97 | 1.26 | 1.61 | 1.28 | 1.83 |
| DNBK | 0.20 | 0.53 | 0.71 | 0.72 | 1.15 | 1.55 |
| FED | 0.63 | 0.42 | 0.85 | 1.33 | 0.89 | 1.56 |
| HDBK | 0.56 | 0.71 | 0.79 | 1.16 | 0.94 | 1.28 |
| ICBK | 0.88 | 1.16 | 1.12 | 1.40 | 1.44 | 1.71 |
| IDBI | 1.09 | 1.15 | 1.43 | 1.75 | 1.57 | 1.95 |
| INBA | 0.87 | 0.59 | 0.58 | 1.63 | 1.17 | 1.39 |
| INBK | 1.07 | 0.82 | 0.94 | 1.83 | 1.43 | 1.66 |
| IOBK | 0.76 | 0.68 | 1.11 | 1.46 | 1.29 | 1.66 |
| JKBK | 0.33 | 0.19 | 0.25 | 0.98 | 0.71 | 1.17 |
| KARU | 0.24 | 0.18 | 0.25 | 0.82 | 0.72 | 0.84 |
| KBNK | 0.77 | 0.42 | 1.27 | 1.60 | 0.89 | 2.01 |
| KTKM | 0.67 | 1.17 | 0.96 | 1.38 | 1.37 | 1.46 |
| LVLS | 0.40 | 0.31 | 0.43 | 1.13 | 0.90 | 1.26 |
| ORBC | 0.86 | 0.60 | 1.36 | 1.53 | 1.14 | 2.07 |
| PNBK | 0.94 | 0.75 | 1.13 | 1.48 | 1.09 | 1.88 |
| SBI | 1.00 | 0.94 | 1.09 | 1.46 | 1.05 | 1.63 |
| SBNK | 0.97 | 0.58 | 1.38 | 1.78 | 1.20 | 2.02 |
| SIBK | 0.45 | 0.41 | 0.59 | 1.24 | 0.88 | 1.29 |
| UCBK | 0.78 | 0.83 | 1.55 | 1.39 | 1.22 | 2.34 |
| UNBK | 1.03 | 0.57 | 1.33 | 1.75 | 0.97 | 1.99 |
| VJBK | 0.84 | 0.89 | 1.09 | 1.50 | 1.37 | 1.66 |
| VYSA | 0.27 | 0.33 | 0.29 | 1.15 | 1.03 | 1.02 |
| YESB | 0.66 | 1.00 | 1.28 | 1.42 | 1.37 | 1.79 |
| Average | 0.73 | 0.68 | 0.96 | 1.40 | 1.13 | 1.63 |

The banks which were not listed on NSE for the full sample period are excluded here.

Table 2.7: Summary statistics of continuous, jump and standard CAPM betas of Indian Banks.

*The second, third and fourth columns show the summary statistics of continuous and jump and standard CAPM betas of all sample banking stocks respectively.*

| | BetaC | BetaD | BetaSTD |
|---|---|---|---|
| Mean | 0.75 | 1.42 | 0.96 |
| Max | 1.26 | 1.85 | 1.49 |
| Min | 0.04 | 0.47 | 0.11 |
| Standard Dev | 0.36 | 0.32 | 0.39 |
| Skewness | -0.43 | -0.76 | -0.48 |
| Kurtosis | -1.27 | 0.36 | -1.09 |

Table 2.8: Average monthly continuous, jump and standard CAPM betas for Indian banks

*The second, third and the fourth columns are showing the average monthly continuous, jump and standard betas of 41 listed banks in India.*

| Bank | BetaC | BetaD | BetaStD | Bank | BetaC | BetaD | BetaSTD |
|---|---|---|---|---|---|---|---|
| ADBK | 0.98 | 1.48 | 1.22 | KARU | 0.24 | 0.82 | 0.35 |
| ALBK | 1.01 | 1.61 | 1.25 | KBNK | 0.96 | 1.72 | 1.21 |
| AXBK | 1.09 | 1.56 | 1.27 | KTKM | 0.87 | 1.42 | 1.04 |
| BMBK | 0.48 | 1.21 | 0.69 | LVLS | 0.40 | 1.17 | 0.59 |
| BOB | 1.05 | 1.68 | 1.28 | ORBC | 1.07 | 1.74 | 1.33 |
| BOI | 1.25 | 1.85 | 1.49 | PNBK | 1.01 | 1.63 | 1.23 |
| CBI | 0.75 | 1.47 | 0.97 | PUNA | 0.38 | 1.36 | 0.66 |
| CNBK | 1.12 | 1.74 | 1.37 | SBI | 1.03 | 1.50 | 1.20 |
| CRBK | 0.38 | 1.14 | 0.56 | SBKB | 0.24 | 1.09 | 0.45 |
| CTBK | 0.32 | 1.03 | 0.46 | SBKM | 0.14 | 0.96 | 0.34 |
| DCBA | 1.04 | 1.83 | 1.29 | SBKT | 0.21 | 1.08 | 0.40 |
| DENA | 1.06 | 1.68 | 1.30 | SBNK | 1.11 | 1.83 | 1.40 |
| DNBK | 0.49 | 1.16 | 0.71 | SIBK | 0.51 | 1.23 | 0.69 |
| FED | 0.71 | 1.39 | 0.92 | STNCy | 0.04 | 0.47 | 0.11 |
| HDBK | 0.69 | 1.19 | 0.82 | UBOI | 0.56 | 1.45 | 0.80 |
| ICBK | 1.04 | 1.55 | 1.21 | UCBK | 1.15 | 1.82 | 1.42 |
| IDBI | 1.26 | 1.82 | 1.49 | UNBK | 1.12 | 1.78 | 1.38 |
| INBA | 0.63 | 1.41 | 0.87 | VJBK | 0.97 | 1.56 | 1.20 |
| INBK | 0.98 | 1.71 | 1.20 | VYSA | 0.29 | 1.08 | 0.43 |
| IOBK | 0.92 | 1.54 | 1.16 | YESB | 1.05 | 1.62 | 1.25 |
| JKBK | 0.27 | 1.04 | 0.42 | | | | |

Table 2.9: Impact of continuous and jump beta on stock returns

*The regression results of stock returns on different betas are shown in different columns. All models are estimated using pooled regression with the dependent variable monthly stock returns. The number of banks included cross section is 41. The number of periods is 144 in regression 1 and 3 and 87 in regression 2 and 4. Standard errors are displayed in parentheses below the coefficients. Significance levels: † : 10%, ∗ : 5%, ∗∗ : 1%.*

| Variables | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Constant | -0.0078* | -0.0092* | -0.0106** | -0.0072 |
| | (0.0040) | (0.0056) | (0.0043) | (0.0058) |
| $\beta_i^c$ | 0.0058 | | | -0.0081 |
| | (0.0044) | | | (0.0071) |
| $\beta_i^d$ | | 0.0078∗∗ | | 0.0108∗∗ |
| | | (0.0034) | | (0.0044) |
| $\beta_i^h$ | | | 0.0074** | |
| | | | (0.0038) | |
| Adjusted $R^2$ | 0.0003 | 0.0013 | 0.0005 | 0.0014 |
| $F$-stat | 1.7453 | 5.2009 | 3.91 | 3.24 |
| DW stat | 1.92 | 1.99 | 1.92 | 1.99 |

Table 2.10: Impact of continuous and jump beta on stock returns: the random effect model

*The regression results of stock returns on different betas are shown in different columns. All models are estimated using random effect panel regression with the dependent variable monthly stock returns. The number of banks included cross section is 41. The number of periods is 144 in regression 1 and 3 and 87 in regression 2 and 4. Standard errors are displayed in parentheses below the coefficients. Significance levels: † : 10%, ∗ : 5%, ∗∗ : 1%.*

| Variables | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Constant | -0.0078*** | -0.0092* | -0.0106*** | -0.0072 |
| | (0.0021) | (0.0050) | (0.0026) | (0.0049) |
| $\beta_i^c$ | 0.0058** | | | -0.0061 |
| | (0.0023) | | | (0.0071) |
| $\beta_i^d$ | | 0.0078∗∗ | | 0.0108∗∗ |
| | | (0.0035) | | (0.0047) |
| $\beta_i^h$ | | | 0.0074*** | |
| | | | (0.0023) | |
| Adjusted $R^2$ | 0.0001 | 0.0013 | 0.0005 | 0.0013 |
| $F$-stat | 1.7453 | 5.2009 | 3.9118 | 3.2432 |
| DW stat | 1.92 | 1.99 | 1.92 | 1.99 |

Table 2.11: Summary statistics of firm characteristics

*CAR denotes the capital adequacy ratio, RoA denotes the return on asset, Lev denotes the leverage ratio, Size denotes the logarithm of market capitalization, and RV denotes the realized variation.*

| | CAR | Lev | RoA | Size | RV |
|---|---|---|---|---|---|
| Mean | 9.52 | 2.05 | 1.75 | 4.73 | 0.0123 |
| Median | 8.95 | 1.25 | 1.77 | 4.42 | 0.0089 |
| Maximum | 19.11 | 18.95 | 4.72 | 7.9 | 0.2083 |
| Minimum | 5.04 | 0.14 | -0.96 | 2.01 | 0 |
| Std. Dev. | 2.41 | 2.5 | 0.8 | 1.29 | 0.013 |

Table 2.12: Relationship between firm characteristics and the betas

*The second column shows the regression results of continuous betas on firm characteristic variables, whereas the third column shows the regression results of jump betas on the same firm characteristic variables. Standard errors are shown in parentheses below the coefficients. Both models are estimated using pooled OLS regression. The number of banks is 23, and the number of periods is 144 for models of $\hat{\beta}^c_{i,t}$, and 87 for models of $\hat{\beta}^d_{i,t}$. . Significance levels: † : 10%, ∗ : 5%, ∗∗ : 1%.*

| Variables | cont. beta | jump beta |
|---|---|---|
| Constant | 0.504 | 1.230∗∗∗ |
| | (0.1719) | (0.1509) |
| CAR | -0.024∗∗ | -0.009 |
| | (0.0106) | (0.0085) |
| Lev | 0.029∗∗ | 0.062∗∗∗ |
| | (0.0142) | (0.0123) |
| RoA | -0.005 | -0.008 |
| | (0.025) | (0.0326) |
| Size | 0.126∗∗∗ | 0.068∗∗∗ |
| | (0.0219) | (0.022) |
| Private | -0.147∗ | -0.175∗∗∗ |
| | (0.0773) | (0.0632) |
| 100RV | 0.038∗∗∗ | -0.036 |
| | (0.0098) | (0.0558) |
| AR(1) | 0.837∗∗∗ | |
| | (0.0228) | |
| Adjusted $R^2$ | 0.77 | 0.08 |
| F-stat | 1099.48 | 21.73 |
| DW stat | 2.35 | 1.31 |

Figure 2.1: The occurrence of jump days detected with the BNS test in the CNX500 index

*The figure shows the intensity of jump occurrences in the Indian market represented by CNX500 throughout the sample period of 2004 to 2015. The vertical lines here represent days with jumps detected by the BNS test. Thus more vertical lines within a given period indicates higher intensity of jump occurrences.*

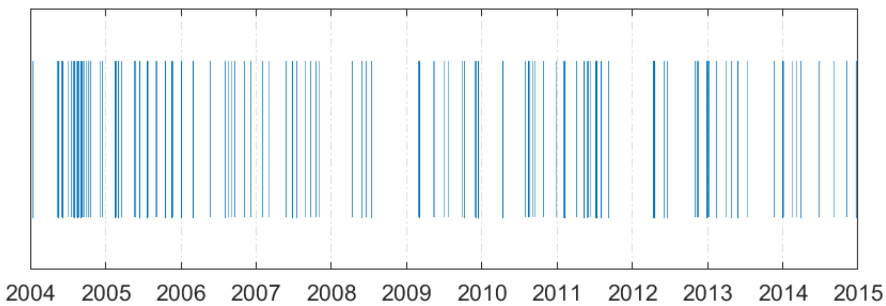


Figure 2.2: Confidence interval of average monthly $\hat{\beta}_i^c$ and $\hat{\beta}_i^d$ of all banks

*The 95% confidence intervals of average monthly continuous betas of all banks are shown by the red lines and of jump betas shown by the blue dots. The lack of overlapping between these two sets of confidence intervals shows that these two components of systematic risks are significantly different to each other.*

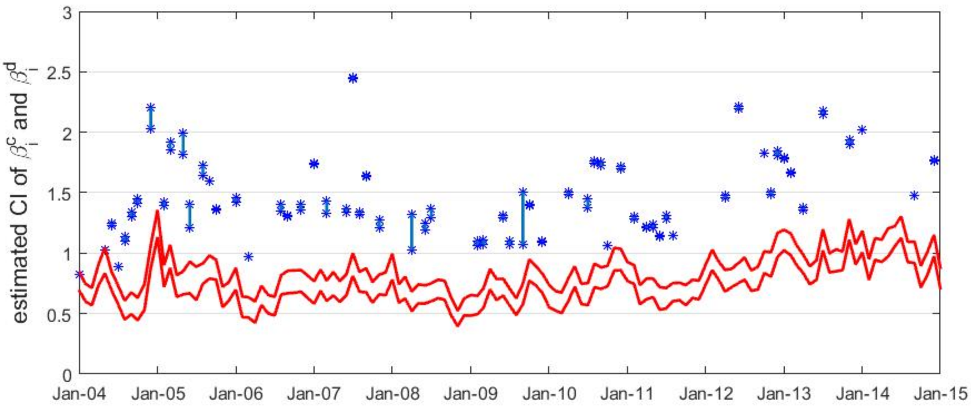
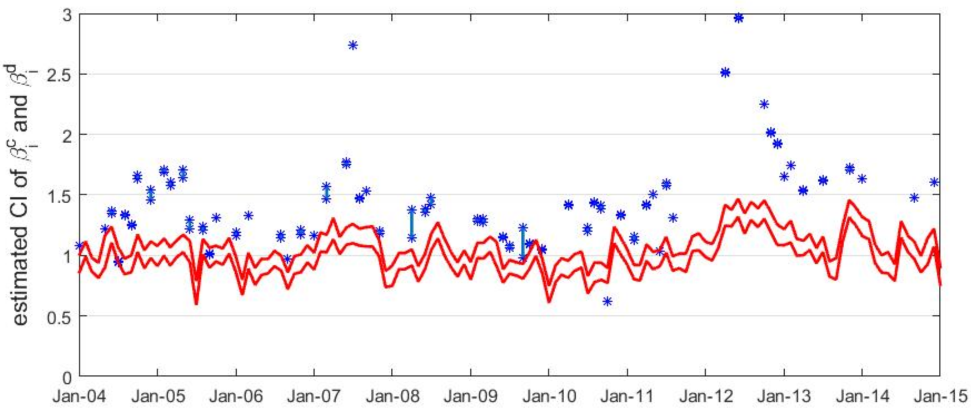



Figure 2.3: Confidence interval of monthly $\hat{\beta}_i^c$ and $\hat{\beta}_i^d$ of SBI from 2004 to 2012

*The 95% confidence intervals of average monthly continuous betas of State Bank of India (SBI) are shown by the red lines and of jump betas shown by the blue dots. The lack of overlapping between these two sets of confidence intervals shows that these two components of systematic risks are significantly different to each other.*



# 3 Jump Risk in Indian Financial Market

## 3.1. Introduction

We show evidence in chapter 2 in favour of the argument in the literature (such as Andersen et al., 2007a) that an asset price process experiences infrequent jumps in addition to the continuous Brownian motion and drift movements. The irregular and unpredictable nature of jumps generates risks for asset investors who price the risk either positively (Driessen and Maenhout, 2013) or negatively (Cremers et al., 2015) in the stock market. Therefore identifying jump risk has gained wide attention from academic researchers as well as practitioners. While papers on jumps have concentrated on the U.S. and other developed markets our second study measures the extent of jump risks and draws out the characteristics of jump occurrences in India, an important emerging market, with especial emphasis on its financial sector.

After the recent global financial crisis (GFC) of 2008-2009, it has become increasingly recognized that the risk of individual banks and financial institutions needs to be addressed at the the systemic level (Haldane and May, 2011). Instability in financial markets can trigger deep economic crises, creating political and social unrest (Crotty, 2009). This motivates us to concentrate our examination of jump risk in the banking and non-banking financial corporations (FI) sectors and make a comparative analysis with the overall market. A series of failures of banks and financial institutions in the U.S.

led the prolonged recession during the GFC. As observed by Morgan (2000), the opacity of banks can create a financial system crisis which can have a substantial contagious and systemic effect on the entire market. Therefore, we make a comparison of jump risks between the financial sectors and the whole economy in the context of an emerging economy where bank-based financial intermediation plays a larger role in the financial system than in the developed markets (Demirgüç-Kunt and Levine, 1996, Kim and Wu, 2008).

The popularity of financial sector stocks in India is associated with a high frequency of trading, and that facilitates the use of non-parametric jump tests requiring high frequency trading data. A complement to the banks, there is a full range of non-bank financial institutions (FIs) that act as effective financial intermediaries. The FIs are companies that are engaged in loans and advances, acquisitions of shares, stocks , bonds, hire-purchase and insurance. Like the commercial banks these companies are regulated by the Reserve Bank of India (RBI) within the framework of the Reserve Bank of India Act, 1934 (Chapter III B). The major differences from commercial banks are that FIs can not accept demand deposits and they are not part of payment and settlement system of the RBI. As the importance of FIs in fulfilling the credit needs of the market is well recognized, appropriate regulatory attention and risk monitoring are required in the interest of financial stability.

This study examines the jump risks of the banking sector represented by 41 Indian banking stocks, and the FI sector represented by 55 FIs, all listed on the National Stock Exchange of India (NSE). Drawing on high frequency intra-day data from the Thompson Reuters Tick History (TRTH) Database provided by SIRCA, we use recent econometric techniques to provide a comprehensive characterization of the jump risk in the Indian financial sector.

We explore the interaction of jump risks between the financial sector and the whole economy. Jumps in asset price series are typically interpreted as associated with sudden arrival of new information to the market (Andersen et al., 2007a). This new information usually causes a rapid movement in prices of assets. Prices of stocks that are popular among the investors and followed by analysts, are likely to show quick reflection of the news/information arrival into the market. Banking stocks are among the large-capitalization stocks in the Indian market and are under constant analysis by market experts. On the other hand, the total market consists of a variety of firms that vary widely in terms of size and liquidity. Thus we hypothesize that the banking industry as a whole experiences a higher amount of jump risk than the overall market. The non-banking financial firms are different from each other from the perspective of operation, size and reputation among the investors. Therefore it is difficult to predict the jump intensity of this industry, and a comparison with the overall market is worth investigating.

We also present a comparison of jump risk exposure between banking and FI sectors as two sub-sectors of the financial sector. Investors get benefit from diversification if different sub-sectors are prone to different degrees of any particular risk. Firms belonging to these two sectors compete with each other for investment funds (Bikker and Haaf, 2002) and thus might be vulnerable to the same shocks. Therefore, it is expected that shocks in one industry will be transmitted into the other industry, especially from the banking sector to the FI sector. We expect to see simultaneous or common jumps in these two sectors in addition to sector-specific jumps. As we are unaware of any paper investigating the sectoral differences in jump risk, this study serves as a beginning at this direction.

When we observe the co-occurrence of jumps (referred as 'common jumps' or 'cojumps' by Jacod and Todorov, 2009) in a sector and in the market, we call it a systematic jump for that sector. When a sector experiences a stand alone jump, we refer it as a sector-specific idiosyncratic jump. Theoretically, idiosyncratic jump risk is diversifiable (Merton, 1976; Bollerslev et al., 2008), but Yan (2011) shows that both systematic and idiosyncratic jump risks are priced at different rates by investors, and thus are important to ascertain. We report the portion of days that the banking and FI sectors experience each type of jump in this study.

An important question for portfolio management is whether occurrences of jumps in the market have causal effects on the jump occurrences in any sector. On a similar note, it is intuitive to think that among two closely related sectors, jumps in one sector may trigger jumps in the other sector. If this is true, then investors in one sector should be aware of jumps not only in that sector but also in the related sectors or the market. We examine this question by applying a probit regression and find that jump occurrences in the overall market in a given period significantly change the probability of jump occurrences both in the banking sector and FI sector. Jumps are not significantly transmitted in either direction between these two sectors.

Jump intensity during a crisis period is another area of interest for researchers. As jumps are often the result of information arrival and generally crisis periods are characterized by arrival of news more frequently than that of calm period, we expect to find more jumps during a crisis. But computationally jumps are measured relative to the volatility of a given window period. Hence, if the overall volatility during a crisis period increases as shown by Aït-Sahalia and Xiu (2016), then we may not be able to detect jumps at a higher rate than a non-crisis and non-volatile period. In this study, we find that during the global financial crisis of 2008-09 jump intensity increased for banking stocks, while the FI stocks experienced no such change in the jump risk during the same period.

We explore the intraday, day of the week and month of the year pattern of jumps in the Indian market. Jumps are described as rare Poisson events in the literature (for example, Merton, 1976 and Ball and Torous, 1985). If this is true then they should appear in stock prices randomly, and only upon the arrival of abnormal information[1].

[1]According to the Merton (1976) price changes caused by arrival of normal information leads to price changes as log normal diffusion while the log-normally distributed jumps in the security return appear

On the other hand, jumps are a particular state of stock returns depending on the overall volatility of window period. It is well established in asset pricing literature that stock prices are subject to time of the day, day of the week, month of the year among other effects, which are considered in literature as anomalies (French, 1980, Chang et al., 1993, Jaffe and Westerfield, 1989). The seasonality of stock prices may be reflected in jump patterns. If jumps are information-driven then corporate announcements may be an important instigator of jumps (Patton and Verardo, 2012). Corporate bodies may have a tendency to declare especially unfavourable earning announcements after trading hours are finished (Michaely et al., 2013) in which case the resultant jumps would occur in the after-hours electronic platforms (Dungey et al., 2009a) or in the early hours of the next trading day. Bollerslev et al. (2008) find the presence of strong intra-day patterns in jumps, with the peak coinciding with the time of news release. We examine the seasonality of jumps in Indian market and find evidence of intra-day patterns in jumps. Jumps in the Indian market cluster largely at the opening hours and to some extent ending hours of the trading period.

The day of the week effect on stock returns is documented in the literature (for example, French, 1980; Chang et al., 1993 and Dubois and Louvet, 1996). Researchers have shown that stock returns are generally lowest and negative on Mondays and highest on Fridays compared with other days of the week in various markets, although Choudhry (2000), Bhattacharya et al. (2003) and Raj and Kumari (2006) report mixed results for this effect for the Indian market. Our findings corroborate the day of the week effect, especially the Monday effect on jumps, in the Indian market. Among different months, the January effect on stock return is most cited by researchers (Ariel, 1987 and Jaffe and Westerfield, 1989). However, due to differences in financial years and religious traditions in different markets, we may see a different pattern of the month effect on jumps. Our results show higher jump intensity in the middle of the year, which matches the April

upon arrival of abnormal information which is a Poisson process.

to March financial year generally followed by Indian companies.

Do jumps have a memory and exhibit clustering behaviour? We apply a model developed by Corsi (2004) to determine the existence of memory as well as seasonality by regressing the binary jump variable with its lag values representing one day, one week and one month time periods. We find significant coefficients for these lag variables showing seasonality and predictability of jump events. Given the extent of jump activity and its seasonal pattern, our findings conform with the conclusion drawn by Bormetti et al. (2015) that jump arrivals can not be described by a Poisson process.

In any study related to jump risk, an intriguing question is which method to apply in identifying jumps. A growing literature in high frequency financial econometrics proposes a number of methodologies for testing for the presence of jumps in the price processes. Dumitru and Urga (2012) conduct a comprehensive comparison of nine alternative testing procedures, and use several stocks listed in the New York Stock Exchange as an empirical example. All of these tests are based on non-parametric estimators of the continuous and jump variations in the price processes that are robust to jumps. However, given such a wide range of testing procedures available to empirical researchers, it is still unclear as to which test should be implemented in practice. In particular, given the distinct behaviour of financial stocks from emerging markets, it is unclear whether the data characteristics can affect the performance of different tests. In order to answer these questions, we apply the most widely-used jump detection procedures to Indian financial stocks. The other two studies that present a comparative analysis of different jump test methods are Theodosiou and Zikes (2009) and Schwert (2009) using the U.S. data. None of these papers report any conclusive evidence about the superiority of any particular method.

The commonly used non-parametric jump detection methods include the tests developed by Barndorff-Nielsen and Shephard (2006) (henceforth BNS method), Andersen et al. (2012) (henceforth ADS method), Aït-Sahalia et al. (2009) (henceforth AJ method), Lee and Mykland (2008) (henceforth LM method), Andersen et al. (2007b) (henceforth ABD method), Jiang and Oomen (2008) (henceforth JO method), Corsi et al. (2010) (henceforth CPR method) . BNS developed the first non-parametric test of jump detection by taking the difference or ratio of the variation and the jump-robust multi-power variation. Multi-power variation can have upward or downward biases as a jump-robust estimator in the presence of zero returns or large returns. To remove this bias in multi-power variation, ABD propose tests using the median or minimum return based realized variation against the total variation. CPR on the other hand use the realized threshold multi-power variation by truncating the large absolute returns. The JO method applies a swap variance test by taking the difference between the simple returns and the logarithmic returns. AJ propose computing a ratio of two time-scale power variation to determine the existence of jumps in a window of returns while ABD and LM use a local volatility measure to identify the jump returns and check how big a particular return is in the context of the local volatility measure.

We implement two versions of the BNS method, one by using quad-power variance (henceforth BNS_QV) and another by using tri-power variation (henceforth BNS_TQ). We use the nonparametric procedures on a market index - CNX500, an equally weighted index of banking industry and on an equally weighted index of the FI industry. The results vary widely across different jump methods, data frequencies and different significance levels. Generally LM/ABD, CPR and BNS_QV methods report a high proportion of jump days and JO, AJ and Min_RV methods are in the opposite end of the spectrum.

One of the problems of jump test applications is to determine the optimal sampling frequency. The asymptotic theory requires high frequency data to ensure data continuity whereas very high frequency data is susceptible to the market micro-structure noise. Market micro-structure noise can be defined as the deviation of the observed stock prices from the fundamental or true values (Bandi and Russell, 2008). This noise results from market frictions, such as the change in transaction price as multiples of ticks (price discreteness) or availability of multiple prices for buyers and sellers (bid-ask bounce). Our estimated variance and other statistics can be biased in the presence of market micro-structure noise, and it can have a significant impact on the tests for jumps in asset prices.

One way to check the effect of market micro-structure noise and suggest the optimal sampling frequency is to use a graphical tool known as the volatility signature plot developed by Andersen et al. (1999). The volatility signature plot may reveal the effect of sampling frequency on volatility by plotting sampling intervals on the horizontal axis and volatility on the vertical axis. The underlying assumption behind the plot is that the variance of a price process is independent of the frequency at which the data is collected. Thus, if we observe a distortion on the realized variance measure at a certain frequency, we can identify that the market micro-structure noise is causing the distortion at that frequency.

In our study, all of the methods detect lower evidence of jumps when we increase the interval of returns, in other words decrease the data frequency. Although our volatility signature plot suggests that a 15-minute data frequency may pacify the effect of market micro-structure noise, some of the methods fail to detect the level of jumps suggested in literature, at this frequency.

This is the first study to conduct a comprehensive analysis of jump risk on the Indian financial market. One of the contributions of this paper is strengthening the notion argued by few recent studies that jump occurrences may not be a Poisson process as is described in the early literature. The clustering behaviour of jumps and the causal relationship between market jumps and sectoral jumps found in this paper are the evidence in this argument. Another contribution of this paper is examining few well-known market anomalies from the perspective of jump occurrences not tested before in the jump literature.

The rest of the chapter proceeds as follows. Section 3.2 reviews the jump detection methods implemented in this study. We outline data collection and cleaning processes along with choices of calibrated parameter values in Section 3.3. Section 3.4 discusses the results of the empirical analysis and Section 3.5 concludes.

## 3.2. Jump testing methods

A short description of the jump detection methods applied in this study are as follows.

### 3.2.1. Barndorff-Nielsen and Shephard (2006)

We describe this model in Section 2.3 of Chapter 2. The model utilizes the difference between two volatility measures - realized variance,

$$RV^{[0,T]} = \sum_{j=1}^{[T/\Delta^n]} |\Delta_j^n p|^2, \tag{3.1}$$

and bi-power variation, defined as

$$BV^{[0,T]} = \mu^{-2} \sum_{j=2}^{[T/\Delta^n]} |\Delta_j^n p||\Delta_{j-1}^n p|. \tag{3.2}$$

The contribution from the jump component to $QV^{[0,T]}$, the total volatility can be estimated by applying the adjusted ratio test statistic in Barndorff-Nielsen and Shephard (2006) as:

$$\hat{\mathcal{J}} = \frac{1}{\sqrt{\triangle^n}} \cdot \frac{1}{\sqrt{\theta \cdot max\,(1, DV^{[0,T]}/(BV^{[0,T]})^2)}} \cdot (\frac{BV^{[0,T]}}{RV^{[0,T]}} - 1), \tag{3.3}$$

where $\theta = \frac{\pi^2}{4} + \pi - 5$ and $DV^{[0,T]} = \sum_{j=1}^{[T/\triangle^n - 3]} |\Delta_j^n p||\Delta_{j+1}^n p||\Delta_{j+2}^n p||\Delta_{j+3}^n p|$ a quad-power as used by Barndorff-Nielsen and Shephard (2006). Andersen et al. (2007a), on the other hand suggest to a use tri-power variation as such -

$$DV^{[0,T]} = (\frac{T/\triangle^n}{T/\triangle^n - 2})\mu_4^{-3}(\sum_{j=1}^{[T/\triangle^n - 2]} |\Delta_j^n p|^{4/3}|\Delta_{j+1}^n p|^{4/3}|\Delta_{j+2}^n p|^{4/3}, \tag{3.4}$$

where $\mu_4 = \frac{\gamma(6/7)}{\gamma(1/2)} 2^{2/3}$ instead of quad-power variation. In the absence of jumps the test statistic $\hat{\mathcal{J}}$ given in (3.3) follows a standard normal distribution asymptotically. Therefore, under the null of no jumps,

$$\hat{\mathcal{J}} \xrightarrow{L} \mathcal{N}(0,1) \ \ as \ \ \Delta^n \to 0. \tag{3.5}$$

We reject the null hypothesis if the test statistic is significantly negative.

### 3.2.2. Andersen et al. (2007b) and Lee and Mykland (2008)

Andersen et al. (2007b) (ABD) and Lee and Mykland (2008) (LM) develop tests that can detect jump at individual return observations instead of a given time span. They propose a test statistic by calculating the ratio of the return at each observation to a local volatility measure that covers variance over a number of returns preceding that return. ABD and LM use different distributions under the null hypothesis when testing if the return is a jump by comparing test statistic with a threshold. The statistics $L_i$ that tests for a jump at time $t_i$ is defined as

$$L_i = \frac{\Delta_{t_i}^n p}{\hat{\sigma}(t_i)}, \tag{3.6}$$

where $\hat{\sigma}(t_i)^2$ is the local volatility measure. Here we use the bipower variation of $K$ observations preceding the relevant observation. Thus the test can identify the presence of jumps in an observation against the volatility in the prior period determined by value of $K$ and can be defined as

$$\hat{\sigma}(t_i)^2 = \frac{1}{K-2} \sum_{j=1-K+2}^{i-1} |\Delta_j^n p||\Delta_{j-1}^n p|. \tag{3.7}$$

Here $\Delta_j^n p$ is the return as defined in the previous section. Lee and Mykland (2008) suggest A window size $K$ between $252 \times n$ and $\sqrt{252 \times n}$, where $n$ is the number of observations in a day so that the window size poses a balance between being a jump-robust volatility measure and being effective in scaling the trend in volatility. In our study, we use 350, 250, 150, 100, 80, 75 and 50 as values of $K$ for the 1-minute, 5-minute, 10-minute, 15-minute, 20-minute, 30-minute and 60-minute sampling intervals, respectively.

The asymptotic distribution of the test statistic is as follows:

$$\frac{max(L_i) - C_n}{S_n} \rightarrow \xi, \tag{3.8}$$

where $P(\xi \leq x) = exp(-e^{-x})$, the constants

$$C_n = \frac{(2logn)^{1/2}}{c} - \frac{log\pi + log(logn)}{2c(2logn)^{1/2}}, \tag{3.9}$$

$$S_n = \frac{1}{c(2logn)^{1/2}}, \tag{3.10}$$

and

$$c = \sqrt{\frac{2}{\pi}}. \tag{3.11}$$

Thus LM test detect jumps by comparing the maximized value of $L_i$ to the critical value from the Gumbel distribution. ABD, on the other hand, propose comparing $L_i$ to a normal threshold as $L_i$ is asymptotically normal. By applying their method, jump is identified when $L_i > \Phi_{1-\beta/2}$ where $\beta = 1 - (1 - \alpha)^{\delta^n}$ for a given nominal daily $\alpha$.

### 3.2.3. Aït-Sahalia et al. (2009)

Aït-Sahalia et al. (2009) develop a test statistic that converges to one if there is jump in a given price process, and to a known number if there is no jump. Utilizing the advantage of higher return moments, their test statistic compares the ratio of the sum of the absolute returns powered by $\tau$ for a given return window of two different sampling intervals $k\Delta^n$ and $\Delta^n$, where $\Delta^n$ is the base sampling interval.

The test statistic is:

$$ASJ(\tau, k, \Delta^n) = \frac{\hat{B}(\tau, k\Delta^n)}{\hat{B}(\tau, \Delta^n)}, \tag{3.12}$$

where

$$\hat{B}(\tau, \Delta^n) = \sum_{i=1}^{n} |\Delta_i^n p|^\tau. \tag{3.13}$$

Under the null hypothesis of no jumps, when $\tau > 2$, $ASJ(\tau, k, \Delta^n)$ converges to $k^{\tau/2-1}$, and one under the alternative hypothesis. The reason is that when $\tau > 2$, $\hat{B}(\tau, \Delta^n)$ can only retain the effect of jump components of the return process and diminishes the continuous component asymptotically. As a result when jumps are present in a return series, $\hat{B}(\tau, \Delta^n)$ will indicate the same number regardless of the sampling frequency used in the calculation.

The null hypothesis of no jumps is rejected when $ASJ < \xi$, where

$$\xi = k^{\tau/2-1} - z_\alpha \sqrt{\hat{V}}, \tag{3.14}$$

where

$$\hat{V} = \frac{\Delta^n M(P, K) \hat{A}(2\tau, \Delta^n)}{\hat{A}(\tau, \Delta^n)^2}, \ \textit{and} \tag{3.15}$$

$$\hat{A}(\tau, \Delta) = \frac{\Delta^{1-\tau/2}}{\mu_\tau} \sum_{i}^{n} |\Delta_i^n p|^\tau \mathbf{1}_{\{|\Delta_i^n p| \leq \alpha \Delta^\varpi\}}. \tag{3.16}$$

In this study we choose $\tau = 4$, $M(4, K) = \frac{16k(2k^2-k-1)}{3}$, $\alpha = 0.05$ ($Z_\alpha = 1.64$) and $\varpi = 0.48$ as the constant values.

### 3.2.4. Jiang and Oomen (2008)

Jiang and Oomen (henceforth JO) propose a test for jumps based on the difference between simple and logarithmic returns. Instead of using a jump robust measure to compare with the realized volatility, as in BNS, JO use a jump-sensitive measure (Theodosiou and Zikes, 2009). The accumulated difference between the simple return and the log return approaches one half of the integrated variance. Thus

$$SwV = 2\sum_{j=2}^{[T/\Delta^n]}(R_j - \Delta_j^n p) \xrightarrow{p} \int_0^T \sigma_s^2 ds, \tag{3.17}$$

where $R_j$ denotes the $j$th arithmetic intra-day return or $\frac{P_j - P_{j-1}}{P_{j-1}}$ as $P$ is the price of an asset, while $\Delta_j^n p$ is the $j$th log return. While there is no jump the difference between $SwV$ and the realized variance becomes 0; If there is jump then the difference converges as follows

$$SwV_t - RV_t \xrightarrow{p} 2\sum_{t_j\in[0,T]}(exp(\kappa_j) - \kappa_j - 1) - \sum_{t_j\in[0,T]}\kappa_j^2. \tag{3.18}$$

Under the alternative, in the limit, the difference $SwV - RV$ captures jumps in exponential form. The test statistic is defined as

$$JO_t = \frac{[T/\Delta^n]BV_t}{\sqrt{\Omega_{SwV}}}(1 - \frac{RV_t}{SwV_t}) \xrightarrow{L} \mathcal{N}(0,1), \tag{3.19}$$

where

$$\hat{\Omega}_{SwV} = \frac{\mu_6}{9}\frac{[T/\Delta^n]^3\mu_{3/2}^{-4}}{[T/\Delta^n]-3}\sum_{i=5}^{n}|\Delta_j^n p|^{3/2}|\Delta_{j-1}^n p|^{3/2}|\Delta_{j-2}^n p|^{3/2}|\Delta_{j-3}^n p|^{3/2}. \tag{3.20}$$

Here $\mu_p$ stands for the $p$th moment of the absolute value of a variable $U \sim N(0,1)$ defined by,

$$\mu_{\scriptscriptstyle 1} = \mathbb{E}(|\ U\ |^p) = \pi^{-1/2}2^{p/2}\Gamma(\frac{p+1}{2}),$$

where Γ denotes the gamma distribution. A jump can be identified from this test as the test statistic becomes very large in the presence of large returns.

### 3.2.5. Andersen et al. (2012)(henceforth MinRV test and MedRV test)

In the presence of jumps multi-power variation can exhibit an upwardly biased estimator of integrated variance while presence of zero returns can result downward biased estimator. To avoid such bias of multi-power variation Andersen et al. (2012) propose a new set of estimators to represent integrated variance in the presence of jumps. They are based on the minimum of two consecutive and median of three consecutive absolute intra-day returns. Thus

$$MinRV_t = \frac{\pi}{\pi - 2}\left(\frac{[T/\Delta^n]}{[T/\Delta^n] - 1}\right) \sum_{j=1}^{[T/\Delta^n]-1} min(|\Delta_j^n|, |\Delta_{j+1}^n|)^2, \tag{3.21}$$

and

$$MedRV_t = \frac{\pi}{6 - 4\sqrt{3} + \pi}\left(\frac{[T/\Delta^n]}{[T/\Delta^n] - 2}\right) \sum_{j=2}^{[T/\Delta^n]-1} med(|\Delta_{j-1}^n|, |\Delta_j^n|, |\Delta_{j+1}^n|)^2. \tag{3.22}$$

These estimators can avoid bias since large absolute returns are eliminated from the calculation by the minimum and median operators. The $MedRV$ estimator has an added benefit of avoiding the impact of zero intraday returns.

ADS propose the test statistic by exploiting $MinRV_t$ and $MedRV_t$ in the same way as BNS:

$$J_t^{MinRV} = \frac{1 - \frac{MinRV_t}{RV_t}}{\sqrt{1.81 \frac{1}{[T/\Delta^n]} max(1, \frac{minRQ_t}{MinRV_t^2})}} \xrightarrow{L} \mathcal{N}(0, 1), \tag{3.23}$$

$$J_t^{MedRV} = \frac{1 - \frac{MedRV_t}{RV_t}}{\sqrt{0.96 \frac{1}{[T/\Delta^n]} max(1, \frac{medRQ_t}{MedRV_t^2})}} \xrightarrow{L} \mathcal{N}(0, 1), \tag{3.24}$$

where $MinRQ_t = \frac{\pi}{3\pi - 8}\left(\frac{[T/\Delta^n]^2}{[T/\Delta^n] - 1}\right) \sum_{j=2}^{[T/\Delta^n]} min(|\Delta_j^n|, |\Delta_{j+1}^n|)^4$ is the minimum realized

Quarticity and $MedRQ_t = \frac{3\pi}{9\pi+72-52\sqrt{3}}(\frac{[T/\Delta^n]^2}{[T/\Delta^n]-2})\sum_{j=3}^{[T/\Delta^n]} med(|\Delta^n_{j-1}|, |\Delta^n_j|, |\Delta^n_{j+1} \quad |)^4$ the median realized quarticity that estimates the integrated quarticity.

### 3.2.6. Corsi et al. (2010)

Mancini (2009) devises a technique to determine a consistent non parametric estimator of the integrated volatility by excluding time intervals where the return of a given asset jumps. Combining the idea of the threshold estimators of Mancini (2009) and the multi-power variation estimation of BNS, Corsi et al. (2010) (henceforth CPR) propose a new test method. The authors eliminate the bias associated with multi-power variation in the presence of jumps by truncating large absolute returns. They construct the corrected realized threshold bi-power variation as an alternative to the $BV_t$ of the BNS method. The new estimator is a variation of bi-power variation discarding returns over a certain threshold. The following test statistic is employed:

$$J^{CPR} = \frac{1-\frac{CTBV_t}{RV_t}}{\sqrt{0.61\frac{1}{[T/\Delta^n]}\, max\,(1, \frac{CTTV_t}{CTBV_t^2})}} \xrightarrow{L} \mathcal{N}(0,1), \tag{3.25}$$

where $CTBV_t$ and $CTTV_t$ represent the corrected realized threshold bi-power and tri-power variation, respectively, defined as:

$$CTBV_t = 1.57\sum_{j=2}^{[T/\Delta^n]} Z\mathbf{1}(\Delta^n_j p, \upsilon_j) Z\mathbf{1}(\Delta^n_{j-1} p, \upsilon_{j-1}), \tag{3.26}$$

$$CTTV_t = 1.74\sum_{j=3}^{[T/\Delta^n]} Z\mathbf{1}(\Delta^n_j p, \upsilon_j) Z\mathbf{1}(\Delta^n_{j-1} p, \upsilon_{j-1}) Z\mathbf{1}(\Delta^n_{j-2} p, \upsilon_{j-2}), \tag{3.27}$$

where $Z\mathbf{1}(\Delta^n_j p, \upsilon_j) = \{\begin{smallmatrix} |\Delta^n_j p|, \;\; [\Delta^n_j p]^2 < \upsilon_j \\ \\ 1.094\upsilon_j^{1/2}, \;\; [\Delta^n_j p]^2 < \upsilon_j \end{smallmatrix}$ is a function of the return at time $t_j$and a threshold $\upsilon_j = c_\upsilon^2 * \hat{V}_j * c_\upsilon^2$ is a scale free constant and $\hat{V}_j$ is a local volatility estimator. We take $c_\upsilon = 3$ , as the authors suggest in computing the threshold, $\upsilon_j$. For the auxiliary local volatility estimate, $\hat{V}_j$, we employ the non-parametric filter proposed by CPR that removes jumps from data in several iterations.

Given the characteristics of data, different methods may overestimate or underestimate jump occurrences. We ultimately employ the jump method that averages out the over-and-under-estimations and detects a reasonable number of jump occurrences. Another criterion for choosing a jump method is whether we want to detect a jump in a given window such as a day, or in each observation. We conduct the above jump tests in detecting jumps in the Indian market and use the results of the jump tests based on these two criteria.

## 3.3. Data

We collect data for the Indian market index, stock prices of listed banks and non banking financial institutes (FIs) from the Thomson Reuters Tick History (TRTH) database provided by SIRCA. We use the stock price of same 41 banks that we have used in chapter 2. For easy reference we repeat the list of banks in Table 3.1 along with the list of non-banking financial companies in Table 3.2. These banks and financial institutions are listed on the National Stock Exchange (NSE). Our sample includes stock prices of all 41 listed banks and 55 out of 88 listed FIs. We exclude 33 FIs due to the low quality of data of these stocks in the TRTH database. This is reflected by a high share of missing observations and the presence of unexplained discontinuities in the data for these series.

Our data extends from January 1, 2004 to December 31, 2013, covering the period of global financial crisis in 2008-09. A total of 2497 trading days exists in our sample period. We collect intra-day 1-minute data from TRTH. We use the last price recorded in each of the 1-minute intervals from 9:15 a.m. to 3:30 pm, the normal trading session of NSE, where missing data are filled with the price of the previous interval which assumes that the price remains unchanged during a non-trading interval. Again we drop the first 15 minutes of each day to avoid noise associated with market opening. Hence, our trading hours are 9.30 am to 3.30 pm local Indian time. We have 360, 72, 36, 24, 20, 12, 6 observations for 1-minute, 5-minute, 10-minute, 15-minute, 20-minute, 30-minute and 60-minute data respectively. Following our previous study we use the CNX500 index as the benchmark market portfolio.

## 3.4. Results

We construct equally weighted indices for the banking industry and non-banking financial institutions industry (FIs) using the returns of the 41 banks and 55 FIs in the sample, respectively. Descriptive statistics of the 1-minute return on the market index, the banking sector and the FI sector are presented in Table 3.3. During the sample period from January 2004 to December 2013, the investor's average returns on the market, banking sector stocks and FI sector stocks (excluding dividend) are all negative. FI stocks experience a lower return than the banking stocks and the overall market. However, the banking stocks experience higher volatility than the FI and the overall market, as shown by both the standard deviation and the average daily volatility measure.

The returns on CNX500, the bank and FI industry indices are plotted in Figure 3.1. The volatility of the return, computed as realized volatility, is shown in Figure 3.2. From these figures it is clear that the banking sector return and volatility pattern resemble the overall market more closely than FI industry. The FI stocks have lower volatility compared with the market and banking sectors. Figure 3.2 shows that the banking and financial sectors as well as the overall market experienced considerable volatility during the global financial crisis of 2008/09. Volatility decreased noticeably after 2009 in all cases and it is lower than the pre-crisis period.

### 3.4.1. Jump test results

We implement the different jump test methods on a daily basis. The BNS methods are applied by using quad-power (QV) variation as a jump robust measure suggested by Barndorff-Nielsen and Shephard (2006) as well as tri-power (TQ) variation suggested by Andersen et al. (2007a). As results from these two tests vary substantially, we report both sets of results separately as BNS_QV test and BNS_TQ test. We apply these methods to the CNX500 index and the equally weighted indices of the banking sector and the FI sector. We identify the days on which the assets experience jumps. We test for jumps using seven different sampling frequencies: 1-minute, 5-minute, 10-minute, 15-minute, 20-minute, 30-minute and 60-minute at three significance levels: 0.1%, 1% and 5%. Dumitru and Urga (2012), Theodosiou and Zikes (2009) and Schwert (2009) show that jump detection rate varies with changes in the sampling frequency and the significance level of the tests.

We can see from Tables 3.4, 3.5, and 3.6 that results vary substantially across different methods, data frequencies and significance levels. Generally the LM/ABD test provides the highest percentage of jump days in higher frequencies (except for the FI index) but as sampling intervals increase the CPR method leads to the highest proportion of jump days. The other two methods that provide a relatively high proportion of jump days are the BNS_QV method and the Med_RV method. Dumitru and Urga (2012) also report a high percentage of jump days on individual US stocks resulting from the ABD/LM test, the CPR test and the BNS tests. They argue that the presence of many zero returns creates downward bias in the multi-power variations as measures of integrated variance. As a result, any test statistics based on the difference between total volatility and integrated volatility will be upward biased. The percentage of jump days in Dumitru and Urga (2012) at different frequencies are higher than what we observe in the Indian market. This may result from our use of an index instead of individual stocks. The impact of jumps in individual stocks in an index can be offset by opposite price movements in other stocks. Thus, it is more likely that we see fewer jumps in the index than in individual stocks.

The most conservative method in our study is the JO followed by the AJ, Min_RV and BNS_TQ methods. These findings are consistent with Theodosiou and Zikes (2009) who ascertain the independence of JO test from the presence of zero returns as the reason of such low jump detection rate. The proportion of detected jump days varies from 72.81% (LM/ABD method) to 11.41% (JO) in different jump tests by using 1-minute CNX500 data tested at 5% significance level, 65.84% (LM/ABD method) to 7.73% (JO) at 1% significance level and 58.19% (LM/ABD method) to 4.73% (JO) at 0.1% significance level. Med_RV method generally provides jump days proportion which is in between the two extremes.

Despite broad differences in the testing results, different tests identify the same days as jump days quite often. Dumitru and Urga (2012), Theodosiou and Zikes (2009) and Schwert (2009) report that combining more than one jump method to detect jumps may improve the jump detection rates. Table 3.7 shows the jump days agreed by any two methods in 5-minute CNX500 return (significance level - 1%) in the upper panel. The diagonal numbers are the number of jump days detected by a specific method and the off-diagonal cells show the jump days agreed by the two methods shown as the column and row headings of the given cell. As expected the methods detecting higher jump proportions produce higher numbers of common jump days. Out of 587 jump days detected by the BNS_QV, 579 jump days are also detected by the CPR method. CPR also detects 317 out of 320 jump days detected by the BNS_TQ test, 564 out of 669 jump days detected by the LM test, 396 out of 397 jump days detected by the Min_RV test, 496 out of 518 jump days detected the Med_RV test and 68 out of 114 jump days detected by the AJ test. Therefore, the CPR method is able to detect a large proportions of jumps detected by other methods using 5-minute data. However, this test agrees with only two of the 18 jump days detected by the JO method. Since the JO test detects jumps most conservatively, common jump days of this method with other methods are relatively rare. Common jump day detection of different tests in association with the AJ test are also relatively low.

Although the BNS method can identify more jumps when used with QV instead of TQ, all the jump days identified by BNS_TQ test agree with the BNS_QV test indicating that TQ is a conservative alternative of QV in detecting jumps. The LM test and the BNS_QV test in general agree most with the other tests whether a given day is a jump day. The results indicate that the BNS_QV, BNS_TQ, LM, Mid_RV, Min_RV and CPR methods identify mostly the same price movements as jumps. However, the JO and AJ methods detect jumps relatively rarely, and the detected jump days are also largely different from those detected by other tests. The middle panel of Table 3.7 shows that the methods also agree mostly in identifying days which are not jump days. This is expected, given the fact that jumps are rare events.

### 3.4.2. Jump test results across different frequencies

We also see differences in Table 3.4, 3.5, and 3.6 in the percentages of jump days across different frequencies for the same test applied. All methods show a declining percentage of jump days as we increase the sampling interval from 1-minute towards 60-minute. Dumitru and Urga (2012) find that the relationship for the U.S. stocks regarding sampling frequency and detected jump day proportion is similar to our finding in the Indian market.

If there is a jump at any moment of a day, then a jump test should be able to detect jumps in that given day irrespective of the frequency of data examined. However, the reality is quite different, as we see that a gradual decrease in data frequency results in varying proportions of detected jump days. We can see a big drop in the proportion of jump day when moving from 1-minute to 5-minute data irrespective of the jump method applied. We attribute this to the effect of market micro-structure noise on higher frequency data. The proportion of jump days continues decreasing, but at a lower rate as we increase the return intervals. Figure 3.3 shows the relative jump signature plot developed by plotting the proportion of jump days detected by different jump tests against the different sampling intervals. We observe the most abrupt decrease in jump days in the LM/ABD test followed by the CPR and BNS_QV methods. It seems that the methods which are liberal in detecting jumps are more vulnerable to market micro-structure noise at higher frequencies (for example, in 1-minute data).

The signature plots for our data are shown in Figure 3.4. We develop these plots by using daily average RV, BV, TQ and QV of the market index, CNX500. It is evident from the figure that the volatility measures moves up and down abruptly as data intervals increase from 1-minute to around 15-minute. After that we observe relative stability in the volatility measure as we increase the data intervals. Therefore, our volatility signature plots suggest that, given the liquidity of Indian capital market, the 15-minute time interval poses the balance between market micro-structure noise and desired continuity of dataset. However, some of the jump methods we apply in this study detect very low or zero jump intensity in our price series contradicting the general notion of jump-diffusion model of asset price. As a result, we emphasize detecting jumps in 1-minute, 5-minute, 10-minute and 15-minute frequencies for our dataset.

We do not observe any definite slope in the signature plots. The plots are upward sloping from 1-minute to 10-minute frequencies and then downward sloping. Andersen et al. (1999) show that the highest levels of volatility occur at the highest sampling frequencies for a liquid asset, and that the lowest levels of volatility occur at the highest sampling frequencies for an illiquid assets. Consequently the volatility signature plot for the liquid asset is a downward sloping curve and the volatility signature plot for the illiquid asset is an upward sloping curve. The pattern of slopes of our signature plots suggests that the Indian stocks are not as liquid as the US stocks.

Based on the discussions above, we see that jump intensities are found different for different jump tests. They are also different for different sampling frequencies. The signature plot method gives us a solution to the problem of choosing the correct sampling frequency which is 15-minute in our case. The best test method should be the one that avoids both overestimation and underestimation, In that case, the method which identifies an average amount of jump intensities among all methods are more likely to refrain from these problems. BNS_QV method seems to fit this criterion in our case. Thus we use this method on 15-minute price observations for our analysis of jump risk in the Indian financial market.

### 3.4.3. Jump days Comparison among market, banks and FIs

In this section we address the question whether jump risk in the banking sector and the non-banking financial sector is higher than the overall market. Figure 3.5 shows the bar chart reporting the percentage of jump days detected in the market (CNX500), banks and FIs at 0.001, 0.01 and 0.05 significance level based on 15-minute data. At the 0.001 significance level the number of jump days is higher in banks than the market using the BNS_QV, LM/ABD, Med_RV and CPR methods. The Min_RV, JO and AJ methods methods report almost no jump occurrences at this significance level. Only one test, the BNS_TQ indicates slightly lower number of jump days in banks compared with the market. At 1% and 5% significance level, only the AJ test method detects lower jump intensity in the banking sector than in the market. All other methods report the opposite. Thus, the overall results suggest that stocks of the banking sector are more sensitive towards shocks such as news arrival than the overall market and thus exhibits higher number of jumps.

In comparison, between the non-banking FI sector and the market, the results are quite similar for all methods at different significance levels. Except for the AJ method, all other methods show lower jump intensity, and thus lower jump risks, in the FI sector than both the market and the banking sector. Only the AJ test reports higher jump risk in this sector compared with the market and the banking sector. Hence, we may draw a conclusion from these results that it is generally the banking sector which bears higher jump intensity and the FI sector is subject to lower jump risk than the market. Investors' may benefit from diversifying their fund allocated for financial stocks to both the banking and FI sectors rather than concentrating on the banking sector.

The higher jump intensity in banking stocks may result from higher sensitivity and awareness of bank investors. Assets of banks are diversified to different sectors of the economy. Thus banking stocks can be affected by a wide range of news. Banking stocks are generally of the large volume and followed by a large number of investors. The arrival of any relevant information is spotted by these investors immediately causing a sharp change in prices of the stocks. Besides, Boudt and Petitjean (2014)and Jiang et al. (2011) show that liquidity shocks are another important source of jump occurrences. As Banking stocks are generally among the highly liquid stocks, any shock in liquidity interrupts the market equilibrium and cause jumps.

Jump risk in the banking sector and FI sector may arise from the overall market shock or it can be attributable to sector-specific shocks. These two sectors are closely linked in the sense that these organizations are involved in similar operations. Thus, shocks in one sector may create jump risks in the other sector. We identify the days on which the banking sector and/or the FI sector experience jumps when the overall market has jumps, reported in Table 3.8, and also the days when both the banking sector and FI experience jumps. There are also trading days when both the sectors along with the market experience jumps. We show the results at four different data frequencies and three significance levels. By considering the 5-minute data at 0.01 significance level we find that common jump days are higher between the banks and the market than between the FIs and the market. FIs' co-jump with the market is higher than its co-jumps with the banks, as evident from majority of the jump test results. We also report the common jump days of the market, banks and FIs in the each fourth columns of the three significance level categories in the Table which confirm that there is a considerable percentage of trading days when all three market jumps together. At 1% significance level the BNS_QV method shows 16.14% common jumps between the market and banks, 27.67% common jumps between the market and the FIs, 19.06% common jumps between the banks and FIs, and 12.9% common jumps in the market and the two sectors. together. We may attribute to large macroeconomic shocks causing this kind of pervasive jumps across the market and different sectors.

Not all jumps in Banks and FIs are associated with market shocks. We have shown the proportion of jump days for banks and FIs when the market does not experience jumps. We can denote these as sectoral idiosyncratic jumps. On the basis of 5-minute data we find that FIs have higher proportion of sector-specific jump days than the banking sector stocks. For example the BNS_QV test reports 17.54% sectoral idiosyncratic jumps in FIs and 7.25% in Banks as shown in Table 3.9. The higher idiosyncratic jumps from the FIs can be explained by the nature of financing that FIs are involved. FIs invest in specialized sectors where banks spread their investment to wider economic sectors. Hence, FIs bear higher exposure to the idiosyncratic jump risk than the banking companies.

We examine further the impact of jump occurrence in the market and one of the banking sector or FI sector on that of the other sector by using regression models. Here a jump occurrence is expressed as a binary variable; if we have jump in a given day we assign 1 to that day, otherwise zero. We run probit regressions based on following model

$$P(J_{i,t} = 1) = \phi(\beta_{0,t} + \beta_{m,t} J_{m,t-1} + \beta_{j,t} J_{j,t-1}), \tag{3.28}$$

and

$$P(J_{j,t} = 1) = \phi(\beta_{0,t} + \beta_{m,t} J_{m,t-1} + \beta_{i,t} J_{i,t-1}), \tag{3.29}$$

where $J_i$ and $J_j$ are the jump risk of banks and FIs and $J_m$ is the jump risks of market. We run two separate regressions to see first, the impact of jump occurrences in the market and the banking sector on jump occurrences in the FI sector, and second, the impact of jump occurrences in the market and the FI sector on jump occurrences in the FI sector. We have used the results of the BNS_QV test using 15 minutes data in these regressions. This is evident from our regression results (shown in Table 3.10) that jump occurrence in the market significantly increases the probability of jump occurrence in banks and FIs in the next period. Jump risk is not transmitted from banking sector to FI sector or in the opposite direction. The marginal effects of the coefficients at the mean value shows that the presence of jumps in the market on a given day increases the chance of having a jump in the banking sector by 7.25% and in the FI sector by 5.20% in the next day. The results strengthen the findings of Bormetti et al. (2015) rejecting the Poisson model which requires a jump in a given asset to be an independent event. The predictability of jumps in one sector following jumps in the market or another sector enables investors to hedge against risks arising from jumps.

By analyzing the year-wise jump-day spread we examine the change of jump intensity during the global financial crisis (GFC) of 2008-09. From Figure 3.6 we see the number of jump days for the banking sector (the upper panel) is higher from mid-2007 to the end of 2009 - a period which coincides with the GFC. Jump intensity has noticeably decreased after that period. On the other hand, the number of jump days of the FI sector was surprisingly lower during the GFC than both the pre-GFC and post-GFC periods. These sectoral differences reiterate the benefit of sectoral diversification in mitigating the jump risk.

### 3.4.4. Jump pattern in Indian market

Knowing the extent of jumps in the market, the question that comes naturally is whether any pattern in jump occurrences exists, in contrast to the definition of Poisson distribution by which jumps are described in the early literature. By pattern, here we mean having any biases towards any unit of time including trading hour(s), day(s) or month(s) in the jump occurrences. These biases may also reflect existences of memories and clustering tendencies in jumps. Given the importance of jumps in decision making for different market players and regulators, the knowledge of patterns in jumps, if they exist, may be useful for the decision makers.

We check the pattern of jumps for the time of the day, day of the week and month of the year basis. Jumps are partially the results of news arrival in the market. If news arrives in the market following a pattern, jumps also could exhibit the same pattern. However, the theoretical rarity and randomness of jumps may limit the possibility of finding any sequence in the jump occurrence. We use the LM test results to identify the jumps in each of the return observations and the relevant time periods. We use 15-minute return data in this exercise.

Figure 3.7 shows the time of the day pattern of jumps found in the market index, banking sector index and FI sector index. Jumps around 9.45 to 10.00 am are strikingly higher than other times of the day. A large portion of news announcements occur after the trading hours are closed. Normal trading in the market starts at 9.15 am on the next day after the pre-open order entry and closing continues from 9:00 am to 9:08 am. Block deals[2] are executed between 9:15 am to 9:50 am. We observe a high concentration

[2]A block deal is a single transaction, of a minimum quantity of 500,000 shares or a minimum value of Rs. 50 million, between two, mostly institutional, parties.

of jump occurrences just after the end of this block deal session and it continues till 10:00 am (the same analysis with 5-minute data show that the exact time period of high jump intensity in the Indian market is from 9:50 am to 10:00 am). Retail investors with overnight news start trading after that, and the liquidity of the market suddenly escalates which may prompt abnormal changes in stock prices in the way news and/or liquidity factors direct. We also observe a small surge of jumps in the final hours of the normal trading period. This jump time pattern is consistent with the findings of Cui and Zhao (2015) who show that jump intensity in the Chinese market is higher at the opening and closing hours of the trading period.

The day of the week effects on jumps in Indian market are shown in Figure 3.8. The Monday effect in stock returns is most commonly found in the literature (see Choudhry (2000)Bhattacharya et al. (2003)Raj and Kumari (2006). We also find a higher number of jumps on Mondays in all three cases. The effects of other days are different for the market and the two sectoral indices. Thus, we can not generalize the effects of Tuesday, Wednesday, Thursday and Friday on the Indian market and the financial sector. The probit regression results confirm the Monday effect on jump occurrences in the market and also in the banking sector as shown in Table 3.11. However, the effect is not statistically significant for the FI sector. The Monday effect may stem from the arrival macroeconomic and company-specific information developed among the investors during the two days weekly holidays. Based on the merit of the information investors want to take a position in the market on Monday as early as possible before other investors. The resulting pressure on the stock price causes jumps.

The month of the year pattern of the jump occurrences is shown Figure 3.9. We do not observe any common pattern in the market and the banking and the FI sectors. The literature suggests evidence of January effect and December effect in the equity markets, although the effects depends on the fiscal year of a particular country. The fiscal year of Indian companies generally ends in March, and we observe a decrease in jump risk in April from March both in the banking and the FI sectors. Generally we see more jumps during the middle of the year than the beginning or ending of the year in the Indian market. We examine the statistical significance of the month of the year effects on jump occurrences by running probit regressions reported in Table 3.12. Here we find that none of the months have statistically significant effects on the jump occurrences in the market or in either of the sectors.

We examine the memory dependence and clustering behaviour in jumps by applying an Heterogeneous Autoregressive (HAR) model following Corsi (2009) and Andersen et al. (2007a). We use here the LM test results identifying jumps in each of the 15-minute return observations. We explore the predictability of jumps based on time of the day and day of the week effects by running a probit regression on the following model:

$$P(J_t = 1) = \phi(\beta_0 + \beta_1 J_{t-1} + \beta_D J_{t-24} + \beta_W J_{t-120} + \beta_M J_{t-528}). \tag{3.30}$$

Here we use different lag values, $i$, that represent different past times including the previous time interval, the same time at the previous trading day and same day at the previous week and the previous month. We apply a probit model here since our dependent variable, having a jump or not in a given return observation is a binary variable. The lag values that have been used in this models 1, 24, 120 and 528 considering 24 return observations per day, 5 days a week and 22 trading days a month windows. Table 3.13 displays the probit regression results. All the lag variables have statistically significant coefficients for the jump occurrence of the market, the banking sector and the FI sector showing existence of daily and weekly seasonal patterns in jump risk of assets. Thus our results again reiterates the findings of Bormetti et al. (2015) that jumps are not a Poisson distribution that can explain multiple jumps of the same asset within a given time window.

## 3.5. Conclusion

This study implements methodologies in identifying jump risks in the financial sector of India. The study examines the jump risks for banking sector represented by 41 Indian banking stocks listed on the National Stock Exchange of India (NSE), as well as 55 FIs. Using intra-day high frequency data we apply eight widely-used jump tests to the price series of the financial institutions listed on the National Stock Exchange of India.

We consider alternative non-parametric jump detection methods that are commonly-used in the literature on CNX500, an Indian market index, then on equally weighted indices of the banking and FI industries. The results vary widely across different jump methods, data frequencies and significance levels. Generally LM/ABD, CPR and BNS_QV methods report high proportion of jump days and JO, AJ and Min_RV methods detect low jump-day percentage. Decreasing sampling frequency results in lower jump detection by all the tests applied in this study. Our volatility signature plot suggests that a 15-minute data establish the balance between market micro-structure noise and data continuity problem. However, some of the tests fail to detect a reasonable amount of jumps, as suggested in literature, at this frequency.

Our test results show that the banking industry is associated with a higher amount of jump risk in comparison with the market using most of the jump methods. The result is reversed for the FI industry as most of the methods show lower jump risk for the FI industry than the market and the banking sector. A probit regression indicates that jumps in the market have significant effects on the probability of jump occurrences in the banking industry and FI industry. Jumps in the banking sector have impact on jumps in the FI sector but we do not find impact in the opposite direction. We analyse the intra-day jump pattern of Indian financial stocks by applying the LM method. The results indicate the existence of intra-day and weekly seasonality in jump patterns, in contradiction with the description of jump occurrences as a Poisson distribution.

Focusing on the sub-sector differences between banks and non-bank financial institutions (FIs) this study provides a comprehensive characterization of the exposure of financial stocks to jump risk in Indian financial market. The paper shows the existence of the jump risk in the Indian market and thus the need to consider this risk in portfolio decisions and risk hedging by investors. It may not be possible to avoid systematic jump risks but investors may reduce the idiosyncratic jump risks by diversifying their portfolio. The jump risk may be also be priced which we have already discussed in chapter 2. The time of the day and day of the week characteristics found in our analysis will help especially the high-frequency traders to hedge or speculate the jump occurrences. The regulators should monitor jump risks and take appropriate measures in stabilizing the market. The literature suggests that news/information arrival in the market causes jumps. But not all jumps can be explained by news/information arrival. Research should be conducted to explore the non-news factors causing jumps. Liquidity can be one of those factors that we examine in the next chapter.

Table 3.1: List of Sample Banks

*The 41 Indian banks listed on the National Stock Exchange (NSE) at the end of 2013. The first column shows the Codes used in TRTH database to identify the banks. The second column shows the name and the third column reports the market capitalization of each bank in thousand Indian Rupees (INR).*

| Codes | Banks | Market Cap. | Codes | Banks | Market Cap. |
|---|---|---|---|---|---|
| ADBK | Andhra Bank | 52,880,344 | KARU | Karur Vysya Bank | 3,795,074 |
| ALBK | Allahabad Bank | 63,253,313 | KBNK | Karnataka Bank | 24,625,022 |
| AXBK | Axis Bank | 608,925,751 | KTKM | Kotak Mahindra Bank | 485,807,555 |
| BMBK | Bank of Maharashtra | 30,010,238 | LVLS | Lakshmi Vilas Bank | 7,934,934 |
| BOB | Bank of Baroda | 278,659,424 | ORBC | Oriental Bank of Commerce | 73,056,998 |
| BOI | Bank of India | 180,260,454 | PNBK | Punjab National Bank | 243,360,705 |
| CBI | Central Bank of India | 49,246,122 | PUNA | Punjab & Sind Bank | 14,796,734 |
| CNBK | Canara Bank | 170,311,355 | SBI | State Bank of India | 1,390,909,091 |
| CRBK | Corporation Bank | 56,903,852 | SBKB | State Bank of Bikaner and Jaipur | 28,913,499 |
| CTBK | City Union Bank | 28,375,184 | SBKM | State Bank of Mysore | 25,957,504 |
| DCBA | Dev. Credit Bank | 10,667,260 | SBKT | State Bank of Travancore | 25,942,498 |
| DENA | Dena Bank | 31,295,233 | SBNK | Syndicate Bank | 66,184,395 |
| DNBK | Dhanlaxmi Bank Ltd | 3,894,987 | SIBK | South Indian Bank | 32,861,116 |
| FED | Federal Bank | 82,160,033 | STNCy | Standard Chartered Bank | N/A |
| HDBK | HDFC Bank | 1,484,995,359 | UBOI | United Bank of India | 20,360,339 |
| ICBK | ICICI Bank | 1,205,864,240 | UCBK | UCO Bank | 41,959,043 |
| IDBI | IDBI Bank | 102,593,696 | UNBK | Union Bank of India | 120,047,218 |
| INBA | Indian Bank | 74,522,115 | VJBK | Vijaya Bank | 23,240,779 |
| INBK | Indusind Bank Limited | 211,649,245 | VYSA | Ing Vysya Bank Ltd | 86,366,707 |
| IOBK | Indian Overseas Bank | 51,964,280 | YESB | Yes Bank | 153,687,577 |
| JKBK | Jammu and Kashmir Bank | 57,729,789 | | | |

Table 3.2: List of Sample Financial Institutions

*The 55 Indian Non banking financial institutions (FIs) listed on the National Stock Exchange (NSE) at the end of 2013. The first column shows the Codes used in TRTH database to identify the banks. The second column shows the name and the third column reports the market capitalization of each bank in thousand Indian Rupees (INR).*

| Codes | Financial Institutes | Market Cap | Codes | Financial Institutes | Market Cap |
|---|---|---|---|---|---|
| ALSL | Almondz Global Sec. | 188,960 | MONE | Capri Global Capital | 3,817,677 |
| BJAT | Bajaj Holdings and Inv. | 101,783,478 | MUTT | Muthoot Finance | 67,688,897 |
| BJFN | Bajaj Finance | 47,461,619 | NAHA | Nahar Capital & Fin. | 661,473 |
| BJFS | Bajaj Finserv | 122,396,915 | NALS | Nalwa Sons Inv. | 19,736,004 |
| CHLA | Chola. Inv. and Fin. | 38,832,286 | NEFI | Network 18 Media & Inv. | 30,660,492 |
| CNFH | Can Fin Homes | 2,823,891 | ONEL | Onelife Cap. Advisors | 1,942,543 |
| CONS | Consolidated Finvest | 1,910,488 | PAIN | Pan India Corp. | 29,821 |
| DWNH | Dewan Housing Fin. | 19,082,228 | PILN | Pilani Inv. & Industries | 10,851,991 |
| EDEL | Edelweiss Fin. | 23,640,919 | PNBG | PNB Gilts | 3,343,131 |
| FCHL | Capital First | 11,043,306 | PTCI | PTC India Fin. Services | 7,863,545 |
| GICH | GIC Housing Finance | 5,662,439 | PWFC | Power Finance Corp. | 239,582,724 |
| GRUH | GRUH Finance | 37,524,720 | RANE | Rane Holdings | 1,121,613 |
| HBSH | HB Stockholdings | 226,977 | RLCP | Reliance Capital | 76,809,379 |
| HDFC | HDFC Ltd. | 1,276,286,598 | RURL | Rural Elect. Corp. | 205,539,584 |
| IDFC | IDFC Ltd. | 217,590,614 | STEL | STEL Holdings | 176,433 |
| IFCI | IFCI Ltd. | 43,347,854 | SKSM | SKS Microfinance | 13,153,253 |
| IGLS | Inventure Growth | 432,600 | SNFN | Sundaram Finance | 28,923,300 |
| ITSL | Indo Thai Sec. | 104,500 | SREI | Srei Infrastructure Fin. | 13,457,559 |
| JMSH | JM Financial | 12,212,868 | SRTR | Shriram Transport Fin. | 222,819,820 |
| JNSW | JSW Holdings | 4,479,253 | TCIF | TCI Finance | 344,982 |
| KRBR | Kirloskar Brothers Inv. | 3,839,609 | TFCI | Tourism Fin. Corp. | 1,723,302 |
| LICH | LIC Housing Fin. | 113,523,940 | TINV | Tata Inv. Corp. | 21,864,015 |
| LTFH | L&T Finance Holdings | 126,939,171 | TRFI | Transwarranty Finance | 157,526 |
| MAGM | Magma Fincorp | 15,661,935 | VLSF | VLS Finance | 382,525 |
| MCDH | McDowell Holdings | 484,831 | VRDM | Vardhman Holdings | 1,465,506 |
| MNFL | Manappuram Finance | 18,254,195 | WICL | Welspun Inv. and Com. | 66,511 |
| MMFS | M & M Fin. Service | 110,482,593 | WILM | Williamson Magor & Co. | 442,089 |
| MOFS | Motil Oswal Fin. | 11,154,108 | | | |

Table 3.3: Descriptive statistics

*The descriptive statistics are computed based on 1-minute data of CNX500, equally weighted index of Banking stocks and equally weighted index of FI stocks.*

| | CNX500 | Banks | FIs |
|---|---|---|---|
| Mean 1-minute return | -3.51E-07 | -8.82E-07 | -1.23E-06 |
| Annualized mean return | -0.031318 | -0.076857 | -0.105972 |
| Standard deviation | 0.000678 | 0.000737 | 0.000663 |
| Average daily RV | 0.000165 | 0.000195 | 0.000158 |
| Average daily BV | 7.21E-05 | 9.57E-05 | 7.27E-05 |

Table 3.4: Jump-day proportion, Significance level: .001

*The upper, middle and the lower panel shows the jump days proportion of eight different jump tests over seven different sampling frequencies for the market index (CNX500), the equally weighted indexes of banks and FIs respectively at 0.1% significance level. The total number of trading days here is 2497.*

| | 1 min | 5 min | 10 min | 15 min | 20 min | 30 min | 60 min |
|---|---|---|---|---|---|---|---|
| | | | | CNX500 | | | |
| BNS_QV | 0.3088 | 0.1678 | 0.1534 | 0.0897 | 0.0957 | 0.0324 | 0.0008 |
| BNS_TQ | 0.1690 | 0.0709 | 0.0581 | 0.0344 | 0.0328 | 0.0116 | 0.0008 |
| LM/ABD | 0.5819 | 0.2018 | 0.1262 | 0.0689 | 0.0565 | 0.0216 | 0.0080 |
| Min_RV | 0.1766 | 0.0885 | 0.0513 | - | - | - | - |
| Med_RV | 0.2227 | 0.1446 | 0.1181 | 0.0701 | 0.0665 | 0.0128 | - |
| JO | 0.0473 | 0.0032 | 0.0008 | 0.0004 | - | - | - |
| AJ | 0.0805 | 0.0184 | 0.0052 | 0.0012 | 0.0008 | 0.0004 | - |
| CPR | 0.4954 | 0.2575 | 0.2087 | 0.1502 | 0.1446 | 0.0721 | 0.0064 |
| | | | | All banks | | | |
| BNS_QV | 0.1950 | 0.1157 | 0.1506 | 0.1005 | 0.0993 | 0.0296 | 0.0004 |
| BNS_TQ | 0.1001 | 0.0449 | 0.0561 | 0.0308 | 0.0376 | 0.0132 | 0.0004 |
| LM/ABD | 0.5691 | 0.1986 | 0.1478 | 0.0797 | 0.0777 | 0.0272 | 0.0100 |
| Min_RV | 0.0765 | 0.0220 | 0.0032 | - | - | - | - |
| Med_RV | 0.1542 | 0.0989 | 0.1181 | 0.0737 | 0.0669 | 0.0140 | - |
| JO | 0.0781 | 0.0028 | 0.0016 | 0.0004 | 0.0004 | - | 0.0004 |
| AJ | 0.0613 | 0.0192 | 0.0068 | 0.0016 | 0.0008 | 0.0012 | 0.0004 |
| CPR | 0.4273 | 0.2579 | 0.2467 | 0.1778 | 0.1734 | 0.0817 | 0.0052 |
| | | | | All FIs | | | |
| BNS_QV | 0.6884 | 0.1438 | 0.1097 | 0.0637 | 0.0625 | 0.0176 | 0.0020 |
| BNS_TQ | 0.3953 | 0.0380 | 0.0288 | 0.0188 | 0.0160 | 0.0056 | 0.0016 |
| LM/ABD | 0.7545 | 0.1418 | 0.0901 | 0.0437 | 0.0437 | 0.0108 | 0.0056 |
| Min_RV | 0.2687 | 0.0120 | 0.0012 | - | - | - | - |
| Med_RV | 0.5186 | 0.1033 | 0.0805 | 0.0416 | 0.0400 | 0.0072 | - |
| JO | 0.1009 | 0.0032 | - | - | 0.0004 | - | - |
| AJ | 0.0713 | 0.0084 | 0.0060 | 0.0012 | 0.0004 | 0.0008 | 0.0004 |
| CPR | 0.8791 | 0.3052 | 0.2091 | 0.1177 | 0.1266 | 0.0364 | 0.0040 |

Table 3.5: Jump day proportion, Significance level - .01

*The upper, middle and the lower panel shows the jump days proportion of eight different jump tests over seven different sampling frequencies for the market index (CNX500), the equally weighted indexes of banks and FIs respectively at 0.1% significance level. The total number of trading days here is 2497.*

| | 1_min | 5_min | 10_min | 15_min | 20_min | 30_min | 60_min |
|---|---|---|---|---|---|---|---|
| | | | | CNX500 | | | |
| BNS_QV | 0.3889 | 0.2351 | 0.2199 | 0.1618 | 0.1618 | 0.0965 | 0.0533 |
| BNS_TQ | 0.2255 | 0.1282 | 0.1133 | 0.0777 | 0.0825 | 0.0461 | 0.0192 |
| LM/ABD | 0.6584 | 0.2679 | 0.2034 | 0.1278 | 0.1201 | 0.0453 | 0.0244 |
| Min_RV | 0.2471 | 0.1590 | 0.1342 | 0.0032 | - | - | - |
| Med_RV | 0.2972 | 0.2074 | 0.1930 | 0.1474 | 0.1466 | 0.0877 | 0.0164 |
| JO | 0.0773 | 0.0072 | 0.0008 | 0.0004 | 0.0004 | - | - |
| AJ | 0.1458 | 0.0457 | 0.0457 | 0.0160 | 0.0156 | 0.0244 | 0.0164 |
| CPR | 0.5727 | 0.3404 | 0.2920 | 0.2363 | 0.2291 | 0.1602 | 0.1197 |
| | | | | All Banks | | | |
| BNS_QV | 0.2467 | 0.1774 | 0.2307 | 0.1826 | 0.1926 | 0.0985 | 0.0641 |
| BNS_TQ | 0.1450 | 0.0805 | 0.1045 | 0.0821 | 0.0921 | 0.0465 | 0.0244 |
| LM/ABD | 0.6344 | 0.2851 | 0.2371 | 0.1586 | 0.1502 | 0.0549 | 0.0320 |
| Min_RV | 0.1065 | 0.0380 | 0.0364 | 0.0028 | - | - | - |
| Med_RV | 0.2191 | 0.1650 | 0.1922 | 0.1602 | 0.1758 | 0.0909 | 0.0240 |
| JO | 0.1165 | 0.0044 | 0.0016 | 0.0004 | 0.0004 | - | 0.0004 |
| AJ | 0.0997 | 0.0541 | 0.0384 | 0.0112 | 0.0160 | 0.0152 | 0.0148 |
| CPR | 0.4950 | 0.3604 | 0.3360 | 0.2851 | 0.2771 | 0.1862 | 0.1486 |
| | | | | All FIs | | | |
| BNS_QV | 0.7805 | 0.2383 | 0.2006 | 0.1318 | 0.1390 | 0.0709 | 0.0376 |
| BNS_TQ | 0.5563 | 0.0925 | 0.0785 | 0.0509 | 0.0577 | 0.0256 | 0.0180 |
| LM/ABD | 0.8714 | 0.2499 | 0.1706 | 0.0945 | 0.0953 | 0.0300 | 0.0192 |
| Min_RV | 0.3757 | 0.0425 | 0.0176 | 0.0028 | - | - | - |
| Med_RV | 0.6508 | 0.2091 | 0.1650 | 0.1185 | 0.1245 | 0.0593 | 0.0128 |
| JO | 0.1622 | 0.0060 | 0.0004 | - | 0.0004 | - | - |
| AJ | 0.1930 | 0.0541 | 0.0465 | 0.0292 | 0.0180 | 0.0228 | 0.0124 |
| CPR | 0.9243 | 0.4325 | 0.3268 | 0.2259 | 0.2303 | 0.1338 | 0.1061 |

Table 3.6: Jump-day proportion, Significance level: .05

*The upper, middle and the lower panel shows the jump days proportion of eight different jump tests over seven different sampling frequencies for the market index (CNX500), the equally weighted indexes of banks and FIs respectively at 5% significance level. The total number of trading days here is 2497.*

| | 1_min | 5_min | 10_min | 15_min | 20_min | 30_min | 60_min |
|---|---|---|---|---|---|---|---|
| | | | | CNX500 | | | |
| BNS_QV | 0.4890 | 0.3128 | 0.3192 | 0.2635 | 0.2575 | 0.1902 | 0.1678 |
| BNS_TQ | 0.3272 | 0.2062 | 0.2026 | 0.1618 | 0.1654 | 0.1221 | 0.0989 |
| LM/ABD | 0.7281 | 0.3740 | 0.2903 | 0.2199 | 0.2078 | 0.0885 | 0.0545 |
| Min_RV | 0.3448 | 0.2559 | 0.3460 | 0.0445 | 0.0216 | - | - |
| Med_RV | 0.4013 | 0.3012 | 0.2928 | 0.2535 | 0.2507 | 0.2211 | 0.1954 |
| JO | 0.1141 | 0.0112 | 0.0020 | 0.0004 | 0.0008 | - | - |
| AJ | 0.2078 | 0.2199 | 0.1550 | 0.1053 | 0.0945 | 0.1350 | 0.1262 |
| CPR | 0.6596 | 0.4437 | 0.3965 | 0.3404 | 0.3540 | 0.2899 | 0.2903 |
| | | | | All Banks | | | |
| BNS_QV | 0.3224 | 0.2815 | 0.3252 | 0.2835 | 0.2895 | 0.2022 | 0.1894 |
| BNS_TQ | 0.1962 | 0.1490 | 0.2042 | 0.1718 | 0.1898 | 0.1254 | 0.1193 |
| LM/ABD | 0.6928 | 0.3765 | 0.3188 | 0.2543 | 0.2423 | 0.1045 | 0.0693 |
| Min_RV | 0.1390 | 0.0801 | 0.0885 | 0.0445 | 0.0300 | - | - |
| Med_RV | 0.3008 | 0.2699 | 0.3100 | 0.2715 | 0.2936 | 0.2231 | 0.2058 |
| JO | 0.1898 | 0.0100 | 0.0020 | 0.0004 | 0.0004 | - | 0.0004 |
| AJ | 0.1434 | 0.1430 | 0.1418 | 0.0829 | 0.0813 | 0.1213 | 0.1157 |
| CPR | 0.5747 | 0.4786 | 0.4465 | 0.3969 | 0.3877 | 0.3084 | 0.3152 |
| | | | | All FIs | | | |
| BNS_QV | 0.8546 | 0.3773 | 0.3192 | 0.2331 | 0.2539 | 0.1698 | 0.1454 |
| BNS_TQ | 0.7117 | 0.2006 | 0.1782 | 0.1286 | 0.1506 | 0.0905 | 0.0825 |
| LM/ABD | 0.9407 | 0.3736 | 0.2647 | 0.1778 | 0.1834 | 0.0697 | 0.0489 |
| Min_RV | 0.5034 | 0.0969 | 0.0613 | 0.0256 | 0.0156 | - | - |
| Med_RV | 0.7725 | 0.3452 | 0.2976 | 0.2247 | 0.2479 | 0.1878 | 0.1626 |
| JO | 0.2731 | 0.0104 | 0.0016 | 0.0004 | 0.0004 | 0.0004 | - |
| AJ | 0.4037 | 0.1698 | 0.1634 | 0.1370 | 0.1133 | 0.1270 | 0.1225 |
| CPR | 0.9596 | 0.5607 | 0.4698 | 0.3600 | 0.3532 | 0.2699 | 0.2707 |

Table 3.7: Jump days agreed by two methods in 5 min data

*Number of jump days agreed by any two methods in 5-minutes return at 1% significance level are shown in the upper panel. The middle panel shows the number of days with no jumps agreed by any tow methods. The lowers panel reports number of days disagreed by any two methods on the existence of jumps. the diagonal cells show the numbers reported by any one method only.*

| | BNS_QV | BNS_TQ | LM | Min_RV | Med_RV | JO | AJ | CPR |
|---|---|---|---|---|---|---|---|---|
| | | | | Agreed on days with jumps | | | | |
| BNS_QV | 587 | | | | | | | |
| BNS_TQ | 320 | 320 | | | | | | |
| LM | 436 | 286 | 669 | | | | | |
| MinRV | 390 | 288 | 327 | 397 | | | | |
| MedRV | 459 | 301 | 403 | 373 | 518 | | | |
| JO | - | - | 5 | - | - | 18 | | |
| AJ | 53 | 33 | 68 | 38 | 50 | - | 114 | |
| CPR | 579 | 317 | 564 | 396 | 496 | 2 | 68 | 850 |
| | | | | Agreed on days with no jump | | | | |
| BNS_QV | 1910 | | | | | | | |
| BNS_TQ | 1910 | 2177 | | | | | | |
| LM | 1677 | 1794 | 1828 | | | | | |
| MinRV | 1903 | 2068 | 1758 | 2100 | | | | |
| MedRV | 1851 | 1960 | 1713 | 1955 | 1979 | | | |
| JO | 1892 | 2159 | 1815 | 2082 | 1961 | 2479 | | |
| AJ | 1849 | 2096 | 1782 | 2024 | 1915 | 2365 | 2383 | |
| CPR | 1639 | 1644 | 1542 | 1646 | 1625 | 1631 | 1601 | 1647 |

Table 3.8: Common jump days across the market, Banking sector and FI sector

*The table shows common jump days in percentage reported by different combinations asset classes by eight jump tests at three significance levels and four different frequencies.*

| | **Mk∩Bks** | **Mk∩FIS** | **Bks∩Fis** | **All** | **Mk∩Bks** | **Mk∩FIS** | **Bks∩Fis** | **All** | **Mk∩Bks** | **Mk∩FIS** | **Bks∩Fis** | **All** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **1 min** | **Sig. level - 0.001** | | | | **Sig. level - 0.01** | | | | **Sig. level - 0.05** | | | |
| BNS_QV | 0.1362 | 0.2082 | 0.1350 | 0.0965 | 0.1614 | 0.2767 | 0.1906 | 0.1298 | 0.2347 | 0.4233 | 0.2771 | 0.2058 |
| BNS_TQ | 0.0553 | 0.0585 | 0.0380 | 0.0240 | 0.0881 | 0.1125 | 0.0753 | 0.0485 | 0.1310 | 0.2295 | 0.1001 | 0.0985 |
| LM | 0.4934 | 0.4734 | 0.4650 | 0.4113 | 0.5607 | 0.5915 | 0.5751 | 0.5118 | 0.6187 | 0.6936 | 0.6600 | 0.5919 |
| MinRV | 0.0396 | 0.0408 | 0.0216 | 0.0108 | 0.0573 | 0.0849 | 0.0380 | 0.0204 | 0.0841 | 0.1714 | 0.0673 | 0.0429 |
| MedRV | 0.0789 | 0.1057 | 0.0745 | 0.0412 | 0.1181 | 0.1902 | 0.1418 | 0.0801 | 0.1770 | 0.3120 | 0.2351 | 0.1414 |
| JO | 0.0172 | 0.0056 | 0.0040 | 0.0016 | 0.0312 | 0.0104 | 0.0136 | 0.0040 | 0.0597 | 0.0176 | 0.0372 | 0.0108 |
| AJ | 0.0188 | 0.0100 | 0.0108 | 0.0048 | 0.0372 | 0.0328 | 0.0296 | 0.0104 | 0.0609 | 0.0761 | 0.0609 | 0.0256 |
| CPR | 0.3556 | 0.4401 | 0.3805 | 0.3224 | 0.4089 | 0.5362 | 0.4622 | 0.3833 | 0.4818 | 0.6400 | 0.5571 | 0.4682 |
| **5 min** | **Sig. level - 0.001** | | | | **Sig. level - 0.01** | | | | **Sig. level - 0.05** | | | |
| BNS_QV | 0.0653 | 0.0288 | 0.0224 | 0.0144 | 0.1049 | 0.0629 | 0.0477 | 0.0300 | 0.1662 | 0.1229 | 0.1177 | 0.0713 |
| BNS_TQ | 0.0172 | 0.0064 | 0.0040 | 0.0020 | 0.0421 | 0.0160 | 0.0120 | 0.0080 | 0.0813 | 0.0481 | 0.0368 | 0.0232 |
| LM | 0.1229 | 0.0641 | 0.0577 | 0.0477 | 0.1850 | 0.0785 | 0.1169 | 0.0901 | 0.2599 | 0.1922 | 0.1930 | 0.1490 |
| MinRV | 0.0100 | 0.0024 | 0.0004 | 0.0004 | 0.0212 | 0.0076 | 0.0032 | 0.0012 | 0.0485 | 0.0276 | 0.0104 | 0.0060 |
| MedRV | 0.0497 | 0.0220 | 0.0156 | 0.0100 | 0.0821 | 0.0505 | 0.0453 | 0.0260 | 0.1434 | 0.1085 | 0.1045 | 0.0581 |
| JO | - | - | - | - | - | - | - | - | 0.0008 | 0.0004 | 0.0008 | 0.0008 |
| AJ | 0.0036 | 0.0016 | 0.0012 | 0.0012 | 0.0120 | 0.0028 | 0.0064 | 0.0020 | 0.0665 | 0.0421 | 0.0300 | 0.0156 |
| CPR | 0.1658 | 0.1113 | 0.1109 | 0.0793 | 0.2347 | 0.1810 | 0.1922 | 0.1358 | 0.3192 | 0.2731 | 0.2984 | 0.2091 |
| **10 min** | **Sig. level - 0.001** | | | | **Sig. level - 0.01** | | | | **Sig. level - 0.05** | | | |
| BNS_QV | 0.0945 | 0.0445 | 0.0453 | 0.0364 | 0.1482 | 0.0877 | 0.0885 | 0.0741 | 0.2147 | 0.1494 | 0.0885 | 0.1169 |
| BNS_TQ | 0.0264 | 0.0092 | 0.0076 | 0.0052 | 0.0597 | 0.0280 | 0.0248 | 0.0188 | 0.1217 | 0.0677 | 0.0697 | 0.0545 |
| LM | 0.0849 | 0.0453 | 0.0473 | 0.0400 | 0.1526 | 0.0921 | 0.0965 | 0.0805 | 0.2215 | 0.1482 | 0.1574 | 0.1306 |
| MinRV | 0.0016 | - | - | - | 0.0304 | 0.0088 | 0.0048 | 0.0044 | 0.0705 | 0.0316 | 0.0188 | 0.0172 |
| MedRV | 0.0661 | 0.0268 | 0.0264 | 0.0196 | 0.1217 | 0.0609 | 0.0597 | 0.0477 | 0.2026 | 0.1241 | 0.1278 | 0.0953 |
| JO | - | - | - | - | - | - | - | - | - | - | - | - |
| AJ | 0.0012 | 0.0004 | 0.0004 | 0.0004 | 0.0148 | 0.0064 | 0.0040 | 0.0024 | 0.0709 | 0.0457 | 0.0352 | 0.0208 |
| CPR | 0.1514 | 0.0937 | 0.1037 | 0.0813 | 0.2091 | 0.1514 | 0.1674 | 0.1245 | 0.2988 | 0.2435 | 0.2671 | 0.1994 |
| **15 min** | **Sig. level - 0.001** | | | | **Sig. level - 0.01** | | | | **Sig. level - 0.05** | | | |
| BNS_QV | 0.0517 | 0.0196 | 0.0224 | 0.0156 | 0.1021 | 0.0533 | 0.0561 | 0.0433 | 0.1698 | 0.1045 | 0.1001 | 0.0773 |
| BNS_TQ | 0.0104 | 0.0032 | 0.0032 | 0.0016 | 0.0396 | 0.0156 | 0.0136 | 0.0116 | 0.0969 | 0.0477 | 0.0485 | 0.0368 |
| LM | 0.0421 | 0.0212 | 0.0236 | 0.0204 | 0.0833 | 0.0445 | 0.0457 | 0.0392 | 0.1538 | 0.0965 | 0.0961 | 0.0797 |
| MinRV | - | - | - | - | 0.0016 | 0.0008 | 0.0008 | 0.0008 | 0.0212 | 0.0064 | 0.0060 | 0.0048 |
| MedRV | 0.0408 | 0.0120 | 0.0104 | 0.0092 | 0.0925 | 0.0412 | 0.0400 | 0.0300 | 0.1634 | 0.0921 | 0.0957 | 0.0713 |
| JO | - | - | - | - | - | - | - | - | - | - | - | - |
| AJ | - | - | - | - | 0.0016 | 0.0008 | 0.0024 | 0.0004 | 0.0284 | 0.0236 | 0.0192 | 0.0100 |
| CPR | 0.1029 | 0.0513 | 0.0541 | 0.0416 | 0.1670 | 0.1069 | 0.1165 | 0.0877 | 0.2455 | 0.1714 | 0.1914 | 0.1410 |

Table 3.9: Sector specific jumps in Banks and Financial Institutions
*Idiosyncratic jump-day percentage in Banking and FI sectors at three significance level and four different frequencies. Number of trading days is 2497 here.*

| | | | BanksFIs | | | |
|---|---|---|---|---|---|---|
| Sig. level | 0.0010 | 0.0100 | 0.0500 | 0.001 | 0.01 | 0.05 |
| | | | 1 min | | | |
| BNS_QV | 0.0589 | 0.0853 | 0.0877 | 0.4802 | 0.5038 | 0.4313 |
| BNS_TQ | 0.0449 | 0.0569 | 0.0653 | 0.3368 | 0.4437 | 6.8899 |
| LM | 0.0757 | 0.0737 | 0.0741 | 0.2811 | 0.2799 | 0.2471 |
| MinRV | 0.0368 | 0.0493 | 0.0549 | 0.2279 | 0.2907 | 0.3320 |
| MedRV | 0.0753 | 0.1009 | 0.1237 | 0.4129 | 0.4606 | 0.4606 |
| JO | 0.0609 | 0.0853 | 0.1302 | 0.0953 | 0.1518 | 0.2555 |
| AJ | 0.0425 | 0.0625 | 0.0825 | 0.0613 | 0.1602 | 0.3276 |
| CPR | 0.0717 | 0.0861 | 0.0929 | 0.4389 | 0.3881 | 0.3196 |
| | | | 5 min | | | |
| BNS_QV | 0.0505 | 0.0725 | 0.1153 | 0.1149 | 0.1754 | 0.2543 |
| BNS_TQ | 0.0276 | 0.0384 | 0.0677 | 0.0316 | 0.0765 | 0.1526 |
| LM | 0.0757 | 0.1001 | 0.1165 | 0.0777 | 0.1714 | 0.1814 |
| MinRV | 0.0120 | 0.0168 | 0.0316 | 0.0096 | 0.0348 | 0.0693 |
| MedRV | 0.0493 | 0.0829 | 0.1266 | 0.0813 | 0.1586 | 0.2367 |
| JO | 0.0028 | 0.0044 | 0.0092 | 0.0032 | 0.0060 | 0.0100 |
| AJ | 0.0156 | 0.0421 | 0.0765 | 0.0068 | 0.0513 | 0.1278 |
| CPR | 0.0921 | 0.1258 | 0.1594 | 0.1938 | 0.2515 | 0.2875 |
| | | | 10 min | | | |
| BNS_QV | 0.0561 | 0.0825 | 0.1105 | 0.0653 | 0.1129 | 0.1698 |
| BNS_TQ | 0.0296 | 0.0449 | 0.0825 | 0.0196 | 0.0505 | 0.1105 |
| LM | 0.0629 | 0.0845 | 0.0973 | 0.0449 | 0.0785 | 0.1165 |
| MinRV | 0.0016 | 0.0060 | 0.0180 | 0.0012 | 0.0088 | 0.0296 |
| MedRV | 0.0521 | 0.0705 | 0.1073 | 0.0537 | 0.1041 | 0.1734 |
| JO | 0.0016 | 0.0016 | 0.0020 | - | 0.0004 | 0.0016 |
| AJ | 0.0056 | 0.0236 | 0.0709 | 0.0056 | 0.0400 | 0.1177 |
| CPR | 0.0953 | 0.1270 | 0.1478 | 0.1153 | 0.1754 | 0.2263 |
| | | | 15 min | | | |
| BNS_QV | 0.0489 | 0.0805 | 0.1137 | 0.0441 | 0.0785 | 0.1286 |
| BNS_TQ | 0.0204 | 0.0425 | 0.0749 | 0.0156 | 0.0352 | 0.0809 |
| LM | 0.0376 | 0.0753 | 0.1005 | 0.0224 | 0.0501 | 0.0813 |
| MinRV | - | 0.0012 | 0.0232 | - | 0.0020 | 0.0192 |
| MedRV | 0.0328 | 0.0677 | 0.1081 | 0.0296 | 0.0773 | 0.1326 |
| JO | 0.0004 | 0.0004 | 0.0004 | - | - | 0.0004 |
| AJ | 0.0016 | 0.0096 | 0.0545 | 0.0012 | 0.0284 | 0.1133 |
| CPR | 0.0749 | 0.1181 | 0.1514 | 0.0665 | 0.1189 | 0.1886 |

Table 3.10: Probit regression results.

*Dependent variable : Jump occurances (dummy variable). Dependent variable : daily jump occurances (dummy variable). The BNS_QV test results on 15 minute data have been used in this regression. Included observations: 2497.*

| Independent variables | Jump in Banks | Jump in FIs |
|---|---|---|
| Jump in markets in the previous period | 0.2747*** | 0.1972** |
| | (0.0781) | (.0976) |
| Jump in banks in the previous period | | 0.0334 |
| | | (0.0771) |
| Jump in FIs in the previous period | -0.1393 | |
| | (0.0904) | |
| Constant value | -0.9357*** | -1.1595*** |
| | (0.0334) | (0.0363) |
| McFadden R-squared | 0.005225 | 0.0035 |

Standard error values are displayed in parentheses below the coefficients. The asterisks *, **, and *** indicate the significance at the 10%, 5%, and 1% level, respectively.

Table 3.11: Probit regresson results of the day of the week effect

*Dependent variable : intraday jump occurances (dummy variable). The BNS_QV intraday test results on 15 minute data have been used in this regression. Included observations: 2497.*

| Variables | Jumps in the Market | Jumps in the Banks | Jumps in the FIs |
|---|---|---|---|
| Mon | 0.1914** | 0.2115** | 0.1028 |
| | (0.0935) | (0.089992) | (0.1002) |
| Tue | -0.0738 | -0.150204 | 0.0990 |
| | (0.0981) | (0.095681) | (0.1002) |
| Wed | 0.0342 | 0.050109 | 0.0723 |
| | (0.0963) | (0.092395) | (0.1011) |
| Thu | 0.1101 | 0.029298 | (0.0289) |
| | (0.0948) | 0.092536 | 0.101874 |
| C | -1.0431*** | -0.9391*** | -1.1793*** |
| | (0.0679) | (0.0652) | (0.0719) |
| McFadden R-Squared | 0.0042 | 0.006545 | 0.000823 |

Standard error values are displayed in parentheses below the coefficients. The asterisks *, **, and *** indicate the significance at the 10%, 5%, and 1% level, respectively.

Table 3.12: Probit regression results for month of the year effetc.
*Dependent variable : intraday jump occurances (dummy variable). The BNS_QV intraday test results on 15 minute data have been used in this regression. Included observations: 2497.*

| Variables | Market | Banks | FIs |
|---|---|---|---|
| Jan | 0.0467 | 0.1155 | -0.2601 |
| | (0.1491) | (0.1431) | (0.1671) |
| Feb | -0.1710 | -0.0811 | -0.0845 |
| | (0.1587) | (0.1504) | (0.1614) |
| Mar | 0.0373 | 0.0880 | -0.0737 |
| | (0.1488) | (0.1432) | 0.1581 |
| Apr | 0.0548 | -0.1134 | -0.2195 |
| | (0.1517) | (0.1523) | (0.1685) |
| May | 0.2345 | 0.2334 | 0.1657 |
| | (0.1433) | (0.1395) | (0.1497) |
| Jun | 0.1126 | -0.0408 | 0.1627 |
| | (0.1458) | (0.1455) | (0.1496) |
| Jul | 0.0701 | 0.1127 | 0.0598 |
| | (0.1466) | (0.1414) | (0.1521) |
| Aug | 0.0698 | 0.1157 | 0.0354 |
| | (0.1476) | (0.1423) | (0.1539) |
| Sep | 0.1079 | 0.0656 | 0.0313 |
| | (0.1476) | (0.1444) | (0.1551) |
| Oct | 0.1212 | 0.0607 | -0.1021 |
| | (0.1480) | (0.1452) | (0.1608) |
| Nov | -0.0430 | 0.1152 | 0.2809 |
| | (0.1527) | 0.1440 | (0.1491) |
| C | -1.0467*** | -0.9674*** | -1.1331*** |
| | (0.1061) | (0.1029) | (0.1100) |
| McFadden R-squared | 0.000823 | 0.004255 | 0.011462 |

Standard error values are displayed in parentheses below the coefficients. The asterisks *, **, and *** indicate the significance at the 10%, 5%, and 1% level, respectively.

Table 3.13: Probit model results of memory dependence of jumps.
*Dependent variable : intraday jump occurances (dummy variable). The LM intraday test results on 15 minute data have been used in this regression. Included observations: 59400.*

| Variables | Market | Banks | FIs |
|---|---|---|---|
| $Jump_{t-1}$ | 0.9662*** | 0.8622*** | 0.8639*** |
| | (0.1170) | (0.1086) | (0.1513) |
| $Jump_{t-24}$ | 1.1041*** | 1.1517*** | 1.1737*** |
| | (0.1086) | (0.0918) | (0.1212) |
| $Jump_{t-120}$ | 1.1416*** | 1.0001*** | 0.9096*** |
| | (0.1086) | (0.1006) | (0.1415) |
| $Jump_{t-528}$ | 1.1297*** | 1.1792*** | 0.8915*** |
| | (0.1083) | (0.0903) | (0.1431) |
| Constant | -2.6489*** | -2.5865 | -2.6986 |
| | (0.0213) | (0.0199) | (0.0229) |
| McFadden R-squared | 0.1258 | 0.1338 | 0.0692 |

Standard error values are displayed in parentheses below the coefficients. The asterisks *, **, and *** indicate the significance at the 10%, 5%, and 1% level, respectively.

Figure 3.1: Return Market Index, Banks and FIs

*The historical one-minute return series from January 2004 to December 2013 the market index CNX500, the equally weighted index of banks and FIs are shown in the upper, middle and lower panel respectively.*

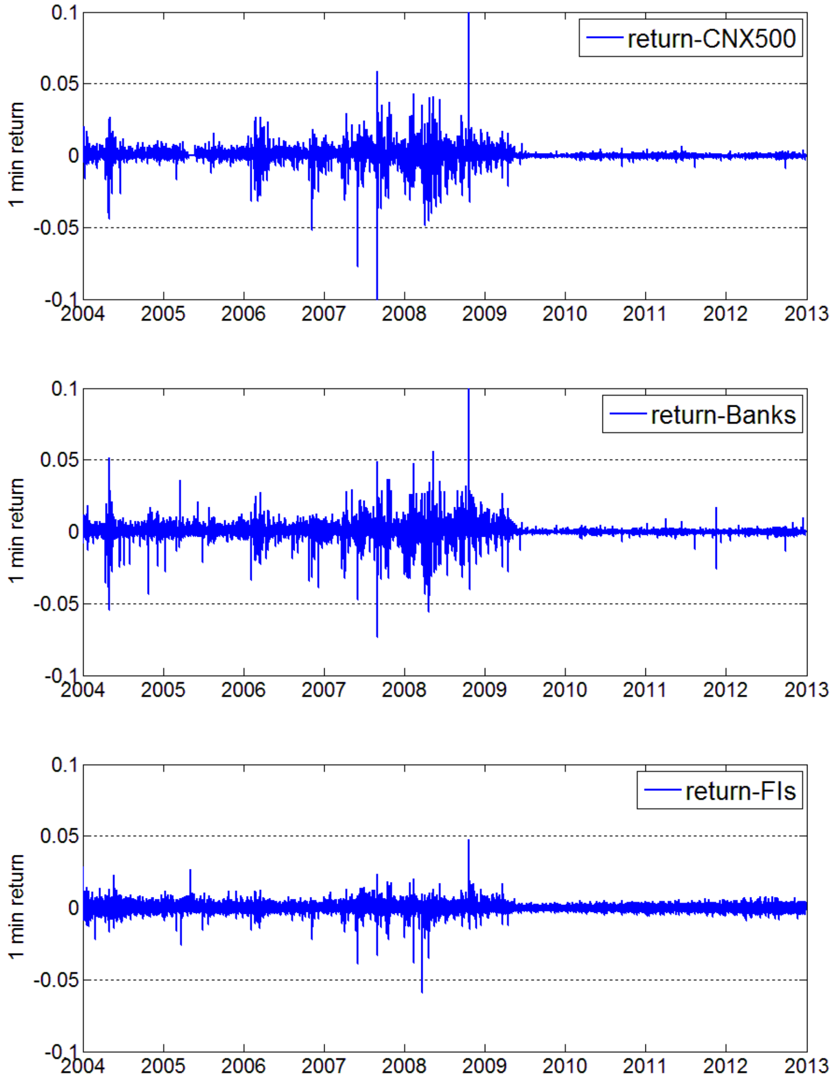


Figure 3.2: Volatility of Returns
The historical one-minute daily realized volatility series from January 2004 to December 2013 the market index CNX500, the equally weighted index of banks and FIs are shown in the upper, middle and lower panel respectively.

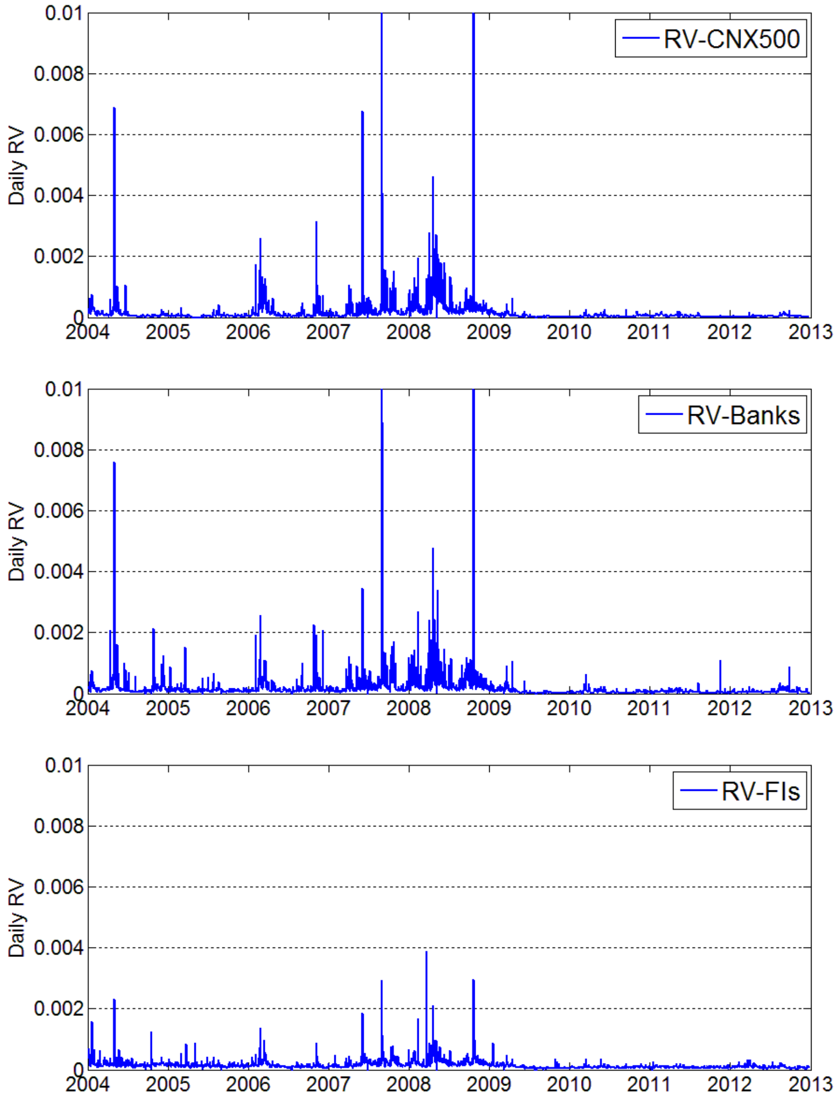


Figure 3.3: Relative Jump Signature Plot
This graph reports the percentage of jump days at different frequencies by the eight methods applied in our study at 1% significance level.

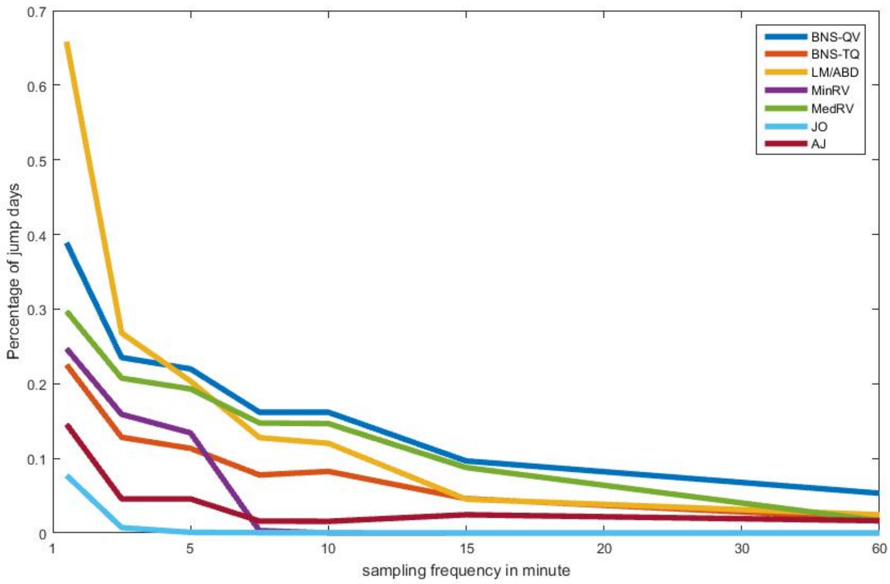



Figure 3.4: Signature Plot
*We draw the signature plots by plotting the a volatility measure in Y-axis and sampling frequencies in the X-axis. In the upper panel graphs we show Realized variation and Bipower variation and as volatility measure and tri-power variation and Quad-power variation in the lower panel graphs.*

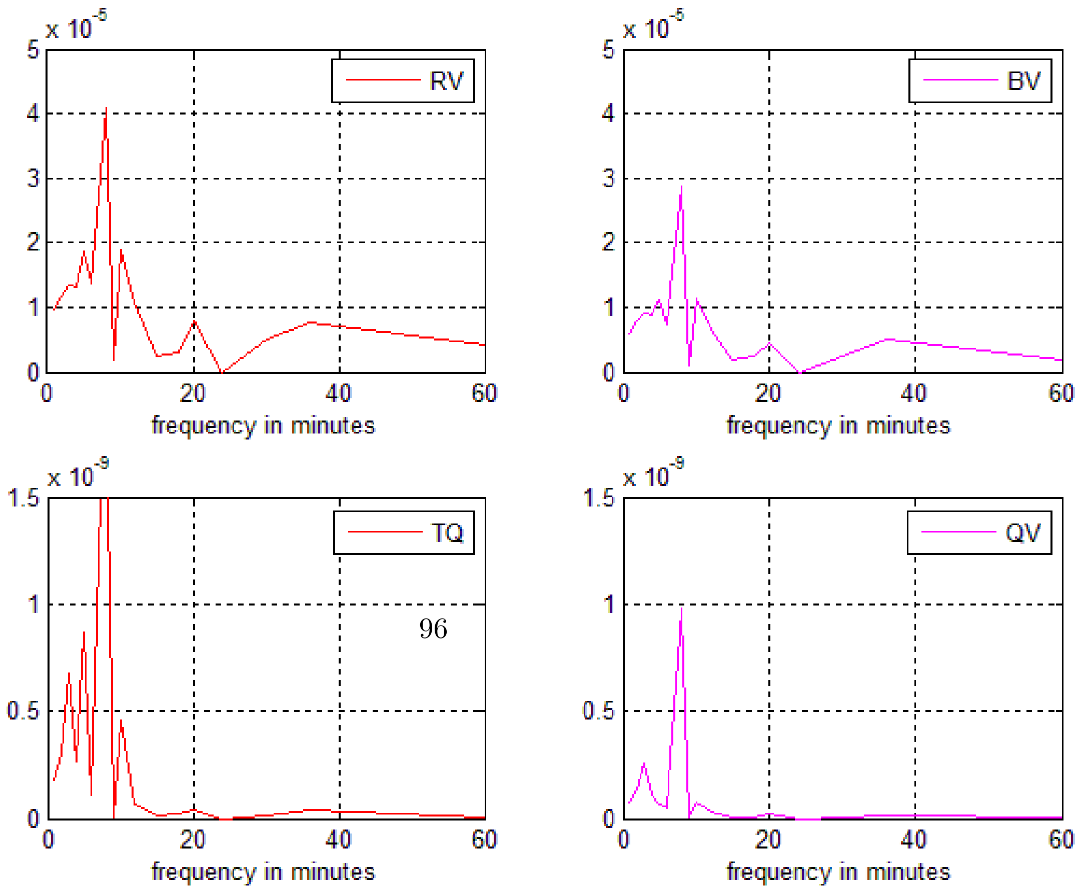


Figure 3.5: Jumps days comparison - Market, Banks and FIs with 15 min data
*The graph shows a comparison of jump days percentage among the Market index, banking industry and the FI industry reported by eight different jump methods. Here the results are taken from jump tests in 15-minutes data at 0.1% significance level in the upper panel, at 1% significance level in the middle panel and 5% level at the lower panel.*

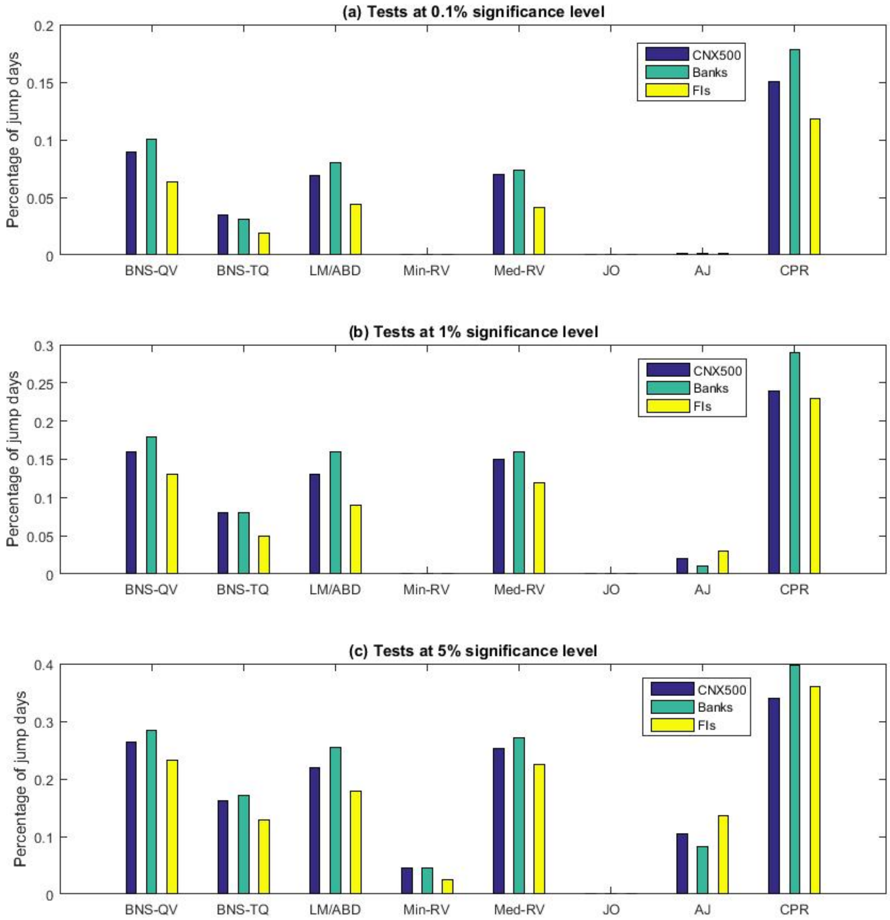


Figure 3.6: Year-wise jump-day spread

*The upper panel shows the jump-day concentration of the banking sector and lower panel shows that of FI sector. We use the BNS_QV test outcomes with 15-minutes data at 1% significance level to construct these graphs.*

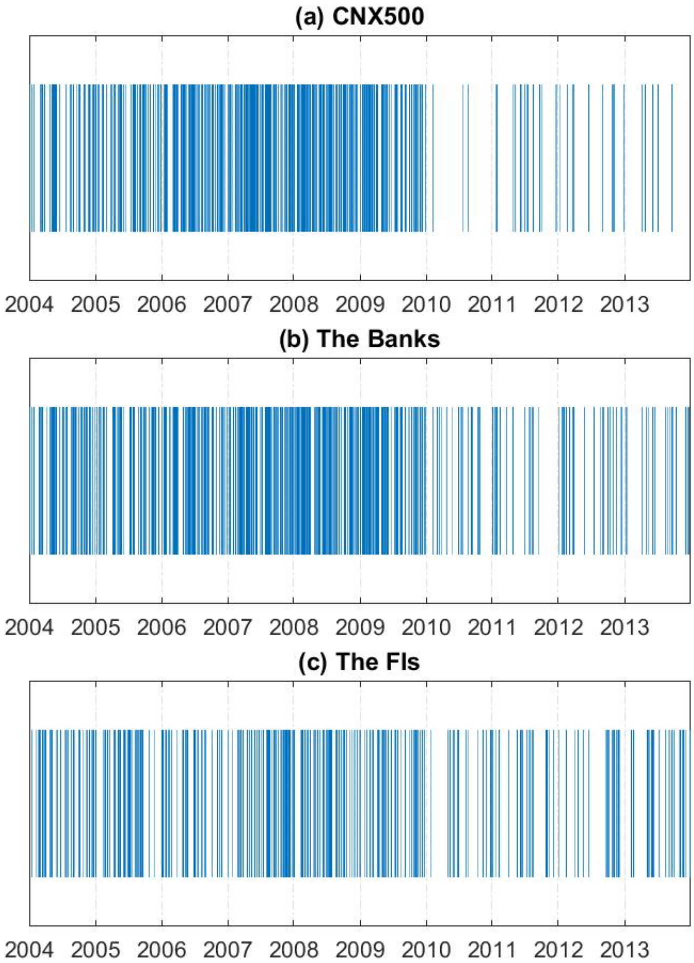


Figure 3.7: Jump time pattern

*The graph shows the frequncy of jump times in the trading days for the market index, the banking sector, and the FI sector in panal a, b and c respectively. We use the LM test outcomes with 15-minutes data at 1% significance level to construct these graphs.*

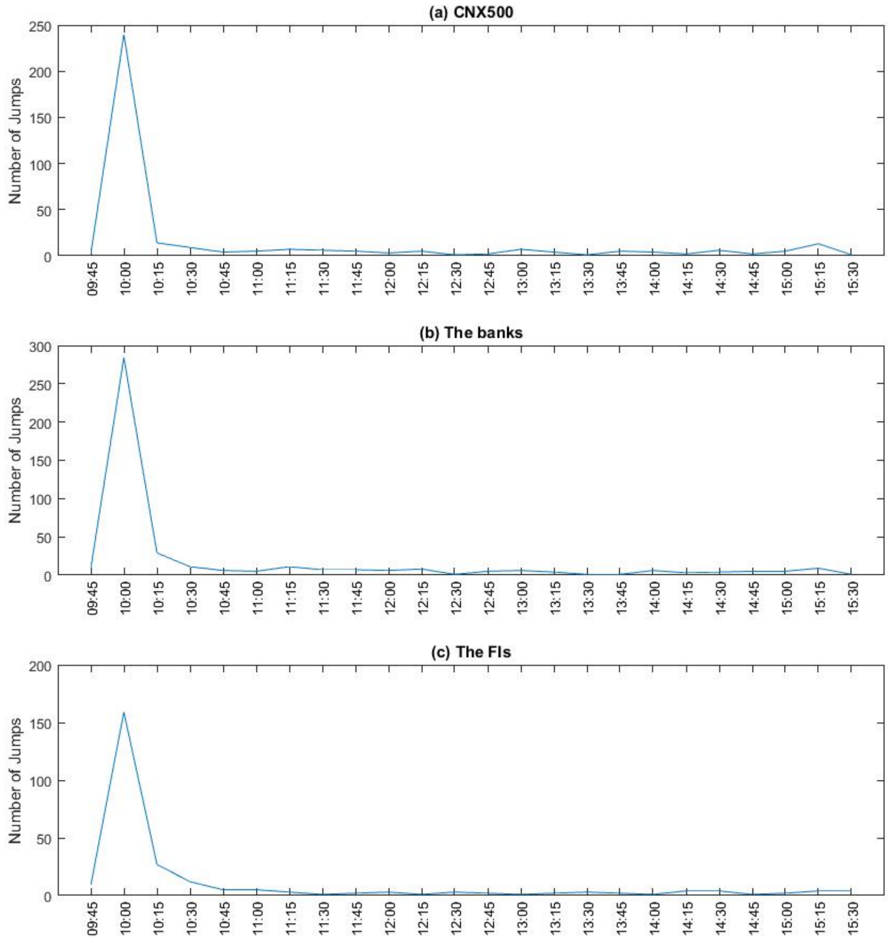


Figure 3.8: Day of the Week Pattern

*The graph shows the frequncy of jump days in 5-day weeks for the market index, the banking sector, and the FI sector in panal a, b and c respectively. We use the BNS_QV test outcomes with 15-minutes data at 1% significance level to construct these graphs.*

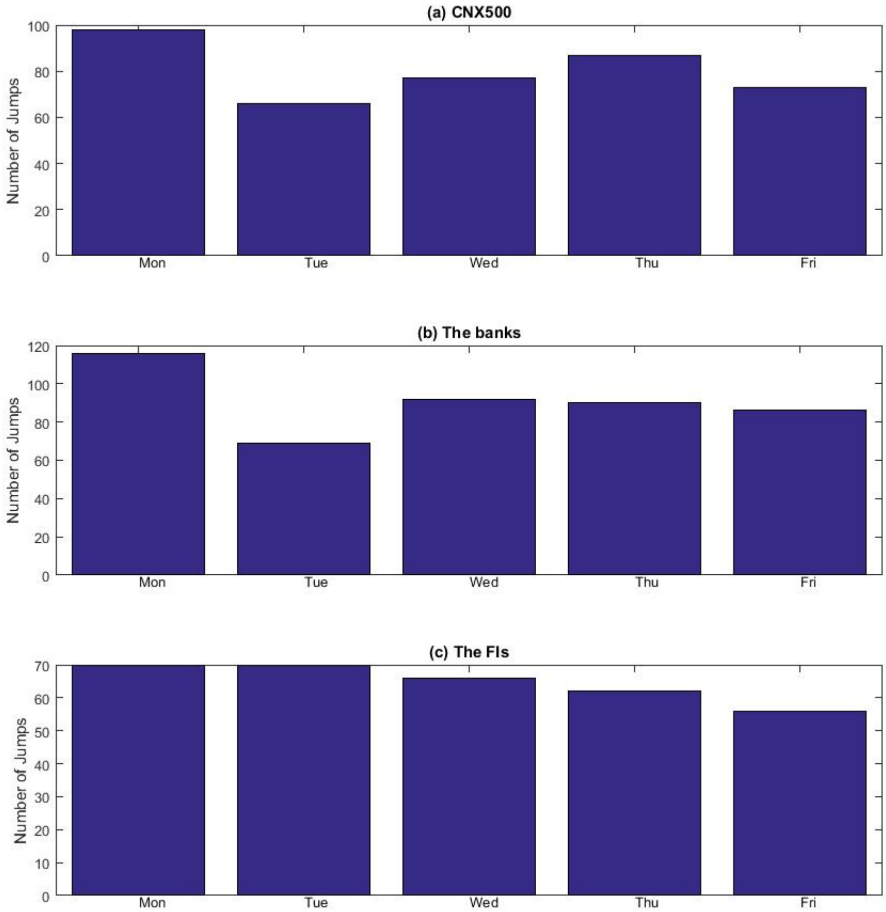
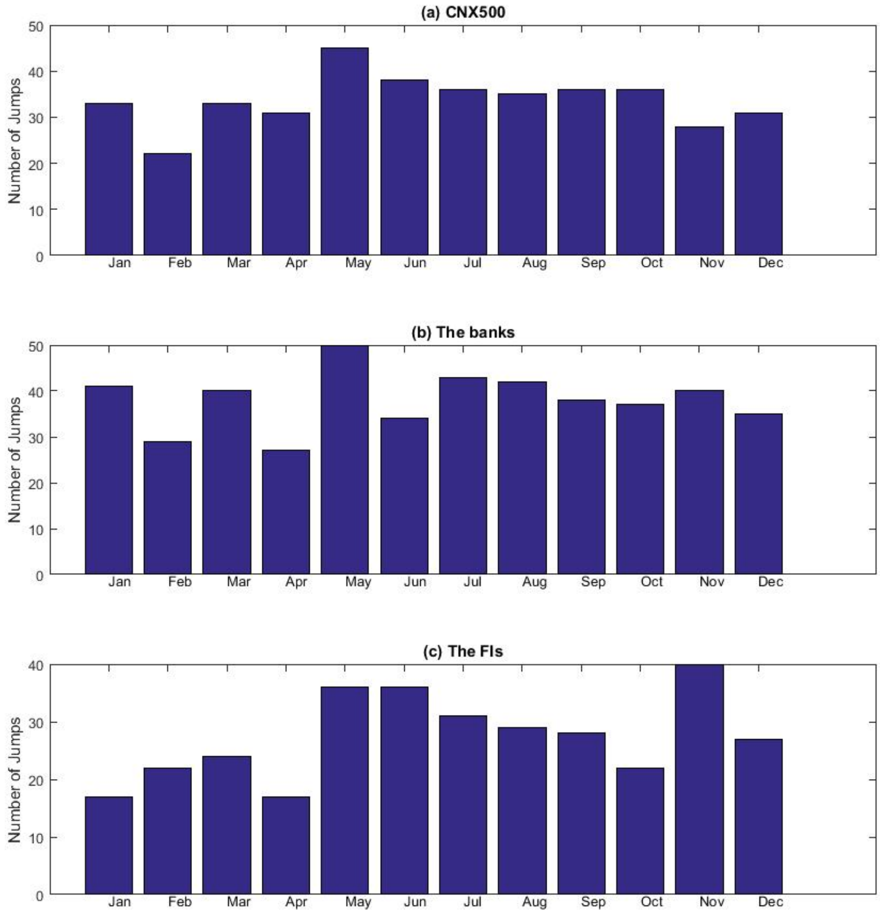


Figure 3.9: Month of the Year Pattern

*The graph shows the frequncy of jump months in our sample years for the market index, the banking sector, and the FI sector in panal a, b and c respectively. We use the BNS_QV test outcomes with 15-minutes data at 1% significance level to construct these graphs.*



# 4 Liquidity and Jumps: An Analysis of the Indian Stock Market

## 4.1. Introduction

As argued in the previous chapters, jumps, described as abrupt changes in return, are important in investors' risk management and hedging decisions. It is believed that in general the arrival of news in the market causes jumps. However, empirical studies show that a large portion of jumps can not be attributed to news arrivals. There must be other factors that are associated with jump occurrences and the importance of jumps warrants examining those factors. Not many studies have been conducted so far, in the direction of unearthing jump-related non-news variables. Our third study presented in this chapter is an effort to bridge the gap in the existing literature by examining the relationship of liquidity variables with the jump movements of equity securities. Using ten of the largest Indian banking stocks we explore the relationship between liquidity variables and the jump returns of these stocks.

The relationship between liquidity and stock return is well studied in the literature.

The effect of liquidity on the expected return may arise from the investor's recognition that they will face transaction costs when selling their stocks in the future. This will prompt discounting of stocks with higher transaction costs or capital restrictions (Batten and Vo, 2014). Amihud and Mendelson (1986) show that in equilibrium, investors with longer investment horizons will hold less liquid assets. As a result of this horizon clientele, the observed asset returns are an increasing and concave function of the transaction costs. Jumps, as a state of returns that is statistically different from other returns given the volatility of a given time window, may result from extreme changes in liquidity conditions.

Some authors argue that liquidity affects stock returns through its positive effect on corporate governance and firm performance (e.g., Karolyi, 2012). Batten and Vo (2014) discuss a number of different ways in which more liquidity may affect corporate governance, such as, by making it easier for non-block-holders to intervene and become block-holders as shown in Maug (1998), by facilitating the information of a toehold stake as shown in Kyle and Vila (1991); by reducing managerial opportunism such as in Edmans (2009), and by stimulating trade and thereby improving investment decisions by informed investors such as in Subrahmanyam and Titman (2001). The liquidity-return relationship prompts us to anticipate that the jumps that can not be explained by news arrival may be related to rapid change in market liquidity, as argued by Lahaye et al. (2011). Boudt and Petitjean (2014) find that jumps are driven by the variations in the demand for immediacy as such jumps occur due to market inability to absorb new orders without moving the price significantly up or down.

Liquidity, by its nature, is a difficult concept to define and hence difficult to estimate (Lesmond, 2005). Kyle (1985) notes that the liquidity concept is “slippery” and “elusive”, and he attributes this to a number of transactional properties of markets encompassed in liquidity, such as tightness, depth, and resiliency. Following this, Lesmond (2005) span the definition of empirical liquidity into direct trading costs (tightness) measured by the bid-ask quotes (quoted or effective), to indirect trading costs (depth and resiliency), measured by price impact. A wide variety of liquidity measures have been used in the literature reflecting its multiple dimensions. For example Liu (2006) defines liquidity as the ability to trade large quantities quickly at low cost and with little price impact. Four dimensions, namely trading quantity (depth), trading speed (immediacy), trading cost (tightness) and price impact (resilience) emerge from this definition. As our motive is to pin down the causes of the jump, we map the different dimensions of liquidity that can be observed in the limit order book, and investigate whether there is any systematic pattern prior to or at the time of a jump.

An important measure of liquidity is trading volume or turnover. Amihud and Mendelson (1986) show that turnover is negatively related to illiquidity costs. Shahzad et al. (2014) explain the relation between volatility and volume by arguing that it is impossible for prices to vary in absence of any trading activity. Individual investors behave as noise or liquidity traders (Barber and Odean (1999). When volume and market depth surge due to increased market activities of uninformed or noise traders, then efficiency would decrease by increasing the volatility in incorporating information. The occurrence of a jump increases uncertainty around fundamental values and it is likely to have a positive impact on future volatility. Thus, there is a practical interest in identifying the jump component of volatility and understanding how market activities contribute to jumps in volatility. Earlier studies have been mainly conducted on the US markets, with the presence of specialists or dealers. However, whether the results for the US market can be replicated in other markets is an open question given that the majority of them are now electronic limit orders (Jain, 2005).

The interaction among public announcement, volume and stock price has been discussed in Kim and Verrecchia (1991) and Atiase and Bamber (1994) and can be summarised as follows: each investor achieves the optimal portfolio prior to a public disclosure based on existing public and private information in the pre-disclosure period. The announcement of public information forces investors to revise their beliefs inducing both price changes and trading volume. After the announcement, investors with more precise private pre-disclosure information will on average make smaller belief revisions than less informed investors with less precise private information. Thus pre-disclosure information asymmetry results in differential belief revisions, in turn, inducing trading volume. Thus it can be shown that trading volume reaction is proportional to both the absolute price change and level of pre-disclosure information asymmetry. When the pre-disclosure information asymmetry is abnormally high, the trading volume reaction will be high enough to induce jumps in the stock price.

An important measure of liquidity is the bid-ask spread or depths at quoted bid and ask prices (Amihud et al., 2006). Amihud and Mendelson (1986) propose that illiquidity can be measured by the cost of immediate execution which can be explained by a trade-off faced by an investor willing to transact. The investor can either choose waiting to transact when the market price matches with his desired price or choose to execute immediately at the current bid or ask price. The quoted ask and bid prices includes a premium or concession for immediate execution of the trade. Thus Amihud and Mendelson (1986) shows that a natural measure of illiquidity is the spread between the bid and ask prices which is the sum of the buying premium and selling concession. Indeed the relative quoted spread on stocks has been found to be negatively correlated with liquidity characteristics such as the trading volume and stock price continuity. The authors predict that the higher-spread assets yield higher expected return. In other words the bid-ask spread, which is often called the quoted spread, is a transaction cost to the trader for immediacy (Copeland and Galai, 1983).

Another spread measure, the effective spread is considered to be one of the best proxies for stock liquidity. The effective spread is defined by Fang et al. (2009) as the difference between the execution price and the midpoint of the prevailing bid-ask quote (the effective spread). Like the quoted spread measure, the effective spread is standardized to adjust for the stock price level converting it to a relative effective spread measure. Liquidity proxies calculated using low frequency stock returns are frequently compared to benchmark liquidity measures calculated using high frequency data to judge their effectiveness as a liquidity proxy. Statman et al. (2006) show that high returns lead to additional trading activity, hence reverse causality is a potential concern for liquidity proxies that rely on trading activity as a measurement input. Fang et al. (2009) argue that the effective spread measure is less subject to this concern than other measures of liquidity.

In addition to liquidity conditions, liquidity shocks may play an important role in asset (fixed income assets in their paper) price jumps as suggested by Jiang et al. (2011). In their analysis, liquidity shocks carries a broad meaning, and it could arise due to pure trading imbalance or order withdrawal. As discussed in Fleming and Piazzasi (2006) dealers tend to withdraw their orders to avoid being picked off in the upcoming information event. Jiang et al. (2011) define a shock in spread as the difference between overall spread in an interval and the mean of overall spread over the previous five intervals scaled by its standard deviation.

Trading imbalance is another variable that provides a link between trading activity and returns, Chordia et al. (2002). Order imbalances, which show imbalance between buy orders less sell orders or excess buy or sell orders, reduce liquidity. Chordia et al. (2002) and Chordia and Subrahmanyam (2004) argue that market-wide returns are strongly affected by contemporaneous and lagged order imbalances. They show that prices and liquidity should be more strongly affected by more extreme order imbalances, regardless of volume, for two reasons. First order imbalances sometimes signal private information, thus reducing liquidity at least temporarily. Second, large order imbalances expose the inventory problem faced by the market maker, who in turn may respond by changing bid-ask spreads by changing price quotations. Hence, order imbalances should be important influences on stock returns and liquidity, conceivably even more important than volume.

To the best of our knowledge, the only three papers that study the liquidity dynamics around jumps are Jiang et al. (2011), Boudt and Petitjean (2014) and Frömmel et al.

(2013). Among these papers only Boudt and Petitjean (2014) examined jumps in stock returns while Jiang et al. (2011) used bond returns and Frömmel et al. (2013) use exchange rate returns to find the effect of liquidity. All of these papers have been conducted on the U.S market which is driven by the market dealer or market makers. Most of the theories discussed in the literature on market activities is based on how the market maker reacts to a change in market activity. Hence, the findings may be different in a market like India which is order driven rather than quote driven. We focus on stocks of the National Stock Exchange in India (NSE) where trading takes place through an open electronic limit order book, in which order matching is done by the trading computer. There are no market makers or specialists and the entire process is order driven, which means that market orders placed by investors are automatically matched with the best limit orders.

The argument in favour of choosing India for this study follows Bekaert et al. (2007). The growing body of research on liquidity primarily focuses on the U.S., arguably the most liquid market in the world. In contrast, our research focuses on an emerging market where liquidity effects may be particularly strong. Emerging markets are known to be less liquid, hence higher liquidity premia should be found in these markets. Thus the focus on emerging markets should yield powerful evidence of liquidity impacts on any variable like jumps. In addition, the vastness of the U.S. market allows a very diversified ownership structure, combining long horizon investors (less subject to liquidity risk) with short-term investors. Hence, the pricing of liquidity is mitigated by the clientele effects in portfolio choice in this market. Such diversity in securities and ownership is lacking in emerging markets, potentially strengthening liquidity effects.

We have chosen ten banking stocks with the largest market capitalization. In countries like India banking stocks are popular, and are among the stocks that are most followed by investors and analysed by experts. Thus, we expect that there will be considerable amount of variation in liquidity variables with the changing market conditions, which enables us to capture the dynamics between liquidity and jumps.

We use the jump test developed by Lee and Mykland (2008). This method has the advantage of identifying jumps in individual return observations. We observe jumps in 1.58% to 1.73% of return observations in the ten banking stocks. In all cases the number of positive jumps is higher than the number of negative jumps. We implement a non-parametric method to analyse the link between intra-day liquidity dynamics and properly identified intra-day jumps regardless of the arrival of information. To complement the non-parametric event study we apply a parametric analysis to assess the contribution of liquidity shocks in both the occurrence of jumps and price discovery process. We find that liquidity measures are largely affected by jumps in the stocks. If we characterize liquidity by the market spread, jumps do improve market liquidity conditions which is in contrast with the findings of Boudt and Petitjean (2014). If trading quantity and immediacy are considered, we observe again an improvement in the market liquidity. The surge in volume can be translated as a sharp increase in investors' orders for immediate execution around jumps. Among the two drivers of volume surges, the rise in average trade size and the rise in number of trades, our analysis reveals that the former is more prominent than the latter. The market depth is deepened at the time of jumps. We show that negative jumps are associated with higher bid and ask depths, indicating the existence of thicker buying and selling pressures. Thus it is the heightened demand of immediacy from the market participants of both sides, rather than the traders' withdrawal of liquidity that causes jumps. The Mann-Whitney test results also confirm the significant changes in the liquidity variable during the jump intervals from non-jump intervals.

We examine the contemporaneous and lagged effect of liquidity factors on the probability of jump occurrences, and find the prevalence of both effects in different degrees for different jump measures. However, the explanatory power of contemporaneous liquidity variables is much higher than the lagged variables for all jumps (19.17% vs 1.54% in the probit regression). The liquidity variables have more explanatory power in determining the probability of negative than that of positive jumps (35% vs 11.53% in the contemporaneous probit regression and 2.18% vs. 1.29% in the lagged probit regression). Negative jumps are more associated with change in liquidity conditions than the positive jumps. Among the liquidity variables, volume, quoted spreads, effective spread shock and order imbalance are key drivers of the occurrences of positive jumps. For negative jump occurrences the effective spread and effective spread shock play important roles.

As investor behaviour may change during a crisis, the dynamics between liquidity variables and jump occurrences may also change. We examine changes by dividing our sample period into pre-crisis, crisis and post crisis periods. However, we do not observe substantial changes in the results in those sub-samples indicating the effects of liquidity variables are general on jump occurrences.

Finally, several liquidity variables are shown to contribute to price discovery. Volume, depth, quoted and effective spreads, effective spread shock and order imbalances are significant contributors to the price discovery process. However, the post jump price discovery process does not appear to be very much related with these liquidity variables.

The study is an addition to a small list of papers examining the relationship between liquidity variables and jump occurrences. the uniqueness of this paper is that it conducts the study on an emerging market which is not dealer driven like the U.S. market. The previous two papers only examined the effects of the lagged liquidity variables on the jumps while we have analysed both the contemporaneous and lagged effects of liquidity on the probability of jump occurrences.

The remainder of the chapter is organized as follows. Section 4.2 documents the liquidity variables used in this study. A description of data used in this study and the jump detection methodology are discussed in section 4.3 and 4.4 respectively. We present the results in section 5.3 followed by conclusion in section 5.4.

## 4.2. Variables

We use the liquidity measures widely used in the literature to examine the relationship between market liquidity and stock returns or jumps. We list these liquidity measures and the respective computing methods below:

We measure the immediacy and depth of the market by volume of stocks traded ($VOL$), depth at best ask price ($DPTA$) and depth at best bid price ($DPTB$) as follows:

(1) $VOL =$ Number of stocks traded

(2) *DPTA* = Best Ask Price × Number of Ask

(3) *DPTB* = Best Bid Price × Number of Bid

Spreads are taken as relative terms and are defined both as quoted spreads (*RSPD*) and effective spreads (*RESPD*) as follows:

(4) *RSPD* = (Best Ask Price - Best Bid Price)/Mid Quote,

where Mid Quote = 1/2 (Best Ask Price + Best Bid Price)

(5) *RESPD* = (Last Price - Mid Quote)/Mid Quote

The spread shock variables are shown as the difference between overall relative quoted (effective) spread in an interval and the mean of overall (effective) spread over intervals $t-5$ to $t-1$, scaled by its standard deviation. Thus

(6) *DDRSPD* = Change in *RSPD* in time interval $t = \frac{RSPD_t - 1/5\sum_{j=1}^{5} RSPD_{t-j}}{\sigma_{RSPD}}$ and

(7) *DDRESPD*: Change in *RESPD* in time interval $t = \frac{RESPD_t - 1/5\sum_{j=1}^{5} RESPD_{t-j}}{\sigma_{RESPD}}$

The order imbalance variable is defined in our study as

(8) *OB* (Order Imbalance) = $DPTA_t - DTPB_t$

Macroeconomic news is considered as the most important causal factor in inciting jumps. Boudt and Petitjean (2014) report that a third of the jumps are caused by macroeconomic news while another 5% of the jumps are associated with firm-specific news. Macroeconomic news tends to effect whole market, hence we should observe a market-wide jump as a consequence of arrival of macroeconomic news. We take the jump occurrences in the market index (CNX500) as a proxy of such market-wide jumps.

(9) *MJump* = Jump in the market - A proxy of arrival in news in the market.

Our dependent variable in the regression analysis is a binary variable indicating the existence of a jump in a given time interval. This variable takes the value of one when the Lee-Mykland jump test detects a jump in a given time interval, otherwise it is zero.

## 4.3. Data

We collect data for the Indian market index, stock prices of listed banks from the Thomson Reuters Tisk History (TRTH) database provided by SIRCA. We take 10 of the largest banks in term of market capitalization at the end of 2013 in our sample shown in Table 4.1 . These 10 banks are listed on the National Stock Exchange (NSE).

Our data covers from the period of January 1, 2004 to December 31, 2013, which includes the global financial crisis in 2008-09. There are a total of 2497 trading days in our sample period. We collect intra-day 15-minute data from TRTH. In chapter 3 we show through a signature plot that data with 15 minutes sampling frequency for Indian stock prices provides a balance between measurement accuracy and market microstructure noise of high frequency data. Following our previous studies we use the last price recorded in each of the 15-minute intervals during the normal trading session of NSE from 9:15 a.m. to 3:30 pm, where missing data are filled with the price of the previous interval which assumes that the price remains unchanged during a non-trading interval. We drop the first 15 minutes of each day to avoid noise associated with market opening. Hence, our trading hours are 9.30 am to 3.30 pm local Indian time. We have 24 observations of 15-minute data for each trading day. We use the CNX500 index as the market index following our previous papers.

## 4.4. Jump Detection Method

We use jump detection method proposed by Lee and Mykland (2008) (LM) which has the advantage of detecting jumps at individual return observation level instead of a given time span. Although the method is already described in Chapter 3 we provide a short description of the method here for easy references. The statistics $L_i$ that tests for a jump at every intra-day period $t_i$ is defined as

$$L_i = \frac{\Delta_{t_i} p}{\hat{\sigma}(t_i)}, \tag{4.1}$$

where $\Delta_{t_i} p$ is the intra-day return and $\sigma(t_i)$ is the local volatility measure. Here we use the bipower variation of $K$ observations preceding the relevant observation. Thus the test can identify the presence of jumps in an observation against the volatility in the prior period and can be defined as

$$\hat{\sigma}(t_i)^2 = \frac{1}{K-2} \sum_{j=i-K}^{i-1} \mid \Delta_{t_j} p \mid\mid \Delta_{t_{j-1}} p \mid . \tag{4.2}$$

Lee and Mykland (2008) suggest a window size $K$ between $252 \times n$ and $\sqrt{252 \times n}$, where $n$ is the number of observations in a day so that the window size poses a balance between being a jump-robust volatility measure and being effective in scaling the trend in volatility. In our study, we use 80 as values of $K$ for our 15-minute sampling interval where $n$=24.

The asymptotic distribution of the test statistic is as follows:

$$\frac{max(L_i) - C_n}{S_n} \to \xi, \tag{4.3}$$

where $P(\xi \leq x) = exp(-e^{-x})$, the constants

$$C_n = \frac{(2logn)^{1/2}}{c} - \frac{log\pi + log(logn)}{2c(2logn)^{1/2}}, \tag{4.4}$$

$$S_n = \frac{1}{c(2logn)^{1/2}}, \tag{4.5}$$

and

$$c = \sqrt{\frac{2}{\pi}}. \tag{4.6}$$

Thus the LM test detects jumps by comparing the maximized value of $L_i$ to the critical value from the Gumbel distribution. We use the LM test method in this study, applying a significance level of 0.01.

## 4.5. Empirical Analysis

We study the dynamics of different liquidity variables such as trading volume, number of trades, depth of ask and depth of bid, the quoted spread ratio and effective spread ratio, the order imbalance in relation to jump occurrences. Further, for each time interval of the event window we use a Mann-Whitney test to examine whether the median value of the liquidity measures on jump intervals is the same on intervals without jumps. We supplement our investigation by undergoing a parametric analysis to assess the impact of liquidity shocks in intra-day jump occurrences and price discovery. Lastly we analyse the impact of economic crisis on the liquidity-jump relationship by comparing sub-sample regression results.

### 4.5.1. Liquidity around jumps

To see how liquidity variables behave around the jump time, we take the average values of the liquidity variables within the jump intervals, 15, 30, 45 and 60 minutes prior to the jump times, and also 15, 30, 45 and 60 minutes after the jump times. We remove all the jumps that we find during the first and last trading hours so that we have the liquidity measures 1 hour before and after all detected jumps. In addition we also discard the jumps when we find two consecutive jumps within a two hour interval to avoid liquidity measures which may have overlapping effects from more than one jump. Table 4.2 presents a summary of the intra-day jumps we detect for the ten sample banks. Out of 87,672 return observations, each bank experiences 1461.5 jumps on average, which is 1.67% of the total observations. 55.41% of all jumps are positive, the remaining 44.59% jumps are negative.

#### 4.5.1.1 Return around jumps

Figure 4.1 shows the average return behaviour around the time intervals when jumps occur. Jump returns are prominently higher than the returns before and after the jump intervals as expected. Panel (a) shows that returns are moving towards zero from positive figures before the jump occurrences. After the jump interval returns become negative and then again start moving toward zero from this point. But if we separate positive and negative jumps in panel (b) and (c) we observe a specific pattern in changes of returns before and after jump intervals. Returns are gradually decreasing before positive jumps, and there is a price correction immediately after the jump return. Returns behave in just the opposite way around the negative jumps. The movement of returns support the overreaction of investors and return reversals hypotheses that have been well documented in the literature (Bondt and Thaler 1985 and Chopra et al. 1992).

#### 4.5.1.2 Trading volume and depth around jumps

We use the increase in trading volume and number of trades as sign of demand increase for immediate execution by the investors. It is evident from our analysis that the demand for immediate execution rises around jumps. Figure 4.2 shows a substantial surge in trading volume, averaged over the sample period at the time when price jumps. In the 15-minute jump interval, the abnormal average volume is three times the median value across the non-jump time intervals. That is consistent with hypothesis that jumps are caused by the market mechanism of moving the price significantly up or down in the face of sudden surge of new orders. These findings support that the demand for immediacy is a driving force behind jump occurrences. The news alone can not explain the jump arrivals, the impact may be transmitted through the market liquidity changes which in turn move the price up and down.

Our figure also shows that volume decreases gradually from one hour before the jump interval, indicating that the informed investors restrain themselves from trading and wait for the arrival of news. They do get involved in trading once the news has arrived thus contributing a surge in the trading volume. During the one hour following the jump, the volume decreases gradually but remains at a level higher than one hour prior to the jump. This may result from the fact that a section of the investors take time to react after the news become public, or that investors wait to observe the market reaction of the news and then start trading. Our results show a slightly decreasing trend of volume measurements leading to the jump time whereas Boudt and Petitjean (2014) show that the graph is pretty flat until right before the jump. This indicates that it is the unexpected part of news content that leads to jump occurrences.

The drivers behind the volume surge may be a higher number of trades or a larger average trade size. Figure 4.3 and 4.4 show an increase in both of these trade variables during the jump intervals. Nonetheless, the rise of average trade size during the jump intervals is more prominent than the number of trades. When news arrives in the market, informed investors become engaged in trading in higher volume per trade, surging the total volume for the stock and creating jumps. This finding is in line with Kim and Wu (2008) and Easley and O'Hara (1987) who show that informed traders incline to be involved in trading in larger sizes. Our findings differ slightly from Boudt and Petitjean (2014) who show that both number of trade and average trade size contributed equally to the rapid surge of volume at the jump time. The subtle difference may arise because of the difference between the U.S. market from the Indian market where information may not spread to a wide number of investors as quickly as in the U.S. market.

Figure 4.5 and 4.6 illustrate how the depth in the market at the best bid and ask price increases around the jump intervals. Although higher spreads, as well as, higher trading volume exist, the quoted market depth is not withdrawn from the market. Our findings here support Boudt and Petitjean (2014) that a greater demand for liquidity instead of a weak liquidity supply, is accounted for price jumps.

#### 4.5.1.3 Spread around jumps

Figure 4.7 and 4.8 show a significant decrease in average spreads at the time of price jumps indicating a fall of one of the three typical cost components of the spread: order processing costs, inventory holding costs, and/or asymmetric information risk. The effective spread, *RESPD* is increasing in the hour before jumps and then shows a slump just at the jump interval and stays low for around 45 minutes. The reduction in spread may result from the increase in the volume in the market around jumps. The result is opposite to that for the U.S. market as shown by Boudt and Petitjean (2014), which they explain as a consequence of having the unusually large trading volume at jump time putting pressure on the specialist's or market maker's inventory. As the Indian market is broker driven rather than dealer driven, the impact of the rise in volume may have different impact on spread. The higher volume increases market efficiency and thus decreases the spread cost.

The spread shows an increasing trend one hour before the positive jump arrival time. We may relate this trend with the decrease in volume at the corresponding time intervals. The gradual fall in volume and rise in spread may indicate that investors adjusts their behaviour in advance before important news are released, unlike the U.S. investors.

The effect of jumps on ex-ante liquidity in terms of *RSPD* is less pronounced as we do not observe any clear fall or rise in *RSPD* in the jump interval from the previous few intervals. Ex-post liquidity is rather more severely affected confirming that liquidity providers do not improve their displayed quoted prices in response to the jump occurrences and the bid-ask spread widens, as a result. However, the post jump quoted spread rises dramatically when the jump is negative and remains there for the whole hour that we examine indicating that after a large negative return the byers and sellers become overcautious in quoting their respective prices. We do not observe any such pattern in quoted spread after a positive jump occurrence.

#### 4.5.1.4 Order imbalance

Figure 4.9 shows the trading activity at the time of a jump occurrence is unbalanced. Positive (negative) jumps can be attributed to large buying (selling) pressure as we observe sharp step up in the order imbalances in the jump intervals. Chordia et al. (2002) relate the degree of order imbalance to the relevance of the released information. Boudt and Petitjean (2014) explain the existence of high number of trades as an indication of large sample of independent observers receiving the same signal and creating a high disequilibrium between buy and sell transactions.

The imbalance measure drops back quickly to its pre-jump level after the jump in the case of negative jumps. In contrast, trading imbalances are more persistent after the positive jumps. The results indicate that initial agreement on the price direction, is dismantled quickly when heterogeneous beliefs among the investors on the fundamental asset value reappear; this is more pronounced for negative jumps, leading to a more balanced interaction between bulls and bears. It also indicates that the overreaction to the news is more prevalent for negative jump returns than the positive ones.

#### 4.5.1.5 Mann-Whitney Test Results

The Mann-Whitney test is used to rank a series from smallest value to largest, and to compare the sum of the ranks from one subgroup to the sum of the ranks from another subgroup. If the groups have the same median, the values should be similar. We use EViews to reports the asymptotic normal approximation to the U-statistic and the p-values for a two-sided test; for details, see Sheskin (2003). The test in Eviews is based on a one-way analysis of variance using only ranks of the data.

Table 4.3 reports the Mann-Whitney test results of whether the liquidity measures in the time interval of jump occurrences come from the same distribution as the ones in intervals without jumps for the ten sample banks. We show the results for all jumps, positive jumps and negative jumps in separate rows for the liquidity variables used in this study. Volume is significantly different during the jump intervals for all ten banks at the 95% confidence level and for both positive and negative jumps, which shows that jump occurrences are strongly related with trading volumes. For example, the median volume of non-jump intervals is 28,335 while the median volume of jump intervals is 30,699 for HDBK bank. The arrival of news prompts investors to trade in the market, and the price changes rapidly depending on the strength of buying or selling pressure. Median values of both the depth measures *DPTB* and *DPTA* (depth is bid and ask) are also significantly higher in the jump intervals, supporting the notion of the sudden change in stock prices backed by investors' desire for immediacy.

The relative spread measures the quoted spread, *RSPD* and the effective spread, *RESPD*, are found to have significantly different values in the jump and non-jump intervals. For *HDBK* Bank the median value of *RSPD* is 0.000854 during the jump intervals which is around twice as large as the median value of 0.000425 in non-jump intervals. We see similar patterns for the relative effective spread measure, *RESPD* showing that extreme price movements are associated with increased transaction costs for the investors.

The order imbalance measure, *OB* also varies significantly in jump and non-jump intervals. The median order imbalance is almost four times higher in jump intervals than the non-jump intervals for *HDBK* Bank. The Mann-Whitney test results show that the difference is more prominent for negative jump intervals than for positive jump intervals. We can interpret this as evidence that the extreme price drops are connected with high selling pressure which creates substantial order imbalance in the market.

Our results are consistent to the findings of Boudt and Petitjean (2014) and Jiang et al. (2011). Although the Indian market is order driven rather than quote driven, our results reveal that the liquidity variables are significantly related to the jump occurrences as in the USA market.

### 4.5.2. Impact of Liquidity on jump probabilities

The empirical findings documented in the previous subsections suggest that liquidity shocks around jumps are substantial. In this subsection, we examine how shocks in volume, depth, effective and quoted spreads and order imbalance variables explain the probability that a jump occurs. The following regression is estimated for each of the 10 banking stocks over the sample period from January 1 2004 to December 31, 2013:

$$\begin{aligned} P(Jump_j &= 1 \mid X) = G(\alpha_j + \beta_1 MJump_j + \beta_2 Vol_j + \beta_3 DPTB_j + \beta_4 RSPD_j + \beta_5 RESPD_j \\ &+\beta_6 OB_j + \beta DDRSPD_j + \beta_8 DDRESPD_j), \end{aligned} \tag{4.7}$$

where $X$ is a vector of regressors. We include a dummy variable, $MJump$ to represent the existence of jumps in the market in a given time interval. We use this variable as a proxy of macroeconomic news arrival with the assumption that the whole market will be affected by the news. We use only one measure of depth, *DPTB* as the co-relation between *DPTB* and *DPTA* is very high. We run two binary dependent variable models, as shown in Table 4.4 and 4.5, to test whether any liquidity variable contributes to the occurrence of stock jumps contemporaneously. The probit and logit models lead to the same conclusions. First, we examine the contemporaneous effect of liquidity on overall jumps, positive jumps and negative jumps. We report the average coefficients of the variables in the second column and from 3rd to 6th columns we show the number of stocks where we find the relationship is positive and significant at 5%, positive and significant at 10%, negative and significant at 5% and negative and significant at 10% level for each independent variables. We also report the average McFadden R-squared values for each set of regressions.

Occurrences of market jumps increase the probability of having jumps in the individual stocks significantly at the 5% level for all of the ten stocks analysed in our study. A jump in the market indicates that the broad investors receive a signal that affects a large number of stocks. The individual stocks are then more likely to react to the signal. The probability of either a positive or negative jump at the time of occurrence of market jumps both increases.

An increase in volume ($VOL$) increases the likelihood of contemporaneous jumps for Indian stocks as shown in all ten of our sample stocks. When volume surges the price changes rapidly in the direction that is dictated by the buying vs. selling pressures. We see the impact of volume is more pronounced for positive jumps than negative jumps, and the signs of the coefficients are also opposite. When volume increases, the market takes it as a bullish signal and the corresponding response generates a positive jump. Conversely, in case of negative jumps we find that the reaction is significantly negative in four regressions and positive in only one regression. We may interpret the results in two ways. First, the abnormal negative returns may arise from bad news rather than from the impact of volume surge. Second, it is the decrease in market volume that increases the chances of having negative jumps in the stock. A fall in volume depresses the market, the investors become bearish, and the stock price falls substantially creating negative jumps.

The market depth at bid price ($DPTB$) has a significant positive coefficient in 4 stocks for positive jumps, and 6 stocks for negative jumps. This shows that the depth is more associated with negative jumps than the positive jumps. The increase in buying pressure implies greater demand for liquidity rather than a weak liquidity supply, resulting in extreme price changes in either direction. However, the depth variable is not as strong as the volume variable in determining the probability of jump occurrences for the Indian banking stocks.

Among the two spread ratios we apply in our study the quoted spread, *RSPD* and effective spread, *RESPD*, we see that *RESPD* affects the probability of jump occurrences in more stocks (10 vs 8). However we see quite different results in the case of positive jumps and negative jumps. In all 10 regressions the quoted spread significantly affects the probability of jump occurrences at the 5% level, whereas the effective spread is negatively significant at 5% in 6 regressions, and positively significant at 5% level in one regression. In contrast, the effective spread can explain the negative jumps significantly in all ten regressions. The results show that an increase in effective spread can increase the probability of having a negative jump. High effective spreads may be indicative of greater market imbalance between buying and selling pressures. The abnormal negative returns or jumps are closely related to such market imbalances, which may result from spread of negative news in the market. The negative coefficient of *RESPD* in 6 stocks in case of positive jumps means that, an increase in *RESPD*s reduces the chance of having an abnormally high positive returns, indicating that positive high returns are not associated with market imbalances rather the higher differences between ask and bid prices.

Changes in the spread ratio in the contemporaneous time intervals from their last five values also significantly affect the probabilities of jump occurrences. Among the two variables, *DDRSPD* (change in quoted spread) and *DDRESPD* (change in effective spread), we find *DDRESPD* has higher impact on jump probabilities. The rapid change in effective spreads has higher likelihood of being accompanied by jump returns either positive or negative.

The liquidity order imbalance variable, *OB* does not seem to be crucial variable for jumps given that it has a significant coefficient at 5% only in two regressions when we look at the overall jumps. However, by analysing the positive and negative jump regression outcomes we see quite a different story. *OB* has a significantly negative coefficient in 9 regressions at the 5% level in the case of positive jumps. This variable is positively significant at the 5% level in 9 out of 10 regressions in the case of negative jumps. Thus an increase in order imbalance is associated with an increase in the probability of negative jumps, and a decrease in the probability of positive jumps.

Overall the liquidity measures along with the market jumps can explain 19.17% of the jump probabilities for all jumps as indicated by the average McFadden $R^2$. The difference in McFadden $R^2$ values between the regressions for positive jumps and the regression for negative jumps is noteworthy. While this value is only 11.53% for positive jumps, it is 35% for the negative jumps. Thus liquidity variables are much more strongly associated with negative returns rather than positive returns contrasting with our initial predictions. Our results indicate that abnormal negative price movements are more sensitive to the liquidity shocks. The probit regression results are largely supported by the logit regression results presented in Table 4.5.

We also examine the lagged effect of the liquidity values on jump occurrences for the Indian banking stocks. Table 4.6 shows that it is primarily the volume depth variables that have significant impact on the probabilities of positive jumps. *VOL* and *DPTA* have significant positive coefficients in 9 and 7 regressions respectively. In the case of negative jumps it is the effective spread and its variations from previous values (*RESPD* and *DDRESPD*) that have significant coefficients. The results indicate that increase in market depth leads to a positive jump in the next 15-minute interval, while the spread change points towards negative jumps.

Next we examine the combined impact of contemporaneous and one order lagged liquidity variables jumps depicted in Table 4.7. Here we report the results obtained on all jumps. We observe that the contemporaneous relationship between the liquidity variables and probability of jumps remain almost same as we show in Table 4.4. These variables have mostly positive relationship with jumps. The lagged version of the variables, except market jumps ($MJump$) and the variations in effective spread ($DDRESPD$) exhibit mostly negative relationships with jumps the jump probabilities. These regressions results are not very much different from regression results we obtain from regressions of jumps with the contemporaneous and lagged liquidity variables separately.

### 4.5.3. Liquidity and the Global Financial Crisis

We examine whether the liquidity-jump relationship of Indian banks shifts during crisis periods. Traders may react differently to the liquidity shocks during the crisis period than the non crisis periods. The results are reported in Table 4.8. As the global financial crisis (GFC) of 2007-2009 falls within our sample period, we analyse the impact by taking sub-samples referring to the pre-crisis, crisis and post-crisis periods. We follow Dungey et al. (2015) in identifying the crisis period, who identify 3rd July, 2007 as the beginning of the crisis period when the connection between the troubled US sub-prime mortgage market and the global credit markets came to light and just to prior to the resignation of the CEO of UBS on 5th July. The second phase of crisis starts from early October 2008, following the bankruptcy of Lehman Brothers and subsequent rescue of the American Insurance Group. The breakpoint from crisis period to post crisis has been identified as 15 May 2009, which is the day of the publication of stress test results and new capital raising by US banks, and the LIBOR rate falling below 1%. In our study we consider both phases of crisis period as one crisis period. Thus in our sample, 1 January 2004 to 2 July 2007 is considered as the pre-crisis period, 3 July 2007 to 15 May 2009 as the crisis period and 16 May 2009 to 31 December 2013 as the post crisis period.

We do not find any notable change in the liquidity-jump relationship among the pre-crisis, crisis and post-crisis periods. The volume, effective spread ratio and the change in effective spread ratio remain dominant in determining the probability of jumps in all three phases. The average McFadden $R^2$ has risen from 19.24% to 22.87% from the pre-crisis period to the crisis period, indicating a rise in explanatory power of liquidity variables in the crisis period. However, the McFadden $R^2$ of the post-crisis period is 22.47% which is similar to the crisis period.

### 4.5.4. Price Discovery and Liquidity

The impact of liquidity variables on stock returns when there are jumps is examined by applying the following mode

$$\begin{aligned}\Delta_{t_i}^n p \;=\; & \alpha_j + \beta_1 Jump_{j-1} + \beta_2 Vol_j + \beta_3 Vol_j * Jump_{j-1} + \beta_4 DPTB_j + \beta_5 DPTB_j * Jump_{j-1} \\ & +\beta_6 RSPD_j + \beta_7 RSPD_j * Jump_{j-1} + \beta_8 RESPD_j + \beta_9 RESPD_j * Jump_{j-1} \\ & +\beta_{10} OB_j + \beta_{11} OB_j * Jump_{j-1} + \beta_{12} DDRSPD_j + \beta_{13} DDRSPD_j * Jump_{j-1} \\ & +\beta_{14} DDRESPD_j + \beta_{15} DDRESPD_j * Jump_{j-1} + v_j. \end{aligned} \tag{4.8}$$

A dummy variable representing the jump with one lag is added to the the model, as well as the interaction of this dummy variable with all the liquidity variables. We can see from Table 4.9 that the jump dummy variable with a lag is positively significant at 5% in only 3 out of 10 regressions. Hence, we do not find strong evidence that a jump in a given time period has forecasting value for the return prediction of the next period. Similarly none of the interaction variables with the jump dummy are overwhelmingly significant in these 10 regressions. Volume itself significantly impacts the contemporaneous return (10 out of 10 regressions at 5% level) but the interaction with the dummy variable with one lag is negatively significant in 5 out of 10 regressions. When we have a jump in one period the volume has a reverse relationship with the return. When jumps increase the uncertainty in the market, investors want to sell their assets immediately, the price drops and buyers are attracted to the respective stock to take advantage of low prices, thus volume rises in the market. The quoted spread, *RSPD*, has a positive and significant (at 5% level) impact on the return, indicating that an increased difference in bid and ask is associated with higher returns. The effective spread, *RESPD*, on the other hand is negatively associated with the return. When the executed price moves away from the mid quote, the return decreases. However, the interaction terms of these two spread variables with the jump dummies are not significant in most of the 10 regressions. The order imbalance variable, *OB*, is negatively significant in the regressions while the interaction term with jump is not significant in any case.

Among the two change in spread variables, the change in effective spread, *DDRESPD*, is found to be negatively significant in determining the return in 8 out of 10 regressions whereas the other variable, change in quoted spread, *DDRSPD*, in only two regressions. Hence it is the effective spread rather than the quoted spread that changes with the return. However, when we incorporate the jump of the previous interval with these variables, none of the variables shows any definite relationship with stock returns.

Overall, it seems that having jumps in the previous time interval does not have a notable impact on the liquidity measures in explaining the variations in stock returns. However, the liquidity measures themselves are found to have significant coefficients in the return regressions. The average adjusted $R^2$ value of these regressions are 36.90%.

## 4.6. Conclusion

Our study examines the relationship of liquidity variables with the jump movements of equity securities. Using ten of the largest Indian banking stocks we explore the relationship of liquidity variables with the jump returns of these stocks.

We use the jump test developed by Lee and Mykland (2008) and observe jumps in 1.58% to 1.73% return observations in ten banking stocks. We implemented an event study method to analyse the link between intra-day liquidity dynamics and properly identified intra-day jumps regardless of the arrival of information. To complement the non-parametric event study we apply a parametric analysis to assess the contribution of liquidity shocks in both the occurrence of jumps and the price discovery process. We find notable variations in the liquidity measures around the jump intervals in the stocks. If we characterize liquidity by market spread, trading quantity and immediacy, market liquidity conditions do improve around jumps. We examine the drivers behind this volume surge and find that the rise in average trade size is more prominent than the rise in number of trade. We show that the negative jumps are associated with higher bid and ask depth. The results indicate that the demand of immediacy of traders may cause jumps in stock returns. The Mann-Whitney test results also confirm the significant changes in the liquidity variable during the jump intervals from non-jump intervals.

We examine the contemporaneous and lagged effects of liquidity factors on the probability of jump occurrences. We find evidence of both effects in different degrees for jump occurrences. Our probit estimation shows that the explanatory power of contemporaneous liquidity variables is much higher than the lagged variables for all jumps. When we divide the sample into negative and positive jumps we observe that the liquidity variables have more explanatory power in determining probability of negative than that of positive jumps. It seems that negative jumps require changes in market activities to occur more than the positive jumps do. Among the liquidity variables, volume, quoted spreads, effective spread shock and order imbalance are the key drivers behind the occurrences of positive jumps. For negative jump occurrences the effective spread and effective spread shock play important roles.

We extend the analysis by dividing our sample into pre-crisis, crisis and post-crisis periods to examine changes in the dynamics between liquidity variables and jump occurrences during the crisis period. We do not observe substantial changes in the results in those sub-samples indicating that the effects of liquidity variables are general.

Finally, several liquidity variables are shown to contribute to price discovery. Volume, depth, quoted and effective spreads, effective spread shock and order imbalances are significant contributors in the price discovery process. However, the post jump price discovery process does not seem to be strongly related to the liquidity variables.

We find mostly similar results for the Indian market as reported by Boudt and Petitjean (2014) and Jiang et al. (2011) for the U.S. market. Boudt and Petitjean (2014) also cite the the demand for immediacy as the main driver of jumps. However, their results show that both number of trade and average trade size contribute to the increase in trade volume at the jump interval whereas for Indian market it is the average trade size which is driving the volume surge in the Indian market. This difference in results indicate that information does not spread to the smaller investors in this market as fast as in the U.S. market. We also see a different scenario in the liquidity spread measure around the jump interval as spread decreases in the Indian market which is opposite in the US market reported by both Boudt and Petitjean (2014) and Jiang et al. (2011). We think that the difference is arising as the Indian market is not dealer driven like the U.S. market who change their quoted spread based on their inventory condition. However, our results conform to the U.S. market findings that liquidity variables such as shocks in spread and market depth have significant explanatory powers regarding jump occurrences.

The findings imply that changes in the liquidity conditions can provide indications of jump arrival in the market. The role of news announcements in causing jumps is well documented in the literature as we discussed in previous sections. However, these studies fail to associate a notable proportion of jumps with news-arrivals. Our study is an addition to the small number of papers offering an alternative explanation of jump probabilities. Investors should be aware of changes in market liquidity conditions to take necessary steps in protecting their assets from the jump risk.

Table 4.1: List of Sample Banks

*We have 41 Indian banks listed on the National Stock Exchange (NSE) at the end of 2013. Ten largest banks in market capitalization shown below have been analyzed in this study. The first column shows the Codes used in TRTH database to identify the banks. The second column shows the name and the third column reports the market capitalization of each bank in thousand Indian Rupees (INR).*

| Codes | Banks | Market Cap. |
|---|---|---|
| HDBK | HDFC Bank | 1,484,995,359 |
| SBI | State Bank of India | 1,390,909,091 |
| ICBK | ICICI Bank | 1,205,864,240 |
| AXBK | Axis Bank | 608,925,751 |
| KTKM | Kotak Mahindra Bank | 485,807,555 |
| BOB | Bank of Baroda | 278,659,424 |
| PNBK | Punjab National Bank | 243,360,705 |
| INBK | Indusind Bank Limited | 211,649,245 |
| BOI | Bank of India | 180,260,454 |
| CNBK | Canara Bank | 170,311,355 |

Table 4.2: Summary Statistics of Jumps in ten banking stocks

*The 2nd column shows percentage of jump returns in total observations. In the fourth and 6th column we report the percentage of positive and negative jumps in total number of jumps respectively. Total Number of return observations: 87672. Jumps are measured using Lee and Mykland (2008) method.*

| Banks | Total Jumps | Percentage of total obs. | Positive jumps | Percentage of total jumps | Negative Jumps | Percentage of total jumps |
|---|---|---|---|---|---|---|
| HDBK | 1454 | 1.66% | 761 | 52.34% | 693 | 47.66% |
| SBI | 1382 | 1.58% | 742 | 53.69% | 640 | 46.31% |
| ICBK | 1465 | 1.67% | 776 | 52.97% | 689 | 47.03% |
| AXBK | 1520 | 1.73% | 869 | 57.17% | 651 | 42.83% |
| KTKM | 1453 | 1.66% | 833 | 57.33% | 620 | 42.67% |
| BOB | 1421 | 1.62% | 779 | 54.82% | 642 | 45.18% |
| PNBK | 1496 | 1.71% | 827 | 55.28% | 669 | 44.72% |
| INBK | 1486 | 1.69% | 857 | 57.67% | 629 | 42.33% |
| BOI | 1470 | 1.68% | 825 | 56.12% | 645 | 43.88% |
| CNBK | 1468 | 1.67% | 832 | 56.68% | 636 | 43.32% |
| Average | 1461.5 | 1.67% | 810.1 | 55.41% | 651.4 | 44.59% |

Table 4.3: Mann-Whitney Results for Liquidity measures

*Here the Mann-Whitney test results of Liquidity variable between jump and nonjump time intervals are shown for all ten banks. The reported values are Wilcoxon/Mann-Whitney test statistics. The asterisks *, **, and *** indicate that the null hypotheisis of equality of the median values of the variables across different subsamples are rejected at the significance level of 10%, 5%, and 1% level, respectively.*

| Variables | Jumps | HDBK | SBI | ICBK | AXBK | KTKM | BOB | PNBK | INBK | BOI | CNBK |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Overall | 4.27*** | 32.76*** | 16.82*** | 11.97*** | 11.68*** | 28.03*** | 27.75*** | 28.96*** | 32.68*** | 25.55*** |
| Volume | Positive | 5.20*** | 24.41*** | 15.34*** | 10.22*** | 10.87*** | 23.84*** | 23.85*** | 27.59*** | 28.18*** | 22.75*** |
| | Negative | 0.78*** | 20.30*** | 9.05*** | 5.57*** | 4.84*** | 15.09*** | 14.29*** | 11.84*** | 17.05*** | 12.43*** |
| | Overall | 16.84*** | 12.68*** | 4.21*** | 17.28*** | 14.65*** | 13.09*** | 6.49*** | 14.67*** | 6.16*** | 7.87*** |
| RSPD | Positive | 6.15*** | 6.08*** | 6.90*** | 8.87*** | 5.85*** | 4.27*** | 3.65*** | 5.58*** | 4.07*** | 4.27*** |
| | Negative | 9.31*** | 3.79*** | 8.67*** | 6.82*** | 6.41*** | 5.04*** | 5.60*** | 6.13*** | 4.64*** | 7.01*** |
| | Overall | 3.38*** | 3.99*** | 4.21*** | 3.38*** | 1.4 | 2.64*** | 21.07*** | 4.14*** | 20.59*** | 20.13*** |
| RESPD | Positive | 4.09*** | 5.37*** | 5.81*** | 7.55*** | 4.38*** | 4.72*** | 6.02*** | 10.12*** | 6.47*** | 5.71*** |
| | Negative | 9.31*** | 22.81*** | 24.54*** | 22.94*** | 19.91*** | 23.96*** | 24.65*** | 22.25*** | 23.61*** | 23.90*** |
| | Overall | 1.74* | 3.59*** | 3.27*** | 7.92*** | 6.95*** | 4.13*** | 3.25*** | 5.70*** | 4.70*** | 5.16*** |
| DPTA | Positive | 10.13*** | 7.90*** | 8.82*** | 11.08*** | 8.27*** | 10.87*** | 6.47*** | 8.19*** | 7.16*** | 9.89*** |
| | Negative | 8.84*** | 5.66*** | 7.48*** | 5.57*** | 5.29*** | 6.94*** | 5.13*** | 7.41*** | 3.85*** | 8.09*** |
| | Overall | 13.76*** | 30.88*** | 12.2 | 12.94*** | 10.02*** | 13.06*** | 9.09*** | 11.73*** | 8.52*** | 13.10*** |
| DPTB | Positive | 9.92*** | 7.39*** | 8.65*** | 10.93*** | 8.20*** | 10.59*** | 6.15*** | 8.44*** | 7.09*** | 9.58*** |
| | Negative | 9.30*** | 6.44*** | 8.49*** | 6.47*** | 5.83*** | 7.64*** | 6.65*** | 7.94*** | 4.76*** | 8.82*** |
| | Overall | 2.30** | 1.03 | 4.7*** | 3.53*** | 2.29** | 2.06** | 4.23*** | 4.50*** | 4.77*** | 1.43 |
| OB | Positive | 2.46** | 5.74*** | 1.57 | 1.97*** | 1.43 | 3.26*** | 5.48*** | 1.13 | 0.96 | 3.80*** |
| | Negative | 5.52*** | 7.76*** | 8.48*** | 7.66*** | 5.03*** | 6.66*** | 12.40*** | 5.55*** | 8.27*** | 6.52*** |

Table 4.4: Regression Results: Jumps vs Liquidity - Probit

*The probit regression results estimated on ten bank data separately are summarized here. The dependent variable is Jump occurrences, a binary variable, the independent variables are as described in Equation 4.7. The average coefficients are shown in the second column. Column three and four report the number of regressions where the positive coefficients are significant at 5% and 10% level respectively and while column five and six show the number of negative coefficients significant at 5% and 10% level respectively. The results are reported for all jumps in the first panel, for positive jumps in the second panel and for negative jumps in the third panel.*

| Variables | Coefficients | Positive at 5% | Positive at 10% | Negative at 5% | Negative at 10% |
|---|---|---|---|---|---|
| | | All Jumps | | | |
| C | -2.7217 | 0 | 0 | 10 | 0 |
| *MJUMP* | 1.4435 | 10 | 0 | 0 | 0 |
| *VOL* | 0.0000 | 10 | 0 | 0 | 0 |
| *DPTB* | 0.0000 | 4 | 0 | 0 | 0 |
| *RSPD* | 60.5248 | 8 | 0 | 0 | 0 |
| *RESPD* | 66.2902 | 10 | 0 | 0 | 0 |
| *OB* | 0.0000 | 0 | 0 | 2 | 2 |
| *DDRESPD* | 0.0521 | 9 | 1 | 0 | 0 |
| *DDRSPD* | -0.0004 | 1 | 0 | 3 | 0 |
| McFadden R-sq. | 0.1917 | | | | |
| | | Positive Jumps | | | |
| C | -2.7216 | 0 | 0 | 10 | 0 |
| *JUMP_MKT* | 1.0295 | 10 | 0 | 0 | 0 |
| *VOL* | 0.0000 | 10 | 0 | 0 | 0 |
| *DPTB* | 0.0000 | 4 | 0 | 0 | 0 |
| *RSPD* | 150.7759 | 10 | 0 | 0 | 0 |
| *RESPD* | -17.9099 | 1 | 0 | 6 | 0 |
| *OB* | -0.0000 | 0 | 0 | 9 | 1 |
| *DDRESPD* | 0.0375 | 9 | 0 | 0 | 0 |
| *DDRSPD* | -0.0007 | 0 | 0 | 5 | 0 |
| McFadden R-sq. | 0.1153 | | | | |
| | | Negative jumps | | | |
| C | -3.2497271 | 0 | 0 | 10 | 0 |
| *JUMP_MKT* | 1.3633 | 10 | 0 | 0 | 0 |
| *VOL* | -0.0000 | 1 | 0 | 4 | 0 |
| *DPTB* | 0.0000 | 6 | 0 | 0 | 0 |
| *RSPD* | 16.4809 | 3 | 1 | 1 | 0 |
| *RESPD* | 102.0840 | 10 | 0 | 0 | 0 |
| *OB* | 0.0000 | 9 | 0 | 0 | 0 |
| *DDRESPD* | 0.0534 | 10 | 0 | 0 | 0 |
| *DDRSPD* | -0.0001 | 0 | 0 | 3 | 0 |
| McFadden R-sq. | 0.3500 | | | | |

Table 4.5: Regression Results: Jumps vs Liquidity - Logit

*The logit regression results estimated on ten bank data separately are summarized here. The dependent variable is Jump occurrences, a binary variable, the independent variables are as described in Equation 4.7. The average coefficients are shown in the second column. Column three and four report the number of regressions where the positive coefficients are significant at 5% and 10% level respectively and while column five and six show the number of negative coefficients significant at 5% and 10% level respectively. The results are reported for all jumps in the first panel, for positive jumps in the second panel and for negative jumps in the third panel.*

| Variables | Coefficients | Positive at 5% | Positive at 10% | Negative at 5% | Negative at 10% |
|---|---|---|---|---|---|
| All Jumps | | | | | |
| C | -5.3756 | 0 | 0 | 10 | 0 |
| *MJUMP* | 2.9173 | 10 | 0 | 0 | 0 |
| *VOL1* | 0.0000 | 9 | 1 | 0 | 0 |
| *DPTB* | 0.0000 | 4 | 2 | 0 | 0 |
| *RSPD* | 120.2242 | 8 | 0 | 0 | 0 |
| *RESPD* | 140.3423 | 10 | 0 | 0 | 0 |
| *OB* | -0.0000 | 0 | 0 | 2 | 1 |
| *DDRESPD* | 0.1080 | 10 | 0 | 0 | 0 |
| *DDRSPD* | -0.0008 | 0 | 0 | 4 | 0 |
| McFadden R-sq. | 0.1798 | | | | |
| Positive Jumps | | | | | |
| C | -5.5192 | 0 | 0 | 10 | 0 |
| *MJUMP* | 2.3664 | 10 | 0 | 0 | 0 |
| *VOL1* | 0.0000 | 10 | 0 | 0 | 0 |
| *DPTB* | 0.0000 | 4 | 0 | 0 | 0 |
| *RSPD* | 333.8768 | 10 | 0 | 0 | |
| *RESPD* | -40.0506 | 1 | 0 | 4 | 0 |
| *OB* | -0.0000 | 0 | 0 | 9 | 1 |
| *DDRESPD* | 0.0771 | 9 | 1 | 0 | 0 |
| *DDRSPD* | -0.0013 | 0 | 0 | 5 | 0 |
| McFadden R-sq. | 0.1032 | | | | |
| Negative jumps | | | | | |
| C | -6.7348 | 0 | 0 | 10 | 0 |
| *JUMP_MKT* | 2.9808 | 10 | 0 | 0 | 0 |
| *VOL1* | -0.0000 | 1 | 0 | 4 | 0 |
| *DPTB* | 0.0000 | 6 | 0 | 0 | 0 |
| *RSPD* | 27.5518 | 4 | 0 | 1 | 0 |
| *RESPD* | 220.2321 | 10 | 0 | 0 | 0 |
| *DDRESPD* | 0.1142 | 10 | 0 | 0 | 0 |
| *DDRSPD* | -0.0001 | 0 | 0 | 0 | 1 |
| McFadden R-sq. | 0.3240 | | | | |

Table 4.6: Regression results with 1 lag liquidity variables

*The probit regression results estimated on ten bank data separately are summarized here. The dependent variable is Jump occurrences, a binary variable, the independent variables are as described in Equation 4.7 in one order lagged form. The average coefficients are shown in the second column. Column three and four report the number of regressions where the positive coefficients are significant at 5% and 10% level respectively and while column five and six show the number of negative coefficients significant at 5% and 10% level respectively. The results are reported for all jumps in the first panel, for positive jumps in the second panel and for negative jumps in the third panel.*

| Variables | Coefficients | Positive at 5% | Positive at 10% | Negative at 5% | Negative at 10% |
|---|---|---|---|---|---|
| | | All Jumps | | | |
| C | -2.2233 | | | 10 | |
| *MJUMP* | 0.8111 | 10 | | | |
| *VOL* | 0.0000 | 7 | | | |
| *DPTB* | -0.0000 | | | 7 | 1 |
| *RSPD* | 17.2791 | 2 | 1 | | |
| *RESPD* | 10.8049 | 4 | 1 | | |
| *OB* | -0.0000 | | | 2 | |
| *DDRESPD* | 0.0165 | 6 | 2 | | |
| *DDRSPD* | -0.0002 | | | 2 | 2 |
| McFadden R-sq. | 0.0154 | | | | |
| | | Positive Jumps | | | |
| C | -2.6401 | | | 10 | |
| *MJUMP* | 0.7594 | 8 | 1 | | |
| *VOL* | 0.0000 | 9 | | | |
| *DPTB* | -0.0000 | 7 | 1 | | |
| *RSPD* | 25.5296 | 3 | | | |
| *RESPD* | -3.2890 | | 1 | 1 | |
| *OB* | -0.0000 | | | 5 | |
| *DDRESPD* | 0.0196 | | 5 | | |
| *DDRSPD* | -0.0006 | | | 2 | 1 |
| McFadden R-sq. | 0.0129 | | | | |
| | | Negative jumps | | | |
| C | -2.8059 | | | 10 | |
| *JUMP_MKT* | 0.9100 | 10 | | | |
| *VOL* | 0.0000 | 2 | | | |
| *DPTB* | -0.0000 | | | 3 | |
| *RSPD* | 10.0960 | 2 | | | |
| *RESPD* | 22.1471 | 9 | | | |
| *OB* | 0.0000 | 2 | | | |
| *DDRESPD* | 0.0155 | 5 | | | |
| *DDRSPD* | -0.0002 | | | 5 | 1 |
| McFadden R-sq. | 0.0217603 | | | | |

Table 4.7: Regression results of jumps on contemporaneous and lagged liquidity variables

*The probit regression results estimated on ten bank data separately are summarized here. The dependent variable is Jump occurrences, a binary variable, the independent variables are the contemporaneous and one order lag of the liquidity . The average coefficients are shown in the second column. Column three and four report the number of regressions where the positive coefficients are significant at 5% and 10% level respectively and while column five and six show the number of negative coefficients significant at 5% and 10% level respectively. The results are reported for all jumps only.*

| Variables | Coefficients | Positive at 5% | Positive at 10% | Negative at 5% | Negative at 10% |
|---|---|---|---|---|---|
| Dependent Variable: All Jumps | | | | | |
| C | -2.6067 | | | 10 | |
| *MJUMP* | 1.3340 | 10 | | | |
| *VOL* | 0.0000 | 10 | | | |
| *DPTB* | 0.0000 | 10 | | | |
| *RSPD* | 56.0611 | 8 | | | |
| *RESPD* | 80.5939 | 10 | | | |
| *OB* | 0.0000 | 2 | 1 | | |
| *DDRESPD* | 0.0409 | 9 | | | |
| *DDRSPD* | -0.0005 | | | 3 | |
| *MJUMP(-1)* | 0.7133 | 9 | | | |
| *VOL(-1)* | -0.0000 | | | 8 | |
| *DPTB(-1)* | -0.0000 | | | 10 | |
| *RSPD(-1)* | -1.2645 | | 1 | 1 | 1 |
| *RESPD(-1)* | -30.6054 | | | 6 | 2 |
| *OB(-1)* | -0.0000 | | | 5 | 1 |
| *DDRESPD(-1)* | 0.0317 | 9 | | | |
| *DDRSPD(-1)* | -0.0003 | | 1 | 3 | |
| McFadden R-sq. | 0.2402 | | | | |

Table 4.8: Regression results to showing the impact of GFC

*The probit regression results estimated on ten bank data separately are summarized here. The dependent variable is Jump occurrences, a binary variable, the independent variables are as described in Equation 4.7. The average coefficients are shown in the second column. Column three and four report the number of regressions where the positive coefficients are significant at 5% and 10% level respectively and while column five and six show the number of negative coefficients significant at 5% and 10% level respectively. The results are reported for pre-crisis period in the first panel, for crisis period in the second panel and for post crisis period in the third panel.*

| | Coefficients | Positive at 5% | Positive at 10% | Negative at 5% | Negative at 10% |
|---|---|---|---|---|---|
| | | | Pre-crisis | | |
| C | -2.5015 | | | 10 | |
| *MJUMP* | 1.3289 | 10 | | | |
| *VOL* | 0.0000 | 10 | | | |
| *DPTB* | 0.0000 | | | 5 | |
| *RSPD* | 15.4059 | 3 | | | |
| *RESPD* | 76.5011 | 10 | | | |
| *OB* | 0.0000 | 1 | 1 | 1 | |
| *DDRESPD* | 0.0575 | 9 | | | |
| *DDRSPD* | 0.0049 | 1 | | 1 | |
| McFadden R-sq. | 0.1924 | | | | |
| | | | Crisis | | |
| C | -2.7774 | | | 10 | |
| *MJUMP* | 1.4725 | 10 | | | |
| *VOL* | 0.0000 | 8 | 1 | | |
| *DPTB* | 0.0000 | | | 7 | 2 |
| *RSPD* | -81.1604 | | | 2 | |
| *RESPD* | 76.3678 | 10 | | | |
| *OB* | 0.0000 | 1 | | 1 | |
| *DDRESPD* | 0.0784 | 10 | | | |
| *DDRSPD* | 0.0073 | | | 3 | |
| McFadden R-sq. | 0.2287 | | | | |
| | | | Post-crisis | | |
| C | -3.3282 | | | 10 | |
| *MJUMP* | 1.6466 | 10 | | | |
| *VOL* | 0.0000 | 8 | 1 | | |
| *DPTB* | 0.0000 | 8 | | | |
| *RSPD* | 74.4250 | 7 | 1 | | |
| *RESPD* | 117.2170 | 10 | | | |
| *OB* | 0.0000 | | | 1 | 2 |
| *DDRESPD* | 0.0534 | 10 | | | |
| *DDRSPD* | -0.0002 | | | 2 | |
| McFadden R-sq. | 0.2247 | | | | |

Table 4.9: Regression of price discovery

*The OLS regression results estimated on ten bank data separately are summarized here. The dependent variable is stock return, the independent variables are as described in Equation 4.8. The average coefficients are shown in the second column. Column three and four report the number of regressions where the positive coefficients are significant at 5% and 10% level respectively and while column five and six show the number of negative coefficients significant at 5% and 10% level respectively.*

| Variables | Coefficients | Positive at 5% | Positive at 10% | Negative at 5% | Negative at 10% |
|---|---|---|---|---|---|
| C | 0.0011 | 10 | | | |
| *JUMP01(-1)* | 0.0006 | 3 | 1 | | |
| *VOL* | 1.5956E-08 | 10 | | | |
| *VOL*JUMP01(-1)* | -7.208E-09 | | | 4 | 1 |
| *DPTB* | 4.8904E-10 | 5 | | 5 | |
| *DPTB*JUMP01(-1)* | -1.48723E-09 | | | | |
| *RSPD* | 0.9433 | 10 | | | |
| *RSPD*JUMP01(-1)* | 0.7797 | 3 | | | |
| *RESPD* | -0.8721 | | | 10 | |
| *RESPD*JUMP01(-1)* | 0.1210 | 1 | 2 | | |
| *OB* | -7.853E-09 | | | 10 | |
| *OB*JUMP01(-1)* | -2.72636E-09 | | | | |
| *DDRESPD* | -0.0001 | | | 8 | |
| *DDRESPD*JUMP01(-1)* | 2.3E-06 | 2 | 1 | 1 | 1 |
| *DDRSPD* | -2.917E-08 | | | 2 | 1 |
| *DDRSPD*JUMP01(-1)* | -2.21449E-06 | | | 4 | |
| Adjusted R-sq. | 0.3690 | | | | |

Figure 4.1: Return around the jump observations

*The average returns at 15, 30, 45 and 60 minutes before and after jump times are shown here.*

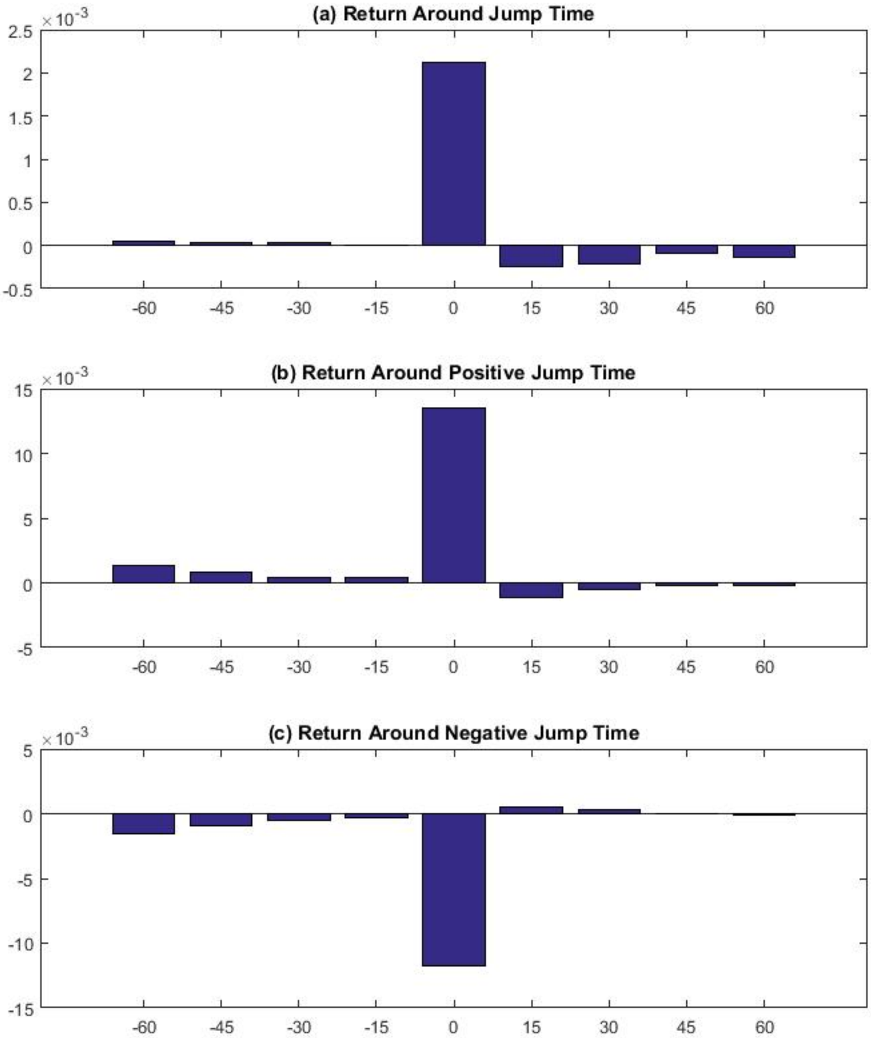


Figure 4.2: Volume around the jump observations

*The average trade volumes at 15, 30, 45 and 60 minutes before and after jump times are shown here.*

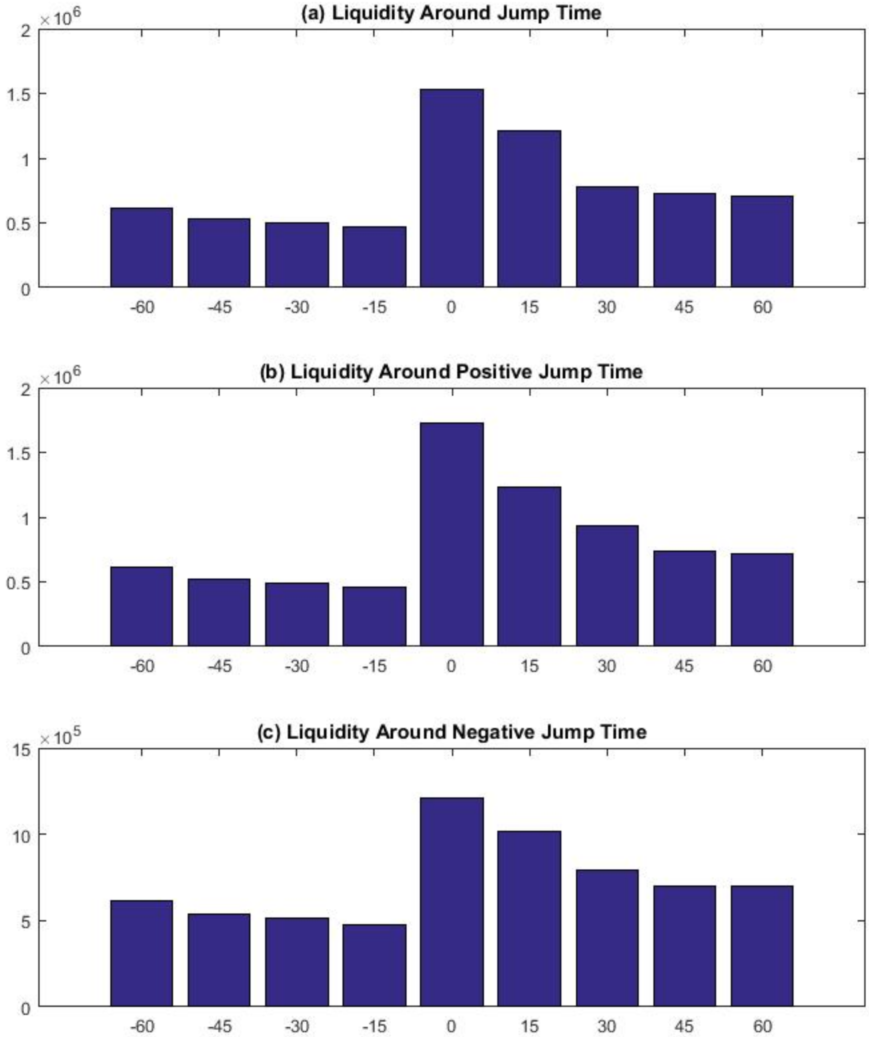


Figure 4.3: Number of trade around jump observations

*The average number of trades at 15, 30, 45 and 60 minutes before and after jump times are shown here.*

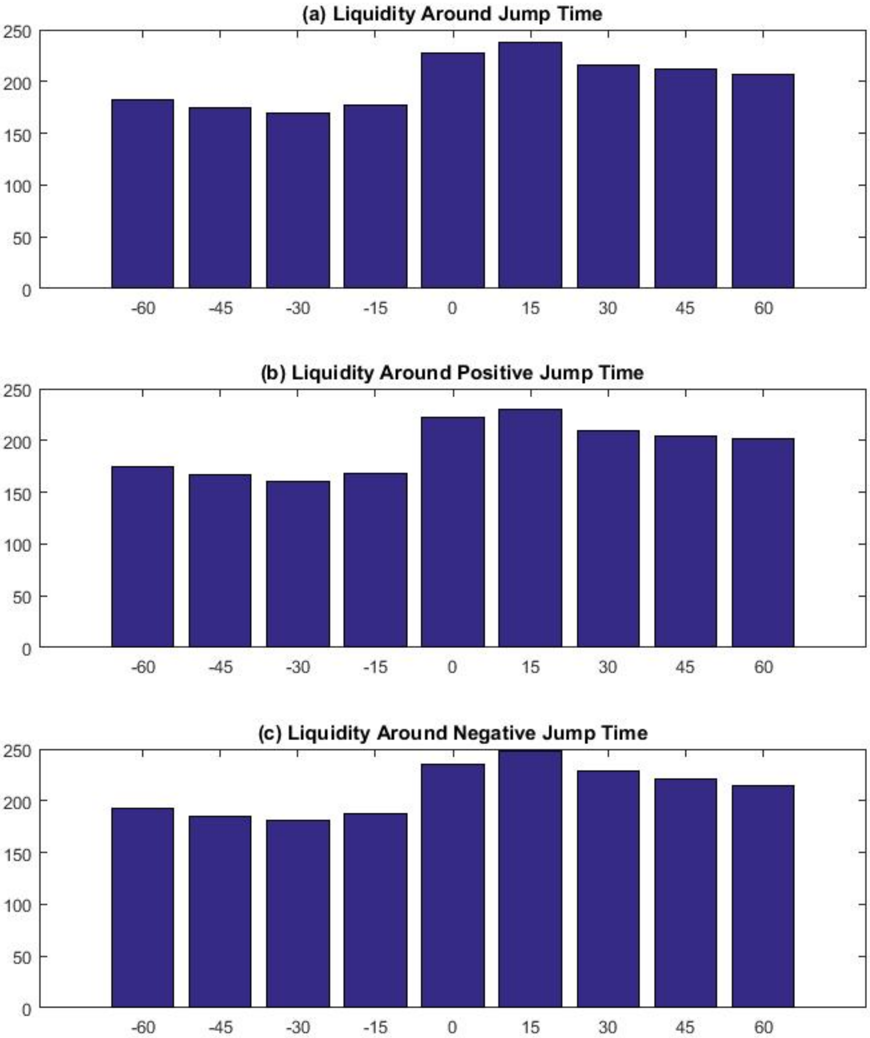


Figure 4.4: Average Trade Size

*The average trade sizes at 15, 30, 45 and 60 minutes before and after jump times are shown here.*

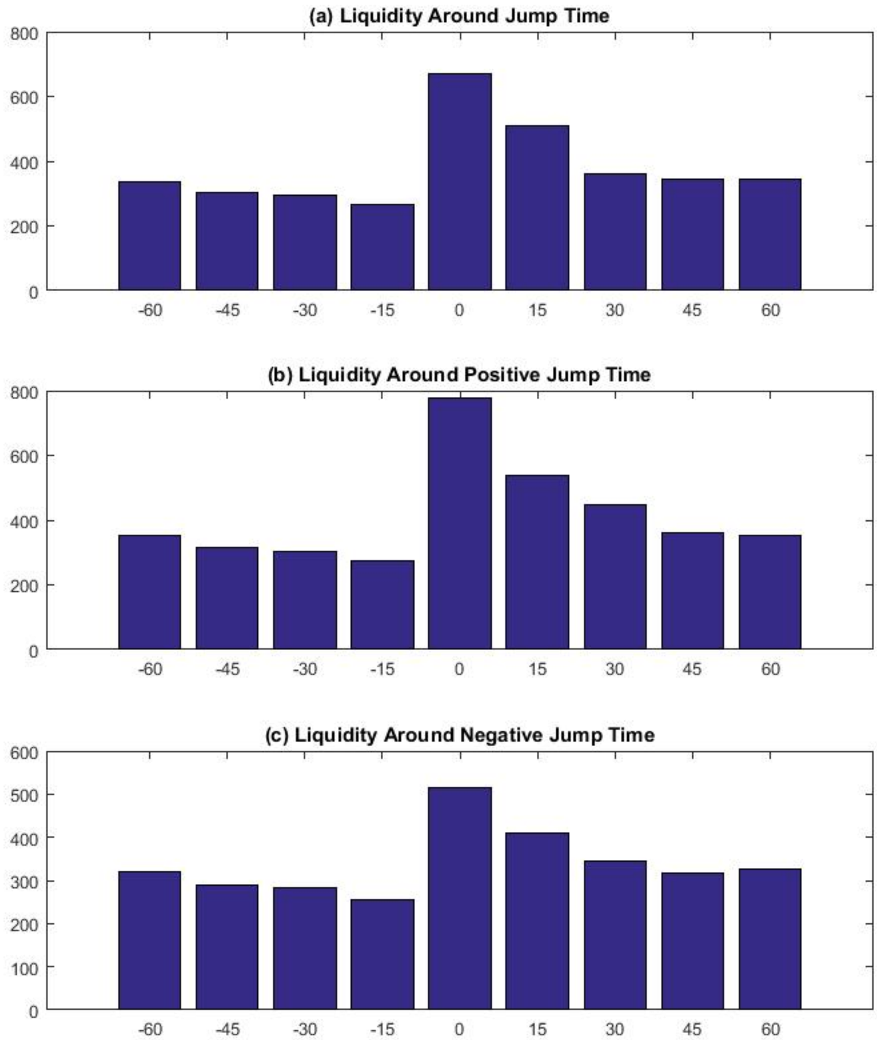


Figure 4.5: Depth of ask around jump observations

*The average depth of ask prices at 15, 30, 45 and 60 minutes before and after jump times are shown here.*

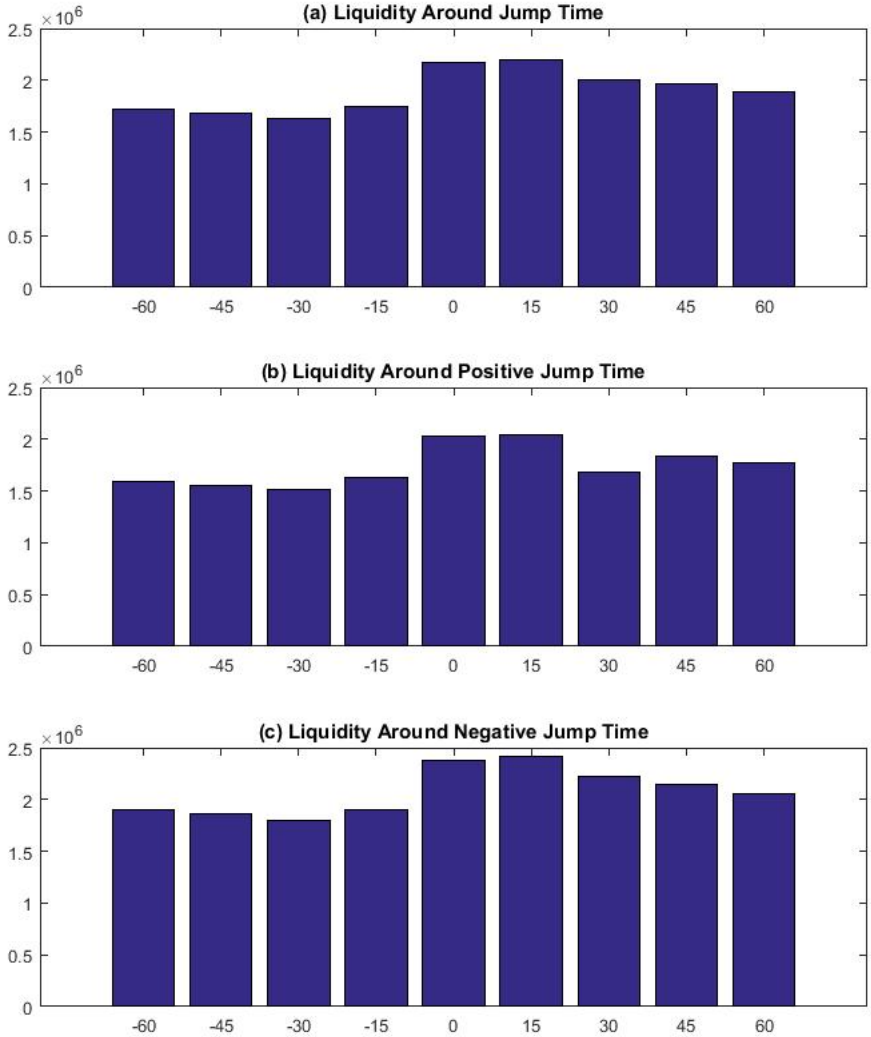


Figure 4.6: Depth of bid around jump observations

*The average depth of bid prices at 15, 30, 45 and 60 minutes before and after jump times are shown here.*

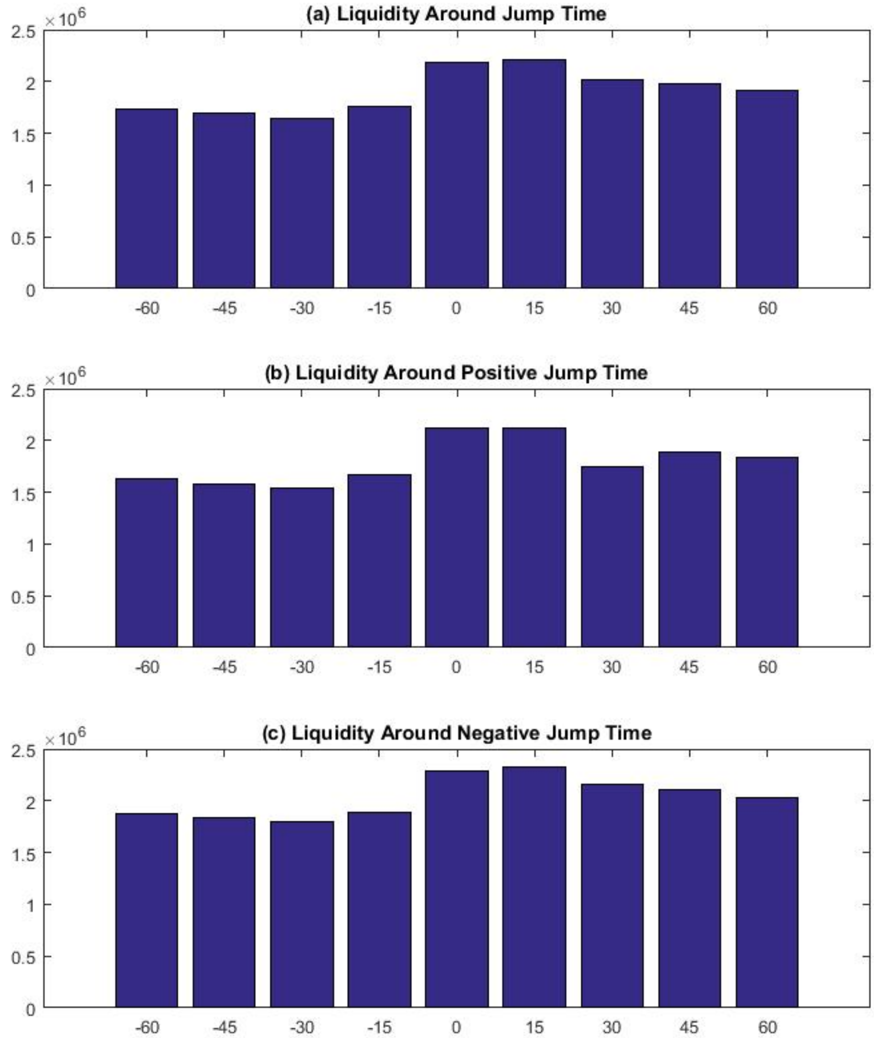


Figure 4.7: RSPD around the jump observations

*The average quoted spread (RSPD) ratios at 15, 30, 45 and 60 minutes before and after jump times are shown here.*

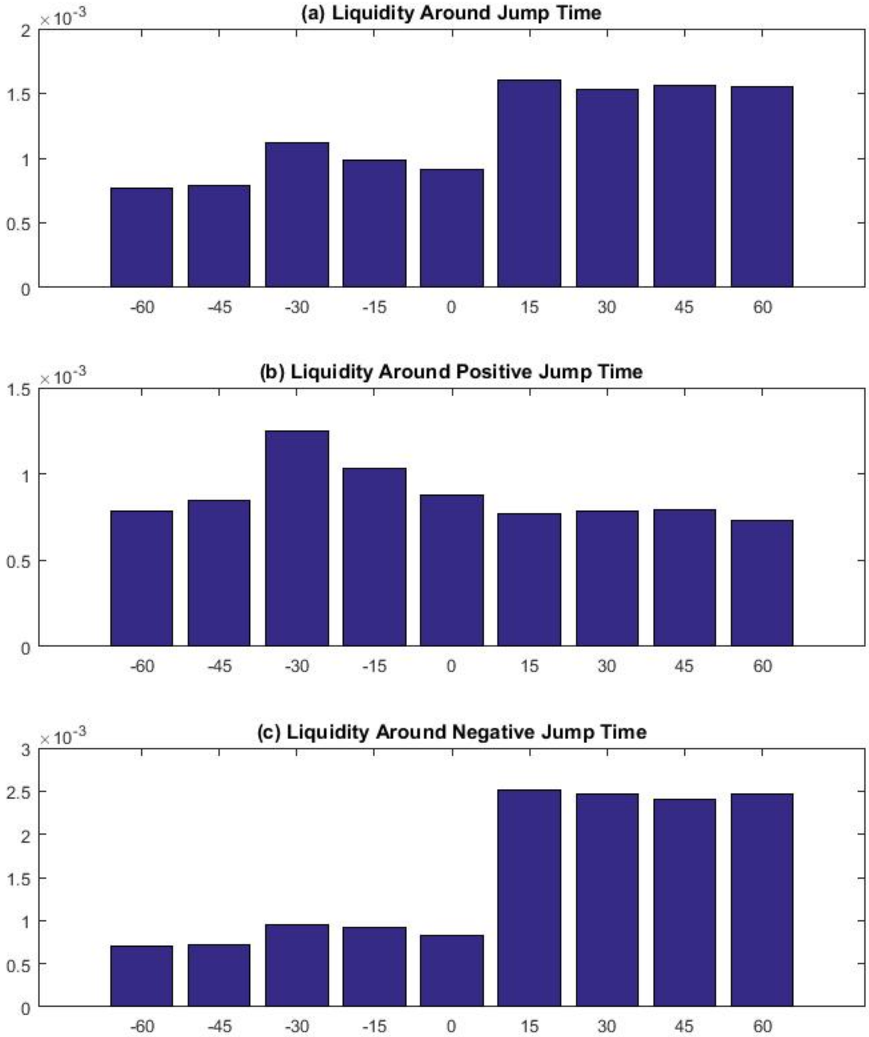


Figure 4.8: RESPD around the jump observations

*The average effective spread ratios (RESPD) at 15, 30, 45 and 60 minutes before and after jump times are shown here.*

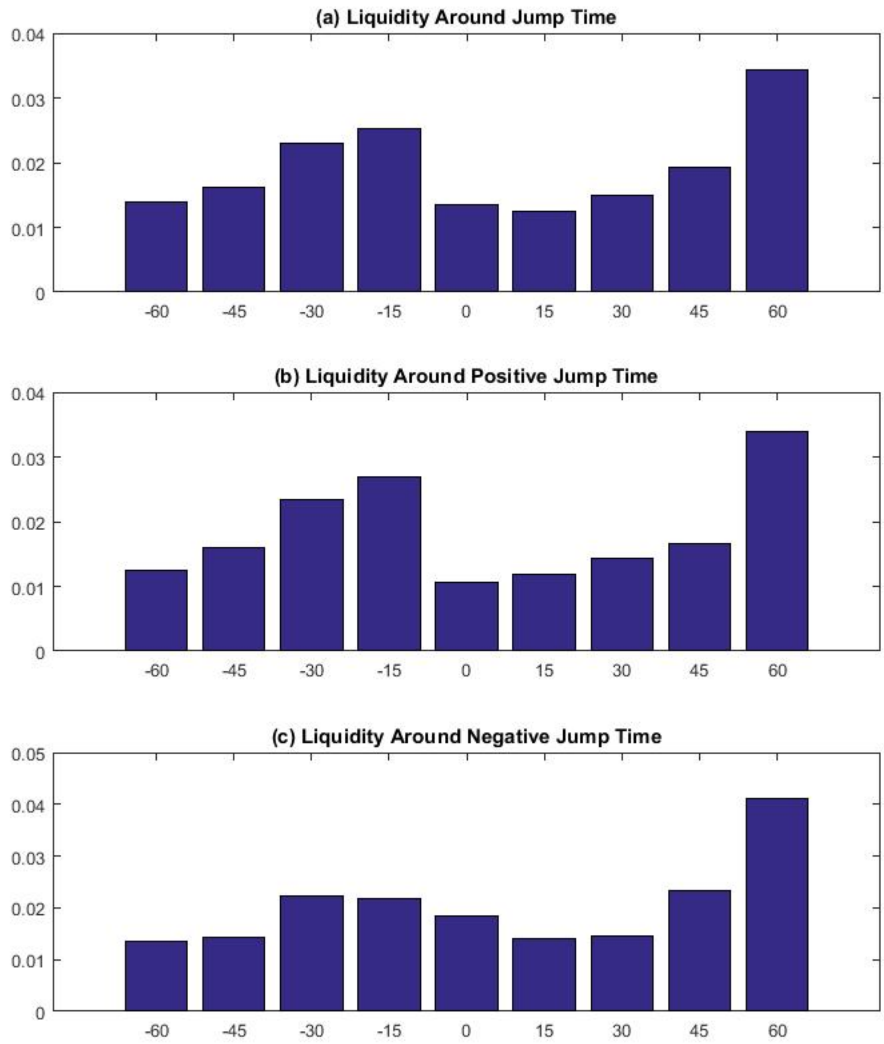
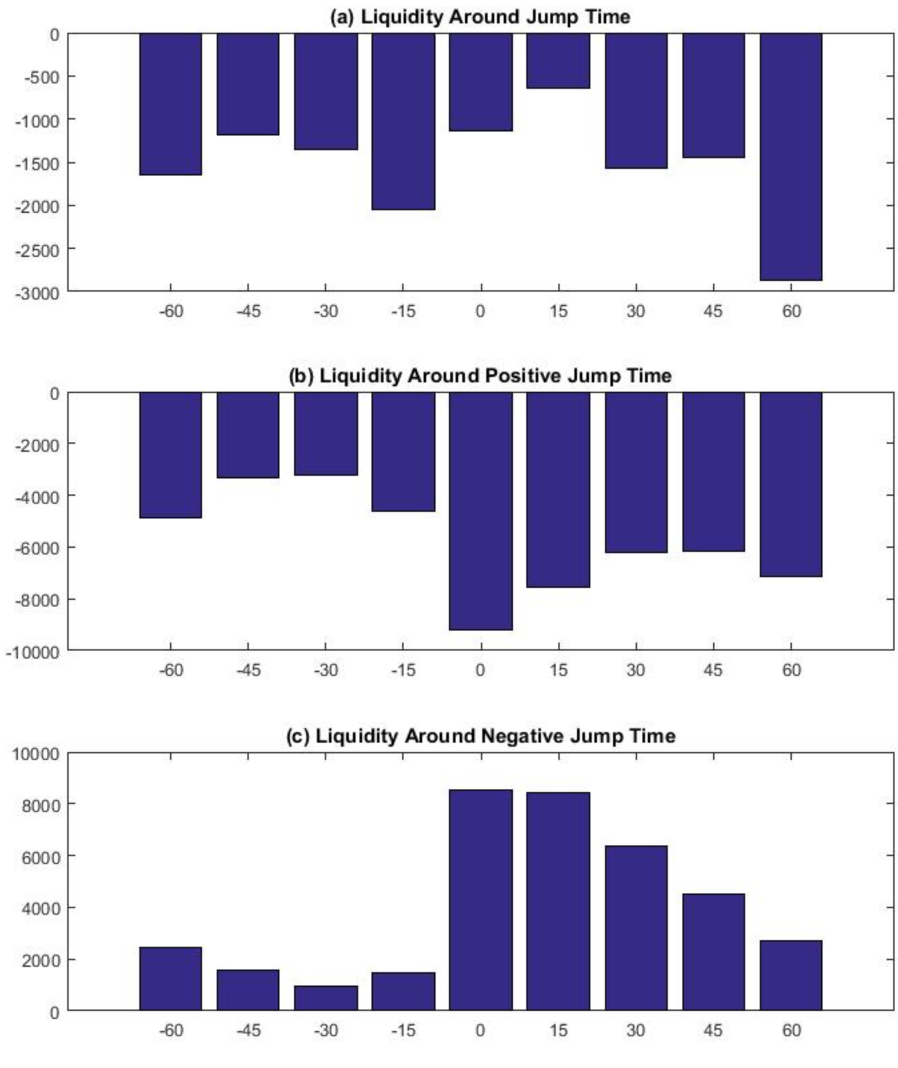


Figure 4.9: OB around the jump observations

*The average order imbalances (OB) at 15, 30, 45 and 60 minutes before and after jump times are shown here.*



# 5 Network Analysis of Systemic Risk: The Case of Indian Banks

## 5.1. Introduction

The systemic effect of the banking network has been a matter of concern for regulators for the last few decades (Freixas et al., 2000, Gauthier et al., 2012 and Billio et al., 2012). The global financial crisis (GFC) of 2007-2009 only reinforced their concern. It was the network of banks and financial institutions through which shocks propagated first to the financial sector and subsequently to the real sectors during the GFC. Thus, a measure of the magnitude and strength of network connectivity within the financial system provides a indication of the extent of systemic risk in an economy. In this chapter, we concentrate on the network analysis of systemic risk for the banking sector of India.

Systemic risk can be defined as the likelihood of propagating financial adversity such as illiquidity, insolvency and losses through a network system of interconnected institutions (Billio et al., 2012). The interconnectedness of financial institutions may arise from investing in the same asset (Acharya and Yorulmazer, 2008), their herding behaviour, stem from regularity requirements (Acharya, 2009), or their investment in illiquid assets expecting that they will borrow from each other in shocks (Bhattacharya and Gale, 1985) among many other explanations. A number of methods has been used in the literature and practised to identify systemic risk[1]. Some of the methods are based on a particular source of systemic risk or channel of transmission. In contrast, a growing number of systemic risk measures use market prices of securities issued by the financial institutions. Here the logic is that in an efficient market the market price absorbs all the information necessary to measure risks (Benoit et al., 2016). We use a method proposed by Dungey et al. (2017) based on market prices in this study.

Not many papers on systemic risk have focused on the Indian banks, and even fewer use network analysis. Acharya and Kulkarni (2010) is the first notable effort in estimating the systemic risk contribution of the Indian banks by using market based data and analysing the impact of ownership structure on bank vulnerability to crisis. Gupta and Jayadev (2016) use equity prices to measure the systemic risk of Indian banks and examine the impact of business strategy choice on such risks. Aggarwal et al. (2013) on the other hand uses the average of the percentile ranking of three measures of systemic risk - Granger Causality, Marginal Expected Shortfall and Conditional Value at Risk in developing a single systemic risk index (SRI) for a firm. One contribution of the current paper is to enrich the network literature of this fast-growing but understudied market. The increasing openness of India's economy is exposing its banking sector to the global financial system postulating the need for measuring and monitoring the systemic risk of

[1]See Bisias et al. (2012) for a wide list of systemic risk measurement methods.

this sector.

The monitoring of systemic risk in India is carried out by the Financial Stability and Development Council (FSDC). A regular Systemic Risk Survey has been instituted by the Reserve Bank of India to obtain the views of market participants and stakeholders to build up an assessment of systemic risk. The FSDC devised a series of stability indices and maps to track movements in the various risk dimensions which may affect the entire financial system. The network model we apply in this study complements the existing models used by the FSDC in this direction.

We use the stock returns of 40 listed commercial banks of India for the period of 2011 to 2015. First we apply a multivariate Granger causality test to establish statistically significant connections between each pair of banks. To measure the strength of each of the links we measure the weights of the link by applying the forecast error variance decomposition method of Diebold and Yilmaz (2009). By combining the weight matrix with the Granger connection matrix we finally derive the network of banks where only the statistically significant links with their respective weights are retained. From this network matrix the most systemically active banks can be identified. We also identify the banks that are most vulnerable to the change in stock returns of other banks within the network. An analysis on the daily rolling window of the network measures shows that the overall network completeness increases during our sample period.

The second contribution of this paper is to show that market liquidity and volatility are related with the network completeness for the first time in literature. Decreases in liquidity and increases in volatility heighten the completeness of networks. In addition, the systematically risky banks are also found to be the more active banks in strengthening network completeness. Not many papers show the relationship between systematic risk and systemic risk of firms. Thus, the third contribution of this paper is to shed light on this relationship increasing the understanding of the sources of these risks.

The remainder of the chapter is presented in 3 more sections. In section 5.2 we describe methodologies and data used in this study. The results are presented in section 5.3. The conclusion is drawn in Section 5.4.

## 5.2. Methods and data

In detecting the Indian bank network we combine the methods applied by Billio et al. (2012) and Diebold and Yilmaz (2009) following Dungey et al. (2017). To measure the connectedness between banks we need to identify statistically significant relationships amongst the banks. Following Billio et al. (2012) we apply Granger causality tests to establish the edges of the network nodes. The directionality of the relationships is found from these tests. Granger causality tests suggest causality if past values of one time series, $Y_1$, stock return series in our case - contain information that help forecast another return series, $Y_2$. These causalities can be represented as a VAR[2]

$$Y_t = \sum_{j=1}^{k} \beta_j Y_{t-j} + \varepsilon_t, \tag{5.1}$$

with $j = 1, ..., p$. Granger causality between banking stock return $Y_i$ and $Y_s$ can be assessed from the WALD test

[2]Here the constant term is suppressed without loss of generality.

$$WT = [e.vec(\hat{II})]'[e(\hat{V}\bigotimes(Y'Y)^{-1})e']^{-1}[e.vec(\hat{II}),$$

in which $Y$ is the matrix of independent variables from (5.1), $vec(\hat{II})$ denotes the row vectorized coefficient of $\hat{II} = [\beta_1, ...., \beta_k]$, $\hat{V} = T^{-1}\sum_{t=1}^{T}\hat{\varepsilon}_t\hat{\varepsilon}_t{}'$ and $e$ is the $k \times 2(2k+1)$ selection matrix

$$e = \begin{bmatrix} 0 & 1 & 0 & 0 & \dots & 0 & 0 & \dots & 0 & 0 \\ 0 & 0 & 0 & 1 & \dots & 0 & 0 & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \dots & 1 & 0 & \dots & 0 & 0 \end{bmatrix},$$

where each row of $e$ picks one of the coefficients to set to zero under the non-causal hypothesis $Y_i \to Y_s$. The matrix $A$ records the Granger causality test results as a binary entries as

$$A = [a_{ij}], \tag{5.2}$$

where,

$$a_{ij} = \begin{cases} 0, \text{ if } Y_i \text{does not Granger cause } Y_j, \\ 1, \text{ if } Y_i \text{Granger causes } Y_j. \end{cases} \tag{5.3}$$

The direction of the edges, which we will refer to *Granger* links henceforth, is only one aspect of the relationship between two banks in the network. Another important aspect is the strength of the relationship which we examine by assigning weight, $W_{ij}$ to each of the significant relationship existing in the network. We use the Diebold and Yilmaz (2009) (henceforth, DY) framework of variance decomposition to obtain these weights and develop the weight matrix $W_{ij} = [wij]$. The spillover is measured based on forecast error variance decompositions in a vector auto-regression framework. Suppose that $j$'s contribution to entity $i'$s $H$ step ahead generalized forecast error variance, $\phi_{ij}^{g}(H)$ is

$$\phi_{ig}^{g}(H) = \frac{V_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' B_h V e_j)^2}{\sum_{h=0}^{H-1} (e_i' B_h V B_h' e_j)}, \tag{5.4}$$

where, $H$ = 1,2,3,....,and $V$ is the variance covariance matrix for the error vector $\varepsilon_t$,$V_{jj}$ is the standard deviation of the error term $j$ and $e_i$ is the selection vector with one as the $i$th element and zero otherwise. $B_i$ is the coefficient matrix as $B_i = \phi_1 B_{i-1} + \phi_2 B_{i-2} +$ ....... $+ \phi_k B_{i-k}$ with $B_0$ an $n \times n$ identity matrix and $B_i = 0$ for $i < 0$. Each entry of the generalized variance decomposition is normalized by the row sum as

$$w_{ij} = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{n} \theta_{ij}^{g}(H)}, \tag{5.5}$$

where $\sum_{j=1}^{n} w_{i,j} = 1$ and $\sum_{i,j=1}^{n}$ and $\sum_{i,j=1}^{n} = n$. We call these values $DY$ weights.

We combine the matrices $A$ and $W$ to form the weighted network by developing the adjacency matrix $\tilde{A}$ as

$$\tilde{A} = A \bigodot W, \tag{5.6}$$

where $\bigodot$ is the Hadamard product. Each element of the adjacency matrix $\tilde{A}$ captures the statistical significance and weight of connectedness between the banks. Henceforth we will call them $GDY$ weights. The completeness of the network is measured as

$$C = \frac{\sum_{i,j=1_{i\neq j}}^{n} \tilde{a_{ij}}}{\sum_{i,j=1_{i\neq j}}^{n} w_{ij}}. \tag{5.7}$$

A high $C$ means banks are highly connected to each other and are subject to domino effects in the case of a large shock in any part of the banking system.

Based on the proposed econometric framework we test the following empirical hypotheses:

**Hypothesis 1** *The change in number of Granger links in the network is negatively related with the change in liquidity of the market. As liquidity conditions deteriorate banking stocks tend to depend on each other more.*

**Hypothesis 2** *The change in the strength of the links expressed as $DY$ weights is positively related to the volatility of the market. In the volatile market conditions the linked banking institutions have a tendency to depend more on each other.*

**Hypothesis 3** *The change in the completeness of the network, given by $GDY$ weights is related to both liquidity and volatility of the market. If liquidity and volatility affect one component each on the network connectivity both may have impact on the completeness of the network.*

**Hypothesis 4** *The banks with higher systematic risk or beta are also more active participants in the networks.*

**Hypothesis 5** *As market forces are not as strong as the developed economies, the Indian banking network is more associated with the negative shocks than the positive* *ones, and exhibits asymmetry.*

### 5.2.1. Data

We examine the connectedness of Indian banks through market based data in an attempt to identify the vulnerability of Indian banks to systemic risk. We use daily stock returns of the banks and measure the connectedness of the returns to form the network. Daily prices of the 41 listed commercial banks of India are collected from Thomson Reuters Tick History database provided by SIRCA. Our sample covers the period of 2011 to 2015 and we have complete data for 40 banks for this time period. Table 5.1. lists these 40 sample banks.

## 5.3. Results

The Granger causality tests shows the statistically significant edges among the Indian banks. Table 5.2 reports the number of outward edges from each the banks in the second column and the number of inward edges in the next column. SBI have the highest influence on the other banks affecting 19 other banks in our sample. KBNK, SBNK and FED each has 14, 14 and 12 outward edges respectively as shown in the Table. Among the 40 banks, HDBK, BOB, and SBKB are the least affecting banks as they only have 2, 4 and 5 statistically significant outward links respectively towards any other bank during our sample period. Mensah and Premaratne (2017) also identify SBI as the most connected bank of India in their multi-country Granger causality tests.

The banks which have the highest inward edges meaning that they are affected by other banks, are VJBK, DENA and LVLS. Conversely, HDBK, ICBK, JKBK, PNBK and SBI are the least three affected banks in our sample. On average each bank Granger causes 8.65 other banks. The banks that are most active in term of both inward and outward edges are VJBK, DENA and KBNK (32, 29 and 28 respectively). On the other hand the least active banks are HDBK, KTKM and ICBK.

To get a complete picture of impacts of one bank on the other we apply the framework of Diebold and Yilmaz (2009). The *DY* weights are shown in Table 5.3. In terms of outward *DY* weights, the top three banks are UCBK, SBNK and IDBI. These banks may not have the widest *Granger* links, but each of their impacts are strong. JKBK, HDBK and STNCy exhibit the weakest *DY* connectivity with other banks. Among these banks, HDBK possesses low Granger causalities as well. UCBK, SBNK and IDBI are associated with the strongest inward *DY* weights. These banks are also the banks with strongest outward *DY* connectivity on other banks. JKBK, HDBK and STNCy again are associated with the weakest inward *DY* weights. Here we observe that the banks with strong (weak) outward *DY* weights are also associated with strong (weak) inward *DY* weights.

Combining the *Granger* links and *DY* weights we draw the complete picture of the network amongst the Indian banks as shown in Equation 5.6 and reported in Table 5.4. According to these results the three most important banks for systemic risk (or with highest outward *GDY* weights) of the Indian banking sector are KBNK, SBNK and CRBK. The lowest systemic risks stem from HDBK, BOB and JKBK. The three most vulnerable banks with inward GDY weights are VJBK, DENA and IDBI. It is noted here that these findings could not be reached by concentrating only on Granger causality tests or $DY$ weight measurements. Thus combining these two sets of results discloses information which may not be evident from the individual tests. The completeness measure (by using equation 5.7) for this Indian banking network is 0.2852. The banking networks illustrated in Figure 5.1 shows the complexity of the network.

### 5.3.1. Rolling window dynamic analysis of the network

Here we provide a dynamic analysis to comprehend the changes in the Indian banking network during the years in our sample. We measure the network connectivity variables, *Granger*, *DY*, and *GDY* on a daily rolling window basis. The estimation window is 20% of our sample period. The window covers around one year of data, thus allows us to account market activities of a full cycle and analyse results from the beginning of 2012. The plots of these variables are shown in Figure 5.2. We observe an overall upward trend with periodic peak and troughs in the average number of *Granger* links shown in panel (a) during the period of 2012 to 2015[3]. After stock markets around the world plummeted in the second half of 2011, amid the Greek debt crisis, markets underwent a continuous recovery in 2012 following the February 12 second EU bailout agreement in that year. After a rise in early 2013, the number of edges obtained from Granger causality tests remains relatively stable up to mid-2014. Then we observe another surge after mid-2014 towards mid-2015 followed by a downfall afterwards. After the declaration of Indian general election results the stock market was buoyant in May, 2014. Stock markets show

[3] We have taken 20% of our sample as the rolling window, thus the plots report variables from 2012 to 2015

reactions after the steep crash of Chinese capital market in June 2015 which continues in July and August. If we link the movements in *Granger* connectivity with these events, we observe that the connectivity increases in calm market conditions. However, *Granger* links are only one component of network connectivity in our model. According to Acemoglu et al. (2015) the increase in links or diversification makes the financial system less fragile unless any negative market shock crosses a certain level of severity; beyond a threshold level, interconnections may trigger propagating the shock. Thus during calm periods the banks may show a tendency to create links with each other as a strategy for reducing small shocks.

The $DY$ spillover index, the other component of the network connectivity in our model plotted in panel (b) of Figure 5.2 maintains a stable movement during 2012 to 2014 followed by a sudden decline in its value with few spikes in 2015. The decline may have eased the pressure on the overall network created by the increasing number of *Granger* links. The combined measure $GDY$ weights plotted in panel (c) combines the effects of changes in *Granger* edges and $DY$ weights. It exhibits a slowly increasing trend which indicates that this measurement is ultimately dominated by the Granger edges. Thus the increasing trend of the $GDY$ weights increases the chance that a negative shock above threshold may be propagated through the network of the banking sector. We also show a volatility measure, realized variance ($RV$) in the same rolling window in panel (d) and observe an increase in volatility in the market first in mid-2012 and again in mid-2014. The volatility of the market decreases largely after mid-2014 which corresponds with the decrease in the $DY$ measure but not in the *Granger* links.

From the *Granger* and *DY* time series plots a structural change from mid-2014 is visible. After this period we see a steep upward trend in *Granger* links and the opposite trend in *DY* weights. We can identify this change more clearly from the rolling window plots of higher moments of our combined network variable, *GDY* in Figure 5.3. The rolling window plots of standard deviation, skewness and kurtosis of *GDY* show that until mid-2014 these measures of higher moments are stable. After mid-2014 we see a sharp increase in all of these measures, indicating a substantial change in network topology.

The general election in India was held from 7the April to 12th May of 2014 and the result was declared on 16th May 2014. The Bharatiya Janata Party (BJP) and its allies won the right to form the largest majority government since the 1984 general election. Mr. Narendra Modi, known for his pro-business vision was nominated as the Prime Minister from BJP and took oath on 26 May. The market was buoyant since then until it was negatively affected by the Chinese market turmoil in the second half of 2015. Therefore, we have divided our sample period into two sub samples, one from January 2011 to May 2014 and another is from June 2014 to December 2015 and compute the network connectivity of these two periods separately the report the changes in Table 5.5. The network is thicker in the second phase as the number of Granger links increased from 298 to 457, whereas the average strength for each link decreased only slightly from 0.0260 to 0.0251. The completeness measure shows that the network is stronger in the second phase than in the first which is attributed to higher number of new links created in the second phase than the number of links removed. Overall the results indicate that after the general election the network of Indian Banks becomes stronger and increases the risk of systemic spread of risks of individual banks upon occurrences of large shocks. This finding is also confirmed by a higher standard deviation of $GDY$ after the election from Figure 5.3.

### 5.3.2. Network, liquidity and volatility

We analyse the impact of market liquidity and volatility on net connectivity expressed as the number of average Granger links, DY weight and DGY weight of the whole network. As the market liquidity measure we use the ratio of daily effective spread ($RESPD$). Here, $RESPD = (LastPrice - MidQuote)/MidQuote$, where $MidQuote = 1/2(BestAskPrice + BestBidPrice)$. Market volatility is represented by realized volatility ($RV$) where $RV^{[0,T]} = \sum_{j=1}^{[T/\Delta^n]} |\Delta_j^n p|^2$ as $\Delta_j^n p$ is the return of any asset at time $j$. Both of the liquidity and volatility measures are computed for each of the banking stocks on daily basis by taking data from their intra-day 5-minute observations. All the variables are taken on a daily rolling window basis and equally weighted for the whole sample of banks.

The following model is used to observe the impact of one order lag values of $RESPD$ and $RV$ on the net variables separately

$$Network_t = \alpha + \beta_1 RESPD_{t-1} + \beta_2 RV_{t-1} + \varepsilon_t, \tag{5.8}$$

where $t = 1, 2, 3.....N$ reflects the days and $Network$ implies one of the $Granger$, $DY$ and $GDY$ measures we use in the previous sections. The regression results are summarized in Table 5.6. We use the first difference of the variables as the variables are found non-stationary at level and stationary at first difference in Augmented Dickey-Fuller (ADF) unit root tests.

When *Granger* is used as the dependent variable the liquidity measure $RESPD$ is negatively significant at 5% indicating that increase in spread decreases the significant linkages among the banks. Increasing the spread is a sign of worsening market liquidity conditions and it seems from the result that when liquidity is low investors become more sensitive in trading and become aware of what is happening to the similar or peer stocks. As a result, the connectivity among the stocks tightens. The volatility measure in this regression is positive though the coefficient is not statistically significant.

The liquidity variable is positive but significant only at the 10% level when $DY$ is used as the network connectivity level. However, the volatility measure $RV$ has a significant and positive coefficient at 5% for this variable. The positive relationship can be explained as higher market volatility intensifying the strength of each of the relationships within the network. As $DY$ is a measure of variance decomposition it is expected that $DY$ is more driven by the volatility measure. The result can be interpreted as when the market is more volatile the banks with linkages between them become more dependent on each other as argued by Dungey et al. (2017). These results support both of Hypothesis 1 and Hypothesis 2 that *Granger* links positively negativey related to market liquidity while $DY$ weights are positively related to market volatility.

Our combined network measure $GDY$ is more affected by *Granger* as discussed in a previous section. Consequently, $GDY$ is significantly affected by the liquidity or in this case, lack of liquidity. The $RV$ does not have a significant coefficient against this variable. Thus the completeness of the network in Indian banking sector is bolstered by the deteriorating liquidity conditions as indicated by its negative coefficient. This result does not support our Hypothesis 3 which predicts that both liquidity and volatility have impacts on the network completeness measure.

### 5.3.3. Systemic risk and systematic risk

Systemic risk is generally associated with a shock that can be propagated to a certain industry and economy. On the other hand systematic risk is defined as the market risk faced by a certain unit such as a bank. Systematic risk is determined based on the co-movement of an asset with the market as a whole and expressed as beta. Todorov and Bollerslev (2010) show that beta should be decomposed into continuous beta and jump beta representing the asset's different sensitivities towards the continuous movements and jump movements of the market (see also Bollerslev et al., 2016 and Alexeev et al., 2017). We examine the cross-sectional relationship between the decomposed measure of systematic risk with the network connectivity variables.

For this analysis we use the beta of Indian Banks computed in Chapter 2. The average monthly values of continuous beta ($BetaC$) and jump beta ($BetaJ$) for our sample period of 2011 to 2015 and the combined network variables $GDY$ outward and $GDY$ inward weights are shown in Table 5.7. The high beta banks are more sensitive to changes in the market, and thus may also be more active agents of systemic risk. We run cross-sectional regressions to check the relationship between these two types of risk variables and report the results in Table 5.8. As *BetaC* and *BetaJ* are highly correlated we run separate regressions to capture the relationships. Both the continuous and jump betas are highly positively related with both the inward and outward *GDY* connectivities supporting the notion that systematically vulnerable banks are also systemically active. However, the magnitude of the relation of both betas are higher with inward *GDY* weights than the outward *DGY* weights implying that systematically vulnerable banks are also the more vulnerable recipients of systemic risk.

The natural step of the study at this point is to examine which component of the network connectivity is more related to the betas. Table 5.9 shows the regression results of *Granger* and *DY* outward and inward connectivities on *BetaC* and *BetaJ*. The results show that it is the *DY* outward and inward weights which are related to the betas and the relationships are positive. We do not find strong relationships of betas with the *Granger* links. The coefficient of betas are significant with only outward *Granger* links at 5% level in case of *BetaC* and 10% level in case of *BetaD*. Thus the positive relationship between systematic risk or betas of banks with the network connectivity is mainly transmitting through the *DY* weights rather than *Granger* links. Overall our results show evidence in favour of our Hypothesis 4 that banks with higher systematic risk are also more active participants in the networks.

### 5.3.4. Network based on volatility

Connectivity of a network can be formed by taking into consideration the volatility of its nodes - the banks in our case. Diebold and Yılmaz (2014) note that volatility connectedness is particularly more useful during the crisis period. We have taken daily realized variance ($RV$) as a measure of volatility of the banks by applying the following formula shown in Chapter 2

$$RV^{[0,T]} = \sum_{j=1}^{[T/\Delta^n]} |\Delta_j^n p|^2, \tag{5.9}$$

where $\Delta_j^n p = p_j - p_{j-1}$, $j = 1, 2, \ldots, [T/\Delta^n]$ is the observed return series of log price, $p_j$ for every $\Delta^n$ interval. We have used 15 minute stock returns of the 40 sample banks in computing daily $RV$s of these banking stocks as this interval is found optimal in Chapter 3 in minimizing the market micro-structure noise in Indian high frequency data.

The rolling window plots of the network variables, *Granger*, *DY* and *GDY* computed based on volatility are shown in Figure 5.4. The *Granger* plot in panel *a* shows that we can identify a larger number of links between the banks when we use volatility instead of return in measuring Granger links between the banks. The average Granger link of volatility based network of the Indian bank is 28.53 per bank whereas this number is 8.65 in return based network. The weight measure of the network, $DY$, shown in panel *b* is slightly higher, 0.9087 than the return based network measure of 0.8642. Ultimately the resulted complete measure of the network, $GDY$, shown in panel *c* is much higher in RV based network than the return based network (0.7632 versus 0.1638). Thus using volatility in developing the network may enable us to reveal the links between the nodes of a network that may not be possible when we use other variables and may be more useful in crisis periods.

Barndorff-Nielsen et al. (2008) introduce the concept of realized semi-variances where

$RV$ is decomposed into upside and downside realized semi-variances

$$RV = RS^{+} + RS.^{-} \tag{5.10}$$

Here $RS^{+} = \sum_{j=1}^{[T/\Delta^n]} |\Delta_j^n p|^2 \mathbf{1}\{\Delta_j^n p \geqq 0\}$ and $RS^{-} = \sum_{j=1}^{[T/\Delta^n]} |\Delta_j^n p|^2 \mathbf{1}\{\Delta_j^n p < 0\}$ where $\mathbf{1}$ is an indicator function. Thus $RS^{+}$is measured by using only positive and zero returns and $RS^{-}$is computed by using only negative and zero returns.

These variances may reveal new source of information especially the asymmetry in any variable from downside and upside volatilities. Barndorff-Nielsen et al. (2008) shows that negative returns are more associated with future volatility than the positive returns. We also show in Chapter 4 that negative jumps have more intensive relationship with the market condition than the positive jumps. Thus, network connectivity may exhibit asymmetry as Baruník et al. (2016) find asymmetry in volatility spillover. The market forces in India are not as efficient and active as we observe in developed economies. It is more likely in such a market that firms as well as the investors will be more cautious and exhibit herding behaviour and thus increase connectedness from the resulting panic in the face of negative volatility than the positive volatility. By using negative and positive realized semi-variance separately in developing the network connectivity measures of Indian banks, we examine this asymmetry in network connectivity, illustrated in Figure 5.5. In panel *a*, the rolling window of total volatility based connectivity $DGY$ is presented. In panel *b*, $DGY$ originating from bad and good volatility are presented as two separate line. As it is clear from the graph that the two series are not coincident, indicating asymmetry in network connectivity. The difference in both types of connectivity is highlighted in panel *c*. Here, the negative domain represents the periods when connectivity from bad volatility dominates the connectivity from the good volatility. We observe the dominance of negative domain from 2012 to the first half of 2015. The positive domain is dominant only in the second half of 2015. Thus a striking disparity in connectivity measure clearly indicates asymmetry in connectivity measures in the Indian banking sector. The results support our 5th hypothesis that Indian banking network connectivity is more related with the negative shocks than the positive ones.

## 5.4. Conclusion

We examine the systemic risk of the Indian banking sector through the network analysis based on stock returns of 40 listed commercial banks of India for the period of 2011 to 2015. First we apply Granger causality tests to establish statistically significant connections or edges between each pair of banks. We find that during the whole sample period 346 bilateral relationship exist among the 40 banks or on average each bank has 8.65 connections with other banks.

To measure the strength of each of the links we measure the weights of the link by applying the variance decomposition method applied by Diebold and Yilmaz (2009). By combining the weight matrix with the Granger connection matrix we derive the network of banks where only the statistically significant links with their respective weights are retained. According to this network matrix KBNK, SBNK and CRBK are the three most systemically active banks. On the other hand, VJBK, DENA and IDBI are the most vulnerable banks whose returns are affected by the change in other banks in the network.

We examine the change in network characteristics over time during our sample period by computing the above measurements on a daily rolling window basis. We observe that the number of significant edges shows an upward trend despite stable $DY$ weights over time. The combined measure - $GDY$ weight also shows an overall upward trend as it is dominated by the changes in $Granger$ links.

We observe a shift in the network connectivity after the general election was held in India in May, 2014. Therefore we divide our sample into pre-election and post-election periods and find that connectivity in the post-election period increases substantially mainly because of new Granger links added to the network.

Regression results suggest the $Granger$ links of the network are affected by liquidity changes in the market while the $DY$ weights are more affected by the volatility changes. Ultimately changes in $GDY$, the combined connectivity is related to the market liquidity as the $GDY$ in our sample is dominated by the $Granger$ links.

A cross-sectional regression show that systematic risk is positively related to network connectivity. Both of our decomposed systematic risk measures - continuous beta and jump beta - of banks are used in the regressions and found statistically significant for both outward and inward connectivity measures. However, the magnitude of the relations are higher for the inward connectivities than for the outward connectivities.

We measure the network connectivity based on a volatility measure, realized variance, $RV$. The volatility based network shows higher connectivity than the network based on stock returns and may offer a better measure in crisis periods. By using positive and negative semi-variances we show that asymmetry exists in volatility based connectivity in networks.

Our results are important for the financial sector regulators as they can apply the method in judging the overall systemic risk of the banks and observe its changes over time. The two aspects of the network strength - *Granger* links and *DY* weights are affected by different variables. Hence it is important to determine which of these two variables is more active in a given state of the banking network so that regulators can pinpoint their focus in controlling the correct set of factors. This will increase the effectiveness of the policies taken by the regulators in mitigating the systemic risk of the financial system.

Further analysis can be done to explore the sources of networking measures that are not used in this study. Examining network connectivity among different subgroups of the banks may also generate findings with important policy implications. These banks are likely to be affected by the interactions with the global financial system. One limitation of this paper is not accounting this effect. A network analysis based on the flow of assets/liabilities with local and foreign banks may render different aspects of the network not captured in our market price based method.

Table 5.1: List of Sample Banks

*We take 40 Indian banks listed on the National Stock Exchange (NSE). The first column shows the Codes used in TRTH database to identify the banks.*

| Codes | Banks | Codes | Banks |
|---|---|---|---|
| ADBK | Andhra Bank | JKBK | Jammu and Kashmir Bank |
| ALBK | Allahabad Bank | KARU | Karur Vysya Bank |
| AXBK | Axis Bank | KBNK | Karnataka Bank |
| BMBK | Bank of Maharashtra | KTKM | Kotak Mahindra Bank |
| BOB | Bank of Baroda | LVLS | Lakshmi Vilas Bank |
| BOI | Bank of India | ORBC | Oriental Bank of Commerce |
| CBI | Central Bank of India | PNBK | Punjab National Bank |
| CNBK | Canara Bank | PUNA | Punjab & Sind Bank |
| CRBK | Corporation Bank | SBI | State Bank of India |
| CTBK | City Union Bank | SBKB | State Bank of Bikaner and Jaipur |
| DCBA | Dev. Credit Bank | SBKM | State Bank of Mysore |
| DENA | Dena Bank | SBKT | State Bank of Travancore |
| DNBK | Dhanlaxmi Bank Ltd | SBNK | Syndicate Bank |
| FED | Federal Bank | SIBK | South Indian Bank |
| HDBK | HDFC Bank | STNCy | Standard Chartered Bank |
| ICBK | ICICI Bank | UBOI | United Bank of India |
| IDBI | IDBI Bank | UCBK | UCO Bank |
| INBA | Indian Bank | UNBK | Union Bank of India |
| INBK | Indusind Bank Limited | VJBK | Vijaya Bank |
| IOBK | Indian Overseas Bank | YESB | Yes Bank |

Table 5.2: Granger links among the Indian banks.
*These measures are derived from the multivariate Granger causality tests between Indian banks and expressed as count numbers*

| Banks | Outward | Inward | Banks | Outward | Inward |
|---|---|---|---|---|---|
| ADBK | 8 | 11 | JKBK | 10 | 0 |
| ALBK | 9 | 13 | KARU | 7 | 9 |
| AXBK | 9 | 1 | KBNK | 14 | 14 |
| BMBK | 8 | 7 | KTKM | 6 | 2 |
| BOB | 4 | 9 | LVLS | 9 | 17 |
| BOI | 11 | 9 | ORBC | 9 | 4 |
| CBI | 8 | 16 | PNBK | 9 | 0 |
| CNBK | 10 | 11 | PUNA | 10 | 10 |
| CRBK | 8 | 7 | SBI | 19 | 0 |
| CTBK | 7 | 9 | SBKB | 5 | 15 |
| DCBA | 6 | 5 | SBKM | 9 | 8 |
| DENA | 9 | 20 | SBKT | 8 | 8 |
| DNBK | 4 | 11 | SBNK | 14 | 8 |
| FED | 12 | 2 | SIBK | 6 | 8 |
| HDBK | 2 | 0 | STNCy | 11 | 5 |
| ICBK | 8 | 0 | UBOI | 8 | 4 |
| IDBI | 9 | 16 | UCBK | 8 | 6 |
| INBA | 8 | 9 | UNBK | 10 | 9 |
| INBK | 7 | 15 | VJBK | 10 | 22 |
| IOBK | 6 | 9 | YESB | 11 | 17 |

Table 5.3: DY Weights of Indian banks derived from the network analysis.
*The DY weights are calculated by applying the DY spillover analysis*

| Banks | Outward | Inward | Banks | Outward | Inward |
|---|---|---|---|---|---|
| ADBK | 0.9060 | 1.3170 | JKBK | 0.2769 | 0.0540 |
| ALBK | 0.9058 | 1.3260 | KARU | 0.7468 | 0.3883 |
| AXBK | 0.6735 | 0.2694 | KBNK | 0.8836 | 1.1016 |
| BMBK | 0.8521 | 0.7503 | KTKM | 0.7372 | 0.4393 |
| BOB | 0.7281 | 0.5561 | LVLS | 0.7804 | 0.5372 |
| BOI | 0.9032 | 1.2861 | ORBC | 0.9021 | 1.2753 |
| CBI | 0.8685 | 0.9205 | PNBK | 0.5918 | 0.1804 |
| CNBK | 0.9035 | 1.2890 | PUNA | 0.8712 | 0.8525 |
| CRBK | 0.6232 | 0.3279 | SBI | 0.4940 | 0.1258 |
| CTBK | 0.6867 | 0.2999 | SBKB | 0.8341 | 0.6664 |
| DCBA | 0.8599 | 0.8860 | SBKM | 0.8063 | 0.5910 |
| DENA | 0.9056 | 1.3189 | SBKT | 0.8164 | 0.6086 |
| DNBK | 0.8333 | 0.6803 | SBNK | 0.9073 | 1.3611 |
| FED | 0.6569 | 0.2512 | SIBK | 0.8369 | 0.7543 |
| HDBK | 0.3317 | 0.0716 | STNCy | 0.3653 | 0.0834 |
| ICBK | 0.5612 | 0.1898 | UBOI | 0.8664 | 0.8229 |
| IDBI | 0.9068 | 1.3569 | UCBK | 0.9113 | 1.4395 |
| INBA | 0.8678 | 0.8593 | UNBK | 0.9034 | 1.2781 |
| INBK | 0.8568 | 0.9178 | VJBK | 0.9031 | 1.3100 |
| IOBK | 0.8992 | 1.2248 | YESB | 0.8728 | 1.0686 |

Table 5.4: *GDY* weights of Indian Banks derived from network analysis.
*These measures are computed by combining the results of Granger causality tests and DY spillover analysis.*

| Banks | Outward | Inward | Banks | Outward | Inward |
|---|---|---|---|---|---|
| ADBK | 0.2656 | 0.3524 | JKBK | 0.0878 | - |
| ALBK | 0.2824 | 0.3919 | KARU | 0.1797 | 0.0850 |
| AXBK | 0.2525 | 0.0076 | KBNK | 0.4144 | 0.4036 |
| BMBK | 0.2537 | 0.1192 | KTKM | 0.1549 | 0.0200 |
| BOB | 0.0693 | 0.3553 | LVLS | 0.2086 | 0.2844 |
| BOI | 0.2842 | 0.3219 | ORBC | 0.2877 | 0.1516 |
| CBI | 0.1949 | 0.4016 | PNBK | 0.1710 | - |
| CNBK | 0.2784 | 0.4020 | PUNA | 0.3002 | 0.2199 |
| CRBK | 0.3699 | 0.0213 | SBI | 0.2901 | - |
| CTBK | 0.1416 | 0.0601 | SBKB | 0.1247 | 0.2110 |
| DCBA | 0.1729 | 0.1169 | SBKM | 0.2299 | 0.1050 |
| DENA | 0.3067 | 0.7657 | SBKT | 0.1881 | 0.0957 |
| DNBK | 0.1151 | 0.2178 | SBNK | 0.3790 | 0.2902 |
| FED | 0.2402 | 0.0145 | SIBK | 0.1916 | 0.1499 |
| HDBK | 0.0138 | - | STNCy | 0.1370 | 0.0100 |
| ICBK | 0.1212 | - | UBOI | 0.1897 | 0.0700 |
| IDBI | 0.2769 | 0.5866 | UCBK | 0.2307 | 0.2259 |
| INBA | 0.2275 | 0.1740 | UNBK | 0.2702 | 0.3098 |
| INBK | 0.1808 | 0.3354 | VJBK | 0.2822 | 0.8146 |
| IOBK | 0.1551 | 0.2502 | YESB | 0.3306 | 0.5100 |

Table 5.5: Change in network connectivity
*The table contains statistics used in the analysis of network structure. The average link strength is computed from DY spillover calculations for each respective network. The number of links is calculated derived using multivariate Granger causality tests between our sample banks. Completeness is calculated via equation 5.7. Phase 1 refers to the pre-election period and phase 2 refers to the post election period of India.*

| | Full sample | Phase 1 | Phase 2 | Formed 1 to 2 | Removed 1 to 2 |
|---|---|---|---|---|---|
| Average Strength | 0.0256 | 0.026 | 0.0251 | 0.0217 | 0.0261 |
| No. of links | 346 | 298 | 457 | 386 | 227 |
| Completeness | 0.2852 | 0.2263 | 0.3842 | 0.2805 | 0.1729 |

Table 5.6: Network, liquidity and volatility

*Here we report the results of time series regressions of network connectivity measures $Granger$, $DY$ and $GDY$ on liquidity measure $RESPD$ and volatility measure RV. We use the first differences of the variables in the regression as the variables are non-stationary at level and stationary at first difference. Number of observation is 993 for each of the regressions.*

| Variables | D(Granger) | D(DY) | D(GDY) |
|---|---|---|---|
| Constant | 0.0056 | -7.20E-05 | 0.0002 |
| | (0.0066) | (0.0001) | (0.0002) |
| D(RESPD(-1)) | -32.8218** | 0.6553* | -1.1114** |
| | (14.8586) | (0.386) | (0.4405) |
| D(RV(-1)) | 18.7053 | 3.4751** | 0.7001 |
| | (11.6607) | (1.6034) | (0.9323) |

Standard error values are displayed in parentheses below the coefficients. The asterisks *, **, and *** indicate the significance at the 10%, 5%, and 1% level, respectively.

Table 5.7: Systematic risk variables and network connectivity variables of Indian banks

*The table shows average monthly continuous betas and jump betas of 40 Indian Banks along with the GDY outward and inward connectivity measures.*

| Banks | BetaC | BetaD | GDY_outward | GDY_inward |
|---|---|---|---|---|
| ADBK | 1.20 | 1.73 | 0.27 | 0.35 |
| ALBK | 1.39 | 1.99 | 0.28 | 0.39 |
| AXBK | 1.19 | 1.72 | 0.25 | 0.01 |
| BMBK | 0.44 | 1.11 | 0.25 | 0.12 |
| BOB | 1.16 | 1.95 | 0.07 | 0.36 |
| BOI | 1.46 | 2.12 | 0.28 | 0.32 |
| CBI | 0.82 | 1.57 | 0.19 | 0.40 |
| CNBK | 1.40 | 2.00 | 0.28 | 0.40 |
| CRBK | 0.34 | 1.06 | 0.37 | 0.02 |
| CTBK | 0.22 | 0.83 | 0.14 | 0.06 |
| DCBA | 1.00 | 1.83 | 0.17 | 0.12 |
| DENA | 1.23 | 1.78 | 0.31 | 0.77 |
| DNBK | 0.74 | 1.57 | 0.12 | 0.22 |
| FED | 0.86 | 1.53 | 0.24 | 0.01 |
| HDBK | 0.79 | 1.32 | 0.01 | - |
| ICBK | 1.13 | 1.72 | 0.12 | - |
| IDBI | 1.45 | 1.97 | 0.28 | 0.59 |
| INBA | 0.57 | 1.44 | 0.23 | 0.17 |
| INBK | 0.98 | 1.70 | 0.18 | 0.34 |
| IOBK | 1.12 | 1.65 | 0.16 | 0.25 |
| JKBK | 0.24 | 1.16 | 0.09 | - |
| KARU | 0.23 | 0.84 | 0.18 | 0.08 |
| KBNK | 1.33 | 2.12 | 0.41 | 0.40 |
| KTKM | 0.94 | 1.44 | 0.15 | 0.02 |
| LVLS | 0.39 | 1.20 | 0.21 | 0.28 |
| ORBC | 1.43 | 2.15 | 0.29 | 0.15 |
| PNBK | 1.20 | 1.97 | 0.17 | - |
| PUNA | 0.38 | 1.39 | 0.30 | 0.22 |
| SBI | 1.11 | 1.70 | 0.29 | - |
| SBKB | 0.25 | 1.08 | 0.12 | 0.21 |
| SBKM | 0.15 | 1.02 | 0.23 | 0.11 |
| SBKT | 0.19 | 0.95 | 0.19 | 0.10 |
| SBNK | 1.41 | 2.04 | 0.38 | 0.29 |
| SIBK | 0.59 | 1.27 | 0.19 | 0.15 |
| STNCy | 0.02 | 0.47 | 0.14 | 0.01 |
| UBOI | 0.54 | 1.41 | 0.19 | 0.07 |
| UCBK | 1.58 | 2.37 | 0.23 | 0.23 |
| UNBK | 1.43 | 2.10 | 0.27 | 0.31 |
| VJBK | 1.07 | 1.62 | 0.28 | 0.81 |
| YESB | 1.30 | 1.80 | 0.33 | 0.51 |

Table 5.8: Regression results - systemic risk and systematic risk- DGY and beta

*These are cross sectional regression results. We use Tobit regressions as the dependent variables DY outward and inward weights as non-zero ratios. The number of observation is in each regression is 40.*

| | GDY outward | | GDY inward | |
|---|---|---|---|---|
| | 1 | 2 | 1 | 2 |
| Constant | 0.1558*** | 0.0983** | 0.02115 | -0.1206* |
| | (0.0243) | (0.0414) | (0.0379) | (0.0644) |
| *BetaC* | 0.0742*** | | 0.212*** | |
| | (0.0235) | | (0.0501) | |
| *BetaJ* | | 0.0785*** | | 0.2096*** |
| | | (0.0258) | | (0.047) |

Standard error values are displayed in parentheses below the coefficients. The asterisks *, **, and *** indicate the significance at the 10%, 5%, and 1% level, respectively.

Table 5.9: Regression results - systemic risk and systematic risk

*These are cross sectional regression results. We use Poisson regression involving the Granger outward and inward measures as dependent variables and Tobit regression involving DY outward and inward weight as dependent variables. Number of observation is in each regression is 40.*

| | Granger Outward | | Granger Inward | | DY weights Outward | | DY weights Inward | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (1) | (2) | (1) | (2) | (1) | (2) |
| Constant | 1.9916*** | 1.8663*** | 2.0203*** | 1.9215*** | 0.6477*** | 0.4978*** | 0.2542*** | -0.2397 |
| | (0.0902) | (0.1786) | (0.1793) | (0.2764) | (0.6424) | (0.0947) | (0.0805) | (0.1236) |
| *BetaC* | 0.1841** | | 0.1529 | | 0.1453*** | | 0.5913*** | |
| | (0.0885) | | (0.1811) | | (0.0539) | | (0.0915) | |
| *BetaJ* | | 0.1839* | | 0.1493 | | 0.1775*** | | 0.6481*** |
| | | (0.1088) | | (0.1682) | | (0.0522) | | (0.0860) |

Standard error values are displayed in parentheses below the coefficients. The asterisks *, **, and *** indicate the significance at the 10%, 5%, and 1% level, respectively.

Figure 5.1: The network of Indian banks during the 2011-2014 period.

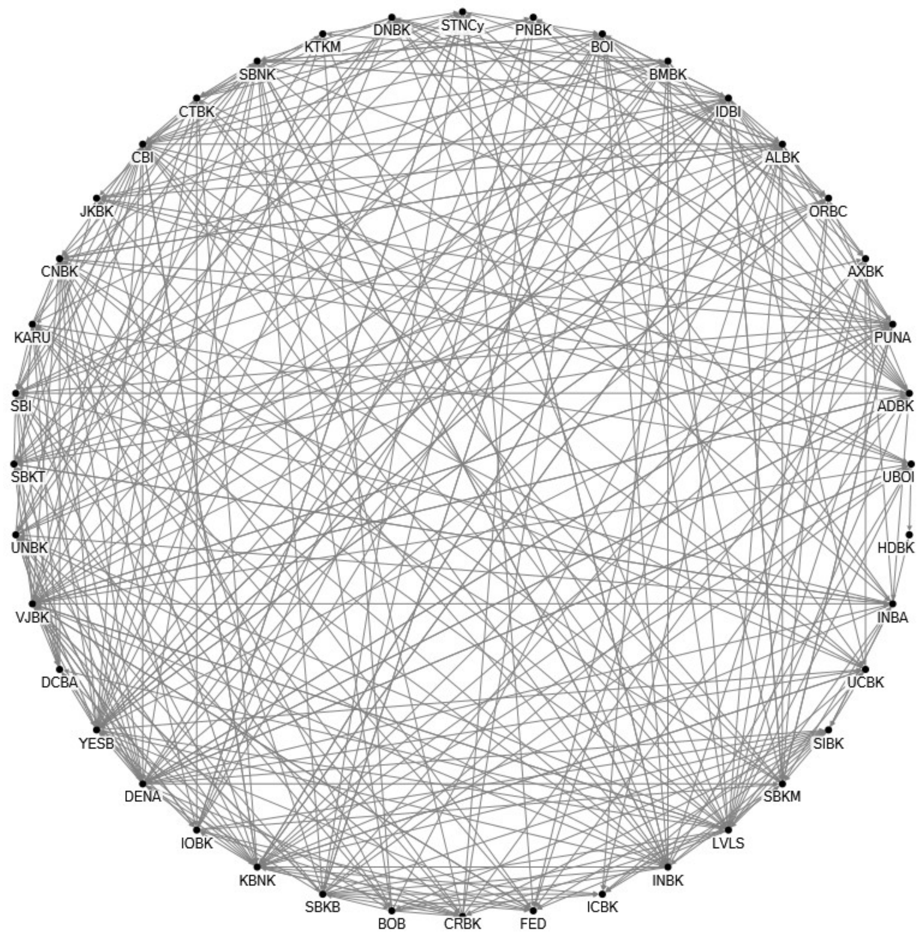


Figure 5.2: Plots of network variables calculated on a rolling window basis.

*The variables are calculated on a daily rolling window basis. The rolling window is 20% of our sample trading days of 1240.*

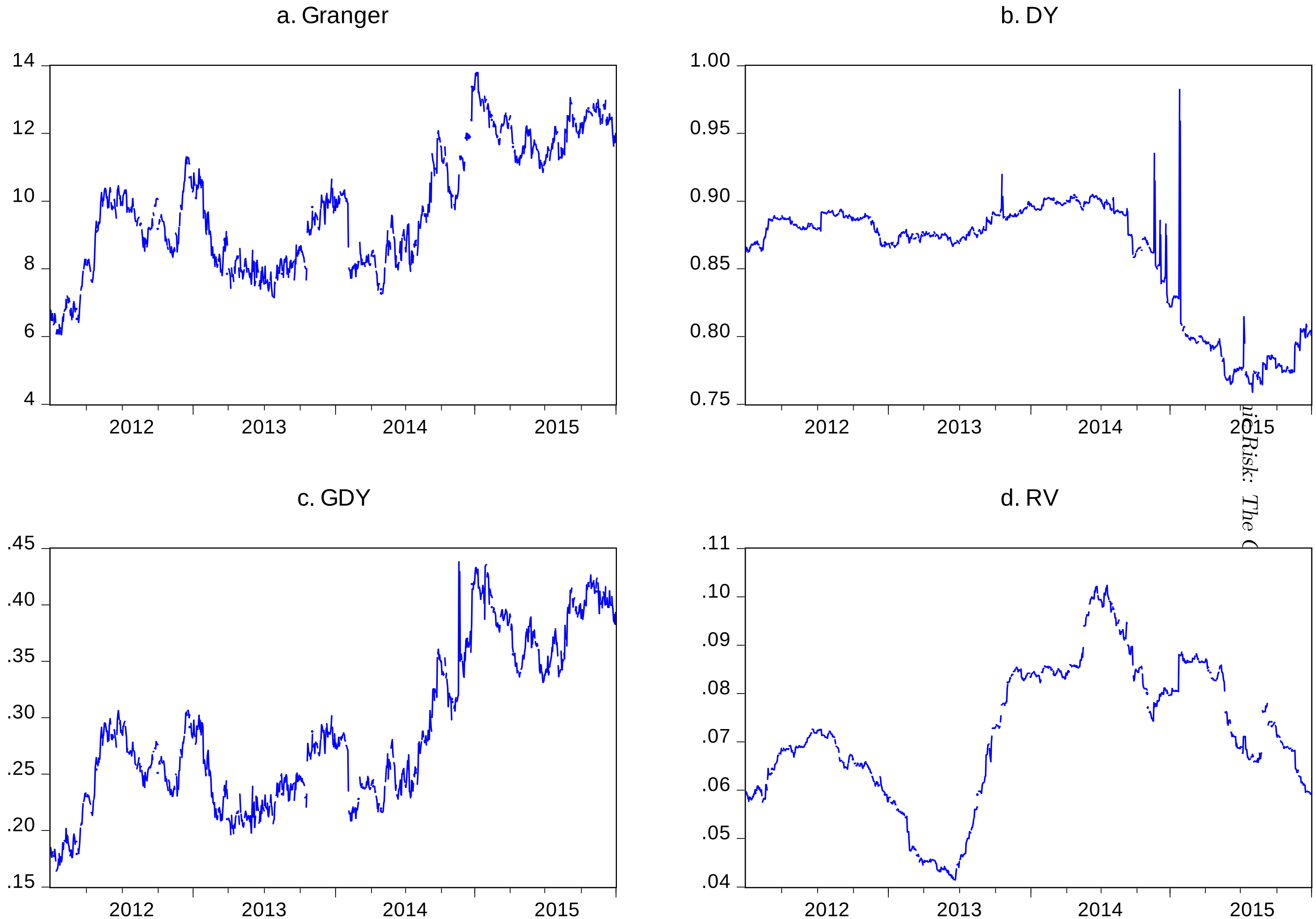


Figure 5.3: Plots of higher moments of *GDY*

*The variables are calculated on a daily rolling window basis. The rolling window is 20% of our sample trading days of 1240.*

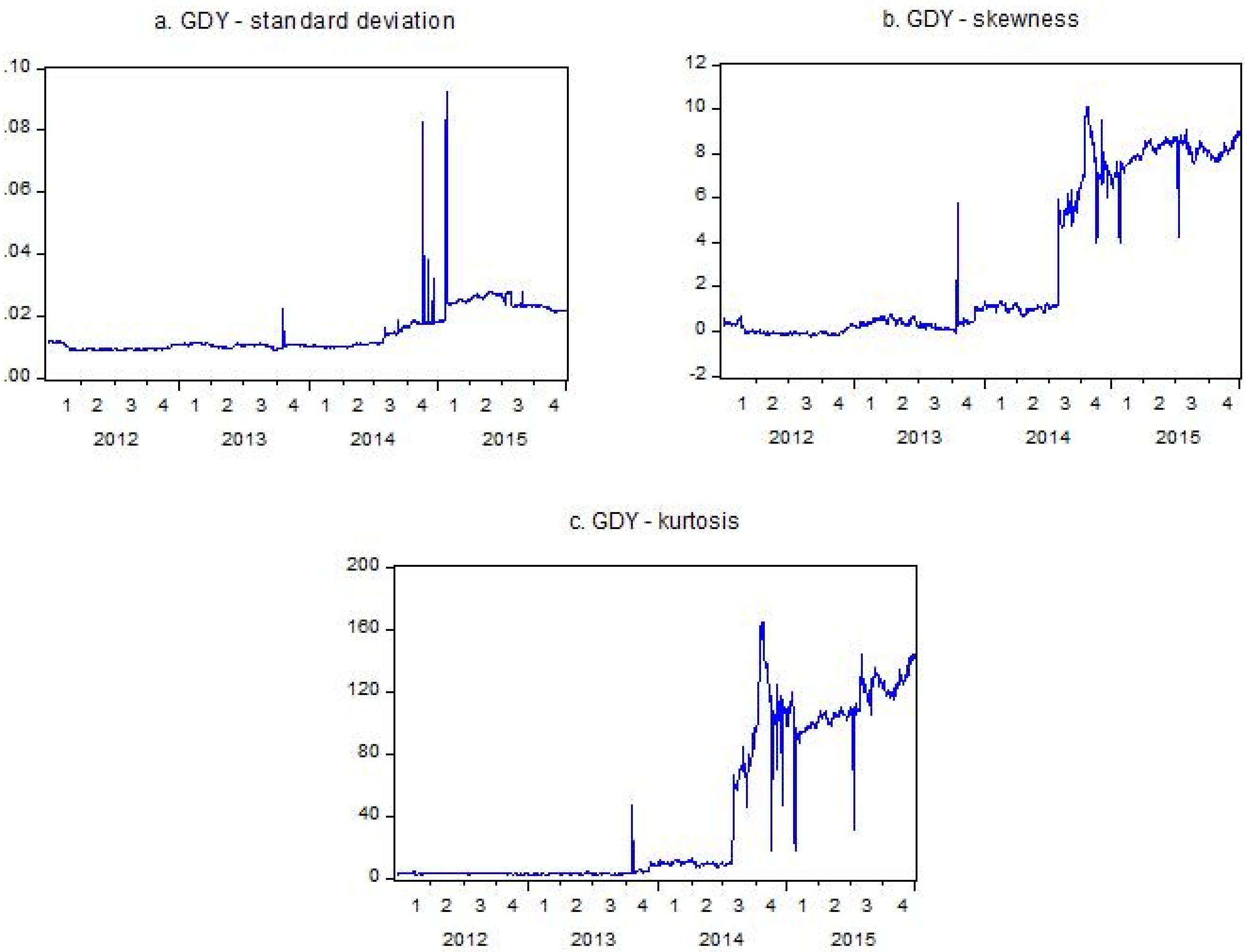


Figure 5.4: Plots of volatility based network variables

*The network variables are computed by using daily realized variances (RV) on a rolling window basis. The rolling window is 20% of our sample trading days of 1240.*

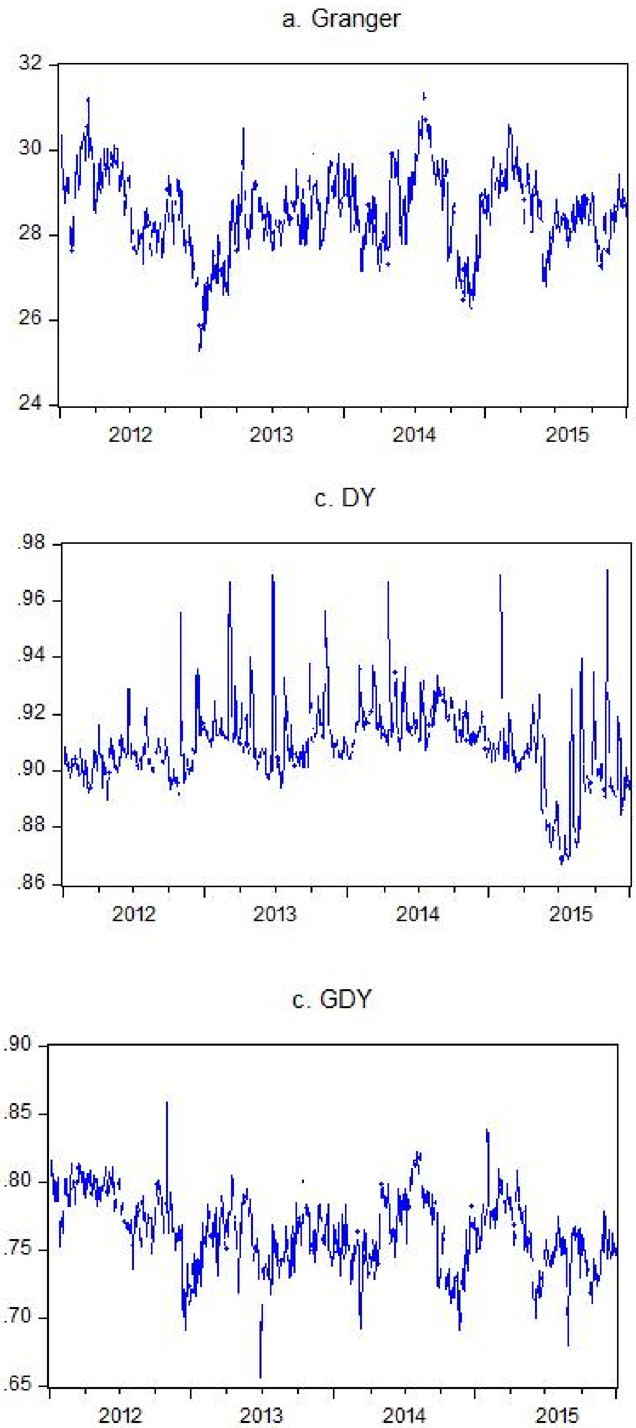
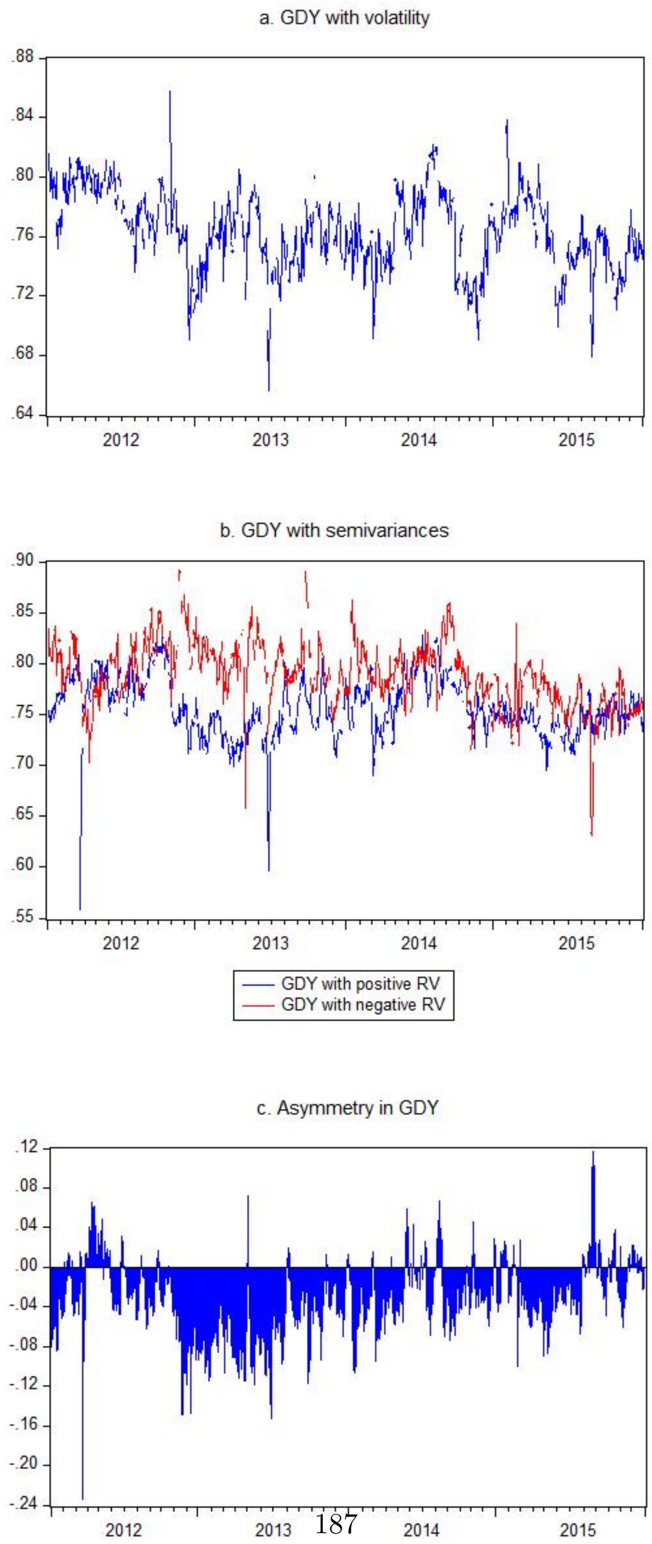


Figure 5.5: Asymmetry in network measurements

*Panel a shows the network completeness measure GDY rolling window line with all RVs. In Panel b the red GDY line is drawn based on negative RVs and the blue GDY line is drawn based on positive RVs. Panel c shows the asymmetry in the network between positive and negative RVs.*



# 6 Conclusion

The idea that the separation of discontinuous jump components from the continuous Brownian component of asset price processes is important for portfolio risk management and asset allocation decisions has resulted in a flurry of jump studies on the U.S. and other developed markets. As we do not know whether the results of those studies hold for other markets such as emerging economies we extend the jump literature to the Indian market which is fast emerging as one of the biggest economies of the world. Four independent studies on Indian financial market especially the banking sector have been incorporated in this thesis where the jump risk of this market, its characteristics, implications, systematic risk and systemic risk are examined.

In the *first paper* we examine whether banking stocks have different sensitivities or systematic risks against the jump movements from the continuous movements in the market. Our paper confirms a similar finding for Indian banking stocks as reported in the existing literature for the US in Todorov and Bollerslev (2010) and Alexeev et al. (2017). Using 5-minute stock price data for 41 listed Indian banks for 2004-2015 period we establish evidence of jumps in the Indian equity markets. The proportion of jumps did not increase during the GFC, also consistent with the small existing literature concerning jump behaviour during crisis periods. The estimates of separate continuous and jump betas for the Indian banks show that the reaction of individual stocks to discontinuities in the market indicator price is substantially higher than the reaction to continuous movements.

The estimated continuous and jump betas are related to various firm characteristics. More particularly, we show that systematic risk of banking stocks can be reduced by increasing bank capital and decreasing leverage but the extent of the reduction in betas that can be produced in this manner are quite small and may not be economically meaningful.

In the *second paper*, we provide a comprehensive characterisation of the exposure of financial stocks to the jump risk by focusing on the sub-sectoral differences between banks and non-bank financial corporations (FIs). We examine the jump risks for banking sector represented by 41 Indian banking stocks and the FI sector represented by 55 FIs of India.

By applying alternative non-parametric jump detection methods on the Indian market index, the banking index and the FI index, we observe a wide variation of reported jump intensities across different jump methods, data frequencies and different significance levels. Our volatility signature plot suggests that a 15-minute data may be optimal in neutralising the market micro-structure noise.

Our test results show that the banking industry is associated with higher amount of jump risk in comparison with the market while the result is opposite for the FI industry. A probit regression indicates that presence of jumps in the market has significant effect on the probability of jump occurrences in the banking industry and the FI industry.

We do not find any such relationship between the banking and non-banking financial corporations.

We also analyse the intra-day jump pattern of Indian financial stocks by testing jumps in each of the return observations. The results indicate the existence of intra-day and weekly seasonality in jump pattern contrasting the general description of jump occurrences as a Poisson distribution and thus reinforce the findings of Bormetti et al. (2015) in this regard. Overall, our results confirm that investors in emerging markets need to consider jump risks in portfolio and risk management decisions and academics applying asset pricing models in this market need to choose jump robust models.

In the pursuit of the non-news related factors causing jumps in the stock price processes our the *third paper* examines the relationship of liquidity with the jump movements using ten of the largest Indian banking stocks. Using a jump test capable of detecting jumps in every return observations we observe jumps in 1.58% to 1.73% of return data in those stocks. We implemented an event study method as well as a parametric analysis to assess the contribution of liquidity shocks in occurrence of jumps. We find notable variations in the liquidity measures immediately before and after the jump intervals in the stocks. Liquidity measures - market spread, trading quantity and immediacy, market liquidity conditions do improve around jumps. The surge in volume can be attributed to the rise in average trade size before the jump interval. The results conform to the literature that the demand of immediacy of traders may cause jumps in stock returns.

We find evidence of both contemporaneous and lagged effects of liquidity factors on the probability of jump occurrences. However, the explanatory power of contemporaneous liquidity variables is much higher than the lagged variables. The liquidity variables have more explanatory power in determining the probability of negative than that of positive jumps. Finally, although several liquidity variables are shown to contribute to price discovery, the post jump price discovery process does not seem to be strongly related to the liquidity variables.

After examining the systematic risks in the first paper we examine another risk which is particularly relevant for the banking sector - systemic risk and try to relate these two risks in our *fourth paper*. Systemic risk is analysed through the network analysis of stock returns of 40 listed Indian banks for the period of 2011 to 2015. Granger causality tests form edges between each pair of banks showing 8.65 connections for each of the banks on the average. The strength of each of the links is measured by applying the variance decomposition method developed by Diebold and Yilmaz (2009). The network of banks is formed by retaining variance decomposition weights of only the statistically significant links. According to this network matrix we identify the more systemically active banks.

The network variables measured on a daily rolling window basis reveal an upward trend in the number of significant edges despite a stable variance decomposition weights over our sample time. The combined measure of the network also shows an overall upward trend as it is dominated by the changes in number of links. We also observe that connectivity in the banking stocks to increase after the general election of May 2014 increasing the risk of systemic nature.

Regression results suggest that the number of links of the network are affected by liquidity changes of the market while the variance decomposition weights are more affected by the volatility changes. Ultimately changes in the combined connectivity is related to market liquidity. Cross-sectional regressions show that systematic risk is positively related to network connectivity. Both of our decomposed systematic risk measures of banks - continuous beta and jump beta - are found statistically significant for both outward and inward connectivity measures.

Overall, we find evidence supporting the existence of jumps in the Indian market and showing that we need to weight a jump diffusion asset price process in applying financial models in these markets. Investors taking portfolio and asset pricing decisions need to consider the concentration of jump occurrences especially at the beginning of trading hours. The clustering behaviour of jumps also provides investors with some hints as when to expect jumps in the price process. Liquidity conditions, beside news announcements, may also indicate the arrival of jumps in a specific stock or the market. Investors, especially those who are very active in trading, should also be aware of the difference in pricing the systematic risk of stocks created from jump market movements versus continuous market movements. The banking stocks in our study show higher sensitivity towards the market jumps than the continuous movements of the market, but the results may be different for different industries (e.g. Alexeev et al., 2017). Lastly, the banks with higher systematic risk are also more active players in spreading systemic shocks in the market and are thus more vulnerable at the time of extreme conditions.

In determining jumps we work with a number of jump methods but do not attempt to ascertain which method fits best with the emerging market settings. While working with real data it is difficult to determine the best method to fit into a particular dataset.

We can solve this problem by running the alternative methods in simulated data which we aspire to do in future. Another option can be using the common jumps detected by a number of methods as proposed by Dumitru and Urga (2012). By taking the intersections of different methods we may solve the underestimation or overestimation of jumps detected by a single method. Choosing the optimal threshold level against which jump is detected is another area where further research is needed to avoid detecting spurious jumps. So far, there is no firm consensus among researchers on the ideal threshold level that will fit into very high frequency data. The ideal threshold level may vary based on liquidity of assets which can be studied in future researches.

We draw the network of banks by combining Granger causality and variance decomposition methods. Utilizing co-jumps of banks can be an alternative way of determining links among the banks. Examining changes of co-jump magnitude and nature during the crisis period can provide useful information on contagion and systemic effects within and across banking sectors (e.g. Aït-Sahalia et al., 2015 and Bormetti et al., 2015). Bormetti et al. (2015) describe the existence of large number of co-jumps across different asset classes as systemic events. Aït-Sahalia et al. (2015) show that jumps in a country which are influenced by jumps in another country can be a measurement of contagion effect. Such cross exciting jumps and co-jumps can become important tools in measuring systemic and contagion effects and further studies can improve our understanding in this direction. Another extension of our research can be a sector wise analysis of jump characteristics and an examination of co-jumps across these sectors. Sectors with higher co-jumps may also be more systemically linked, and demand more attention during crisis periods. Lastly, a cross-country comparison of different emerging economies in terms of jumps and banking networks may confirm whether we can generalize the India-based research results to other emerging countries.

# Bibliography


Acemoglu, D., Ozdaglar, A., and Tahbaz-Salehi, A. (2015). Systemic risk and stability in financial networks. *The American Economic Review*, 105(2):564–608.

Acharya, V. V. (2009). A theory of systemic risk and design of prudential bank regulation. *Journal of Fnancial Stability*, 5(3):224–255.

Acharya, V. V. and Kulkarni, N. (2010). State ownership and systemic risk: Evidence from the indian financial sector during 2007-09. *Unpublished paper, NYU–Stern, New York*.

Acharya, V. V. and Yorulmazer, T. (2008). Cash-in-the-market pricing and optimal resolution of bank failures. *Review of Financial Studies*, 21(6):2705–2742.

Aggarwal, N., Arora, S., Behl, A., Grover, R., Khanna, S., and Thomas, S. (2013). A systematic approach to identify systemically important firms. *Indira Gandhi Institute of Development Research Working Paper*, (2013-021).

Aït-Sahalia, Y. (2004). Disentangling diffusion from jumps. *Journal of Financial Economics*, 74(3):487–528.

Aït-Sahalia, Y., Cacho-Diaz, J., and Laeven, R. J. (2015). Modeling financial contagion using mutually exciting jump processes. *Journal of Financial Economics*, 117(3):585–606.

Aït-Sahalia, Y. and Jacod, J. (2012). Analyzing the Spectrum of Asset Returns: Jump and Volatility Components in High Frequency Data. *Journal of Economic Literature*, 50(4):1007–50.

Aït-Sahalia, Y., Jacod, J., et al. (2009). Testing for jumps in a discretely observed process. *The Annals of Statistics*, 37(1):184–222.

Aït-Sahalia, Y., Mykland, P. A., and Zhang, L. (2005). How often to sample a continuous-time process in the presence of market microstructure noise. *Review of Financial Studies*, 18(2):351–416.

Aït-Sahalia, Y. and Xiu, D. (2016). Increased correlation among asset classes: Are volatility or jumps to blame, or both? *Journal of Econometrics*, 194(2):205–219.

Alexeev, V., Dungey, M., and Yao, W. (2017). Time-varying continuous and jump betas: The role of firm characteristics and periods of stress. *Journal of Empirical Finance*, 40:1–19.

Amihud, Y. and Mendelson, H. (1986). Asset pricing and the bid-ask spread. *Journal of Financial Economics*, 17(2):223–249.

Amihud, Y., Mendelson, H., and Pedersen, L. H. (2006). *Liquidity and asset prices.* Now Publishers Inc.

Andersen, T. G., Benzoni, L., and Lund, J. (2002). An empirical investigation of continuous-time equity return models. *The Journal of Finance*, 57(3):1239–1284.

Andersen, T. G. and Bollerslev, T. (1998). Deutsche Mark-Dollar Volatility: Intraday

Activity Patterns, Macroeconomic Announcements, and Longer Run Dependencies. *The Journal of Finance*, 53(1):219–265.

Andersen, T. G., Bollerslev, T., and Diebold, F. X. (2007a). Roughing It Up: Including Jump Components in the Measurement, Modeling, and Forecasting of Return Volatility. *The Review of Economics and Statistics*, 89(4):701–720.

Andersen, T. G., Bollerslev, T., Diebold, F. X., and Labys, P. (1999). Realized volatility and correlation. Technical report, L.N. Stern School of Finance Department Working Paper 24.

Andersen, T. G., Bollerslev, T., Diebold, F. X., and Labys, P. (2001). The Distribution of Realized Exchange Rate Volatility. *Journal of the American Statistical Association*, 96(453):42–55.

Andersen, T. G., Bollerslev, T., Diebold, F. X., and Wu, J. G. (2005). A Framework for Exploring the Macroeconomic Determinants of Systematic Risk. Technical report, National Bureau of Economic Research.

Andersen, T. G., Bollerslev, T., and Dobrev, D. (2007b). No-arbitrage semi-martingale restrictions for continuous-time volatility models subject to leverage effects, jumps and iid noise: Theory and testable distributional implications. *Journal of Econometrics*, 138(1):125–180.

Andersen, T. G., Dobrev, D., and Schaumburg, E. (2012). Jump-robust volatility estimation using nearest neighbor truncation. *Journal of Econometrics*, 169(1):75–93.

Ariel, R. A. (1987). A monthly effect in stock returns. *Journal of Financial Economics*, 18(1):161–174.

Atiase, R. K. and Bamber, L. S. (1994). Trading volume reactions to annual accounting earnings announcements: The incremental role of predisclosure information asymmetry. *Journal of Accounting and Economics*, 17(3):309–329.

Bakshi, G. and Panayotov, G. (2010). First-passage probability, jump models, and intra-horizon risk. *Journal of Financial Economics*, 95(1):20–40.

Ball, C. A. and Torous, W. N. (1985). On jumps in common stock prices and their impact on call option pricing. *The Journal of Finance*, 40(1):155–173.

Bandi, F. M. and Russell, J. R. (2008). Microstructure noise, realized variance, and optimal sampling. *The Review of Economic Studies*, 75(2):339–369.

Barada, Y. and Yasuda, K. (2012). Testing for Levy Type Jumps in Japanese Stock Market under the Financial Crisis Using High Frequency Data. *International Journal of Innovative Computing Information and Control*, 8(3 B):2215–2223.

Barber, B. M. and Odean, T. (1999). The courage of misguided convictions. *Financial Analysts Journal*, 55(6):41–55.

Barndorff-Nielsen, O. E., Kinnebrock, S., and Shephard, N. (2008). Measuring downside risk-realised semivariance.

Barndorff-Nielsen, O. E. and Shephard, N. (2004a). Econometric Analysis of Realized Covariation: High Frequency Based Covariance, Regression, and Correlation in Financial Economics. *Econometrica*, 72(3):885–925.

Barndorff-Nielsen, O. E. and Shephard, N. (2004b). Power and Bipower Variation with Stochastic Volatility and Jumps. *Journal of Financial Econometrics*, 2(1):1–37.

Barndorff-Nielsen, O. E. and Shephard, N. (2005). Variation, jumps, market frictions and high frequency data in financial econometrics.

Barndorff-Nielsen, O. E. and Shephard, N. (2006). Econometrics of Testing for Jumps in Financial Economics Using Bipower Variation. *Journal of Financial Econometrics*, 4(1):1–30.

Baruník, J., Kočenda, E., and Vácha, L. (2016). Asymmetric connectedness on the us stock market: Bad and good volatility spillovers. *Journal of Financial Markets*, 27:55–78.

Batten, J. A. and Vo, X. V. (2014). Liquidity and return relationships in an emerging market. *Emerging Markets Finance and Trade*, 50(1):5–21.

Bekaert, G., Harvey, C. R., and Lundblad, C. (2007). Liquidity and expected returns: Lessons from emerging markets. *Review of Financial Studies*, 20(6):1783–1831.

Benoit, S., Colliard, J.-E., Hurlin, C., and Pérignon, C. (2016). Where the risks lie: A survey on systemic risk. *Review of Finance*, page rfw026.

Bhattacharya, K., Sarkar, N., and Mukhopadhyay, D. (2003). Stability of the day of the week effect in return and in volatility at the indian capital market: a garch approach with proper mean specification. *Applied Financial Economics*, 13(8):553–563.

Bhattacharya, S. and Gale, D. (1985). Preference shocks, liquidity, and central bank policy. *Liquidity and Crises*, 35.

Bianconi, M., Yoshino, J. A., and de Sousa, M. O. M. (2011). BRIC and the U.S. Financial Crisis: An Empirical Investigation of Stocks and Bonds Markets. Discussion Papers Series, Department of Economics, Tufts University 0764, Department of Economics, Tufts University.

Bikker, J. A. and Haaf, K. (2002). Competition, concentration and their relationship: An empirical analysis of the banking industry. *Journal of Banking & Finance*, 26(11):2191–2214.

Billio, M., Getmansky, M., Lo, A. W., and Pelizzon, L. (2012). Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics*, 104(3):535–559.

BIS (2013). ITriennial Central Bank Survey: Foreign Exchange Turnover in April 2013: Preliminary Global Results. Report, Bank for International Settlements.

Bisias, D., Flood, M. D., Lo, A. W., and Valavanis, S. (2012). A survey of systemic risk analytics. *US Department of Treasury, Office of Financial Research*, (0001).

Black, A., Chen, J., Gustap, O., and Williams, J. M. (2012). The Importance of Jumps in Modelling Volatility during the 2008 Financial Crisis. Technical report.

Black, F., Jensen, M. C., and Scholes, M. S. (1972). *Studies in the Theory of Capital Markets*, chapter The Capital Asset Pricing Model: Some Empirical Tests. Praeger Publishers Inc.

Bollerslev, T., Engle, R. F., and Wooldridge, J. M. (1988). A Capital Asset Pricing Model with Time-varying Covariances. *Journal of Political Economy*, pages 116–131.

Bollerslev, T., Law, T. H., and Tauchen, G. (2008). Risk, jumps, and diversification. *Journal of Econometrics*, 144(1):234–256.

Bollerslev, T., Li, S. Z., and Todorov, V. (2016). Roughing up beta: Continuous versus discontinuous betas and the cross section of expected stock returns. *Journal of Financial Economics*, 120(3):464–490.

Bollerslev, T. and Zhang, B. Y. (2003). Measuring and Modeling Systematic Risk in Factor Pricing Models Using High-frequency Data. *Journal of Empirical Finance*, 10(5):533–558.

Bollerslev, T. and Zhou, H. (2002). Estimating stochastic volatility diffusion using conditional moments of integrated volatility. *Journal of Econometrics*, 109(1):33–65.

Bondt, W. F. and Thaler, R. (1985). Does the stock market overreact? *The Journal of Finance*, 40(3):793–805.

Bormetti, G., Calcagnile, L. M., Treccani, M., Corsi, F., Marmi, S., and Lillo, F. (2015). Modelling systemic price cojumps with hawkes factor models. *Quantitative Finance*, (ahead-of-print):1–20.

Boudt, K. and Petitjean, M. (2014). Intraday liquidity dynamics and news releases around price jumps: Evidence from the djia stocks. *Journal of Financial Markets*, 17:121–149.

Buchanan, B. G., English II, P. C., and Gordon, R. (2011). Emerging Market Benefits, Investability and the Rule of Law. *Emerging Markets Review*, 12(1):47–60.

Buiter, W. and Rahbeir, E. (2012). Debt, Financial Crisis and Economic Growth. In *Conference on Monetary Policy and the Challenge of Economic Growth at the South Africa Reserve Bank, Pretoria, South Africa, November*, pages 1–2.

Chang, E. C., Pinegar, J. M., and Ravichandran, R. (1993). International evidence on the robustness of the day-of-the-week effect. *Journal of Financial and Quantitative Analysis*, 28(04):497–513.

Chopra, N., Lakonishok, J., and Ritter, J. R. (1992). Measuring abnormal performance:

do stocks overreact? *Journal of Financial Economics*, 31(2):235–268.

Chordia, T., Roll, R., and Subrahmanyam, A. (2002). Order imbalance, liquidity, and market returns. *Journal of Financial Economics*, 65(1):111–130.

Chordia, T. and Subrahmanyam, A. (2004). Order imbalance and individual stock returns: Theory and evidence. *Journal of Financial Economics*, 72(3):485–518.

Choudhry, T. (2000). Day of the week effect in emerging asian stock markets: evidence from the garch model. *Applied Financial Economics*, 10(3):235–242.

Chowdhury, B. (2014). Continuous and Discontinuous Beta Estimation Using High Frequency Data: Evidence from Japan. manuscript.

Christensen, K., Oomen, R. C., and Podolskij, M. (2014). Fact or friction: Jumps at ultra high frequency. *Journal of Financial Economics*, 114(3):576–599.

Copeland, T. E. and Galai, D. (1983). Information effects on the bid-ask spread. *The Journal of Finance*, 38(5):1457–1469.

Corsi, F. (2004). A simple long memory model of realized volatility. *Available at SSRN 626064*.

Corsi, F. (2009). A simple approximate long-memory model of realized volatility. *Journal of Financial Econometrics*, 7:174–196.

Corsi, F., Pirino, D., and Reno, R. (2010). Threshold bipower variation and the impact of jumps on volatility forecasting. *Journal of Econometrics*, 159(2):276–288.

Cox, J. C. and Ross, S. A. (1976). The valuation of options for alternative stochastic processes. *Journal of Financial Economics*, 3(1-2):145–166.

Cremers, M., Halling, M., and Weinbaum, D. (2015). Aggregate jump and volatility risk in the cross-section of stock returns. *The Journal of Finance*, 70(2):577–614.

Crotty, J. (2009). Structural causes of the global financial crisis: a critical assessment of the "new financial architecture". *Cambridge Journal of Economics*, 33(4):563–580.

Cui, J. and Zhao, H. (2015). Intraday jumps in China's Treasury bond market and macro news announcements. *International Review of Economics & Finance*.

Demirgüç-Kunt, A. and Levine, R. (1996). Stock markets, corporate finance, and economic growth: an overview. *The World Bank Economic Review*, pages 223–239.

Diebold, F. X. and Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal*, 119(534):158–171.

Diebold, F. X. and Yılmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, 182(1):119–134.

Driessen, J. and Maenhout, P. (2013). The world price of jump and volatility risk. *Journal of Banking & Finance*, 37(2):518–536.

Dubois, M. and Louvet, P. (1996). The day-of-the-week effect: The international evidence. *Journal of Banking & Finance*, 20(9):1463–1484.

Duffie, D. and Pan, J. (2001). Analytical value-at-risk with jumps and credit risk. *Finance and Stochastics*, 5(2):155–180.

Dumitru, A.-M. and Urga, G. (2012). Identifying jumps in financial assets: a comparison between nonparametric jump tests. *Journal of Business & Economic Statistics*, 30(2):242–255.

Dungey, M., Fakhrutdinova, L., and Goodhart, C. (2009a). After-hours trading in equity futures markets. *Journal of Futures Markets*, 29(2):114–136.

Dungey, M., Harvey, J., and Volkov, V. (2017). The changing international network of sovereign debt and finanicial institutions.

Dungey, M., McKenzie, M., and Smith, V. (2009b). Empirical Evidence on Jumps in the Term Structure of the US Treasury Market. *Journal of Empirical Finance*, 16:430–445.

Dungey, M., Milunovich, G., Thorp, S., and Yang, M. (2015). Endogenous crisis dating and contagion using smooth transition structural garch. *Journal of Banking and Finance*, 58:71–79.

Easley, D. and O'Hara, M. (1987). Price, trade size, and information in securities markets. *Journal of Financial Economics*, 19(1):69–90.

Edmans, A. (2009). Blockholder trading, market efficiency, and managerial myopia. *The Journal of Finance*, 64(6):2481–2513.

Evans, K. P. (2011). Intraday jumps and us macroeconomic news announcements. *Journal of Banking & Finance*, 35(10):2511–2527.

Fabozzi, F. J. and Francis, J. C. (1978). Beta as a Random Coefficient. *Journal of Financial and Quantitative Analysis*, 13(01):101–116.

Faff, R., Ho, Y. K., and Zhang, L. (1998). A Generalised Method Of Movements (GMM) Test Of The Three-Moment Capital Asset Pricing Model (CAPM) In The Australian Equity Market. *Asia Pacific Journal of Finance*, 1:45–60.

Fama, E. F. and French, K. R. (1993). Common Risk Factors in the Returns on Stocks and Bonds. *Journal of Financial Economics*, 33(1):3–56.

Fama, E. F. and MacBeth, J. D. (1973). Risk, Return, and Equilibrium: Empirical Tests. *Journal of Political Economy*, 81(3):pp. 607–636.

Fang, V. W., Noe, T. H., and Tice, S. (2009). Stock market liquidity and firm value. *Journal of Financial Economics*, 94(1):150–169.

Fleming, J., Kirby, C., and Ostdiek, B. (2003). The economic value of volatility timing using "realized" volatility. *Journal of Financial Economics*, 67(3):473–509.

Fraser, P., Hamelink, F., Hoesli, M., and MacGregor, B. (2000). *Time-varying Betas and Cross-sectional Return-risk Relation: Evidence from the UK*. Université de Genève, Faculté des sciences économiques et sociales, Section des hautes études commerciales.

Freixas, X., Parigi, B. M., and Rochet, J.-C. (2000). Systemic risk, interbank relations, and liquidity provision by the central bank. *Journal of Money, Credit and Banking*, pages 611–638.

French, K. R. (1980). Stock returns and the weekend effect. *Journal of Financial Economics*, 8(1):55–69.

Friend, I. and Westerfield, R. (1980). Co-skewness and Capital Asset Pricing. *The Journal of Finance*, 35(4):897–913.

Frömmel, M., Han, X., and Van Gysegem, F. (2013). News, liquidity dynamics and intraday jumps: evidence from the huf/eur market. *Faculteit economie en bedrijfskunde: working papers (2013)*, 2013:1–51.

Gauba, R. (2012). The indian banking industry: Evolution, transformation & the road ahead. *Pacific Business Review International*, 5(1):85–97.

Gauthier, C., Lehar, A., and Souissi, M. (2012). Macroprudential capital requirements and systemic risk. *journal of Financial Intermediation*, 21(4):594–618.

Gupta, R. and Jayadev, M. (2016). Business strategy and systemic risk-evidence from indian banks.

Haldane, A. G. and May, R. M. (2011). Systemic risk in banking ecosystems. *Nature*, 469(7330):351–355.

Hanousek, J. and Novotný, J. (2012). Price Jumps in Visegrad-country Stock Markets: An Empirical Analysis. *Emerging Markets Review*, 13(2):184–201.

Harvey, C. R. and Siddique, A. (2000). Conditional Skewness in Asset Pricing Tests. *The Journal of Finance*, 55(3):1263–1295.

Huang, X. and Tauchen, G. (2005). The Relative Contribution of Jumps to Total Price Variance. *Journal of Financial Econometrics*, 3(4):456–499.

Jacod, J. and Todorov, V. (2009). Testing for common arrivals of jumps for discretely observed multidimensional processes. *The Annals of Statistics*, pages 1792–1838.

Jaffe, J. and Westerfield, R. (1989). Is there a monthly effect in stock market returns?: Evidence from foreign countries. *Journal of Banking & Finance*, 13(2):237–244.

Jarrow, R. A. and Rosenfeld, E. R. (1984). Jump risks and the intertemporal capital asset pricing model. *Journal of Business*, pages 337–351.

Jermann, U. and Quadrini, V. (2012). Macroeconomic effects of financial shocks. *The American Economic Review*, 102(1):238–271.

Jiang, G. J., Lo, I., and Verdelhan, A. (2011). Information shocks, liquidity shocks, jumps, and price discovery: Evidence from the us treasury market. *Journal of Financial and Quantitative Analysis*, 46(02):527–551.

Jiang, G. J. and Oomen, R. C. (2008). Testing for jumps when asset prices are observed with noise: a swap variance approach. *Journal of Econometrics*, 144(2):352–370.

Jorion, P. (1988). On jump processes in the foreign exchange and stock markets. *Review of Financial Studies*, 1(4):427–445.

Karolyi, G. A. (2012). Corporate governance, agency problems and international cross-listings: A defense of the bonding hypothesis. *Emerging Markets Review*, 13(4):516–547.

Kim, O. and Verrecchia, R. E. (1991). Trading volume and price reactions to public announcements. *Journal of Accounting Research*, pages 302–321.

Kim, S.-J. and Wu, E. (2008). Sovereign credit ratings, capital flows and financial sector development in emerging markets. *Emerging Markets Review*, 9(1):17–39.

Kraus, A. and Litzenberger, R. H. (1976). Skewness Preference and the Valuation of Risk Assets. *The Journal of Finance*, 31(4):1085–1100.

Kyle, A. S. (1985). Continuous auctions and insider trading. *Econometrica: Journal of the Econometric Society*, pages 1315–1335.

Kyle, A. S. and Vila, J.-L. (1991). Noise trading and takeovers. *The RAND Journal of Economics*, pages 54–71.

Laeven, L. and Valencia, F. (2013). Systemic banking crises database. *IMF Economic Review*, 61(2):225–270.

Lahaye, J., Laurent, S., and Neely, C. J. (2011). Jumps, Cojumps and Macro Announcements. *Journal of Applied Econometrics*, 26(6):893–921.

Lee, S. S. and Mykland, P. A. (2008). Jumps in financial markets: a new nonparametric test and jump dynamics. *Review of Financial Studies*, 21(6):2535–2563.

Lesmond, D. A. (2005). Liquidity of emerging markets. *Journal of Financial Economics*, 77(2):411–452.

Liao, Y., Anderson, H. M., and Vahid, F. (2010). Do Jumps Matter? Forecasting Multivariate Realized Volatility allowing for Common Jumps. Technical Report 11/10, Monash University, Department of Econometrics and Business Statistics.

Lintner, J. (1965). The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. *Review of Economics and Statistics*, 47(1):pp. 13–37.

Liu, J., Longstaff, F. A., and Pan, J. (2003). Dynamic asset allocation with event risk. *The Journal of Finance*, 58(1):231–259.

Liu, W. (2006). A liquidity-augmented capital asset pricing model. *Journal of Financial Economics*, 82(3):631–671.

Mancini, C. (2009). Non-parametric threshold estimation for models with stochastic diffusion coefficient and jumps. *Scandinavian Journal of Statistics*, 36(2):270–296.

Maug, E. (1998). Large shareholders as monitors: Is there a trade-off between liquidity and control? *The Journal of Finance*, 53(1):65–98.

Meh, C. A. and Moran, K. (2010). The role of bank capital in the propagation of shocks. *Journal of Economic Dynamics and Control*, 34(3):555–576.

Mensah, J. O. and Premaratne, G. (2017). Systemic interconnectedness among asian banks. *Japan and the World Economy*, 41:17–33.

Mensi, W., Hammoudeh, S., Reboredo, J. C., and Nguyen, D. K. (2014). Do Global

Factors Impact BRICS Stock Markets? A Quantile Regression Approach. *Emerging Markets Review*, 19(C):1–17.

Merton, R. C. (1976). Option pricing when underlying stock returns are discontinuous. *Journal of Financial Economics*, 3:125 – 144.

Michaely, R., Rubin, A., and Vedrashko, A. (2013). Corporate governance and the timing of earnings announcements. *Review of Finance*, 18(6):2003–2044.

Mor, N., Chandrasekar, R., and Wahi, D. (2006). *China and India Learning From Each Other Reforms and Policies for Sustained Growth*. Washington: International Monetary Fund, Publication Services.

Morgan, D. P. (2000). Rating banks: Risk and uncertainty in an opaque industry. *FRB of New York Staff Report*, (105).

Novotný, J., Hanousek, J., and Kočenda, E. (2013). Price Jump Indicators: Stock Market Empirics During the Crisis. William Davidson Institute Working Papers Series wp1050, William Davidson Institute at the University of Michigan.

Patton, A. J. and Verardo, M. (2012). Does beta move with news? Firm-specific information flows and learning about profitability. *Review of Financial Studies*, 25:2789–2839.

Prasad, A., Ghosh, S., et al. (2007). Competition in indian banking. *South Asia Economic Journal*, 8(2):265–284.

Press, S. J. (1967). A compound events model for security prices. *Journal of Business*, pages 317–335.

Raj, M. and Kumari, D. (2006). Day-of-the-week and other market anomalies in the indian stock market. *International Journal of Emerging Markets*, 1(3):235–246.

Rathinam, F. X. and Raja, A. V. (2010). Law, Regulation and Institutions for Financial Development: Evidence from India. *Emerging Markets Review*, 11(2):106–118.

Ratti, M. (2012). Indian financial system & indian banking sector: A descriptive research study. *International Journal of Management and Social Science Research*, 1:3–8.

Ross, S. A. (1976). The Arbitrage Theory of Capital Asset Pricing. *Journal of Economic Theory*, 13(3):341–360.

Schwert, M. (2009). Hop, skip and jump-what are modern'jump'tests finding in stock returns? *Available at SSRN 1648986*.

Sen, R. and Mehrotra, P. (2016). Modeling jumps and volatility of the indian stock market using high-frequency data. *Journal of Quantitative Economics*, 14(1):137–150.

Shahzad, H., Duong, H. N., Kalev, P. S., and Singh, H. (2014). Trading volume, realized volatility and jumps in the australian stock market. *Journal of International Financial Markets, Institutions and Money*, 31:414–430.

Sharpe, W. F. (1964). Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk. *The Journal of Finance*, 19(3):425–442.

Sheskin, D. J. (2003). *Handbook of parametric and nonparametric statistical procedures.* CRC Press.

Statman, M., Thorley, S., and Vorkink, K. (2006). Investor overconfidence and trading volume. *Review of Financial Studies*, 19(4):1531–1565.

Subrahmanyam, A. and Titman, S. (2001). Feedback from stock prices to cash flows. *The Journal of Finance*, 56(6):2389–2413.

Theodosiou, M. and Zikes, F. (2009). A comprehensive comparison of alternative tests for jumps in asset prices. *Imperial College London*.

Todorov, V. and Bollerslev, T. (2010). Jumps and Betas: A New Framework for Disentangling and Estimating Systematic Risks. *Journal of Econometrics*, 157(2):220–235.

Yan, S. (2011). Jump risk, stock returns, and slope of implied volatility smile. *Journal of Financial Economics*, 99(1):216–233.

Zhou, H. and Zhu, J. Q. (2012). An Empirical Examination of Jump Risk in Asset Pricing and Volatility Forecasting in China's Equity and Bond Markets. *Pacific-Basin Finance Journal*, 20(5):857–880.