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Abstract

Using high-frequency stock returns in the Indian banking sector we find that the beta on jump movements substantially exceeds that on the continuous component, and that the majority of the information content for returns lies with the jump beta. We contribute to the debate on strategies to decrease systemic 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.

High Frequency Characterization of Indian Banking Stocks

1. Introduction

The risk of an investment is typically divided into two parts: idiosyncratic risk and systematic risk which results from exposure 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 paper 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 21st 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 2012, 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 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 also 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 a significantly higher jump beta (but not continuous beta) in line with the hypothesis that these firms may be taking more risk to achieve these profits.

The rest of the paper is organized as follows. Section 2 reviews the literature related to the decomposition of CAPM and Sections 3 elaborates the methodology employed for jump detection and beta estimation. We outline data collection and cleaning process along with choices of calibrated parameter value in Section 4. Section 5 discusses the results of the empirical analysis and Section 6 concludes.

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 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 paper takes the approach of decomposing the price process into a continuous and jump component consistent with recent evidence (see Andersen et al., 2007; Barndorff-Nielsen and Shephard, 2004*b*, 2006; Huang and Tauchen, 2005; Dungey et al., 2009; 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:

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

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 β_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:

$$r_i = \alpha_i + \beta_i^c r_0^c + \beta_i^d r_0^d + \varepsilon_i, \quad \text{for} \quad i = 1, \ldots, N, \tag{2}$$

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 β_i^c, and jump beta β_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, 2004*a*; Patton and Verardo, 2012), allows estimation of β_i^c, and jump beta β_i^d using the methods proposed in Todorov and Bollerslev (2010).

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

$$dp_t = \mu_t dt + \sigma_t dW_t + \kappa_t dq_t, \qquad 0 \le t \le T, \tag{3}$$

where μ_t is the drift term, σ_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. κ_t is the size of the jump at time t. The quadratic variation for the process in (3) is defined as

$$QV^{[0,T]} = \int_0^T \sigma_s^2 \mathrm{d}s + \sum_{0<s\le T} \kappa_s^2. \tag{4}$$

In practice, we can only observe the asset price at discrete time intervals, say, every Δ^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),

$$RV^{[0,T]} = \sum_{j=1}^{[T/\Delta^n]} |\Delta_j^n p|^2 \xrightarrow{p} QV^{[0,T]} \quad \text{as} \quad \Delta^n \to 0. \tag{5}$$

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

$$BV^{[0,T]} = \mu^{-2} \sum_{j=2}^{[T/\Delta^n - 1]} |\Delta_j^n p||\Delta_{j+1}^n p|, \tag{6}$$

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,

$$RV^{[0,T]} - BV^{[0,T]} \xrightarrow{p} \sum_{0<s\le T} \kappa_s^2 \quad \text{as} \quad \Delta^n \to 0. \tag{7}$$

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

$$\hat{\mathcal{J}} = \frac{1}{\sqrt{\Delta^n}} \cdot \frac{1}{\sqrt{\theta \cdot \max(1/T, DV^{[0,T]}/(BV^{[0,T]})^2)}} \cdot \left(\frac{BV^{[0,T]}}{RV^{[0,T]}} - 1 \right), \tag{8}$$

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 (8) follows a standard normal distribution asymptotically. Therefore, under the null of no jumps,

$$\hat{\mathcal{J}} \xrightarrow{L} \mathcal{N}(0,1) \quad \text{as} \quad \Delta^n \to 0. \tag{9}$$

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 β_i^c and β_i^d in (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, β_i^c can be expressed as

$$\beta_i^c = \frac{[p_i^c, p_0^c]_{(0,T]}}{[p_0^c, p_0^c]_{(0,T]}}, \qquad i = 1, \ldots, N. \tag{10}$$

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

$$\hat{\beta}_i^c = \frac{\sum_{j=1}^{[T/\Delta^n]} \Delta_j^n p_i \Delta_j^n p_0 \mathbb{1}_{\{|\Delta_j^n p| \le u_n\}}}{\sum_{j=1}^{[T/\Delta^n]} (\Delta_j^n p_0)^2 \mathbb{1}_{\{|\Delta_j^n p| \le u_n\}}}, \quad i = 1, \ldots, N, \tag{11}$$

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 $|\Delta_j^n p| \le u_n$. 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 α_i.

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

$$\beta_i^d = \text{sign}\left\{\sum_{s\leq T}\text{sign}\{\Delta p_i\Delta p_{0,s}\}|\Delta p_{i,s}\Delta p_{0,s}|^{\tau}\right\} \times \left(\frac{|\sum_{s\leq T}\text{sign}\{\Delta p_{i,s}\Delta p_{0,s}\}|\Delta p_{i,s}\Delta p_{i,s}|^{\tau}|}{\sum_{s\leq T}|\Delta p_{0,s}|^{2\tau}}\right)^{\frac{1}{\tau}}. \tag{12}$$

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

$$\hat{\beta}_i^d = \text{sign}\left\{\sum_{j=1}^{[T/\Delta^n]}\text{sign}\{\Delta_j^n p_i\Delta_j^n p_0\}|\Delta_j^n p_i\Delta_j^n p_0|^{\tau}\right\} \times \left(\frac{|\sum_{j=1}^{[T/\Delta^n]}\text{sign}\{\Delta_j^n p_{i,s}\Delta_j^n p_0\}|\Delta_j^n p_i\Delta_j^n p_0|^{\tau}|}{\sum_{j=1}^{[T/\Delta^n]}|\Delta_j^n p_0|^{2\tau}}\right)^{\frac{1}{\tau}}, \tag{13}$$

where $i = 1, \ldots, N$, and the power τ 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 $\hat{\beta}_i^d$.

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, 2012. We collate data on 5-minute stock returns for 41 commercial banks listed on the

National Stock Exchange of India (NSE) shown in Table 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 US$ 0.99 billion.

The sampling frequency of 5 minutes is relatively standard in the high frequency literature, posing 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.

Table 1: Banks listed on the 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			

We use the last price recorded in each of the 5-minute intervals from 9:15am to 3:30pm 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, the first 5-minute intervals is 9.30

am to 9.35 am and we capture 72 price observations on each trading day. To represent the market index we use the CNX500 index, which represents 96.76% of the free float market capitalization of stocks listed on the NSE, as the benchmark portfolio.

We apply the calibrated parameter values implemented by Todorov and Bollerslev (2010) and Alexeev et al. (2014). Following those authors we estimate both daily and monthly betas, so that $T = 1$ represents one day in the first case and one month in the second. As Δ^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, Δ^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 (12) follows Todorov and Bollerslev (2010).

5. Empirical analysis

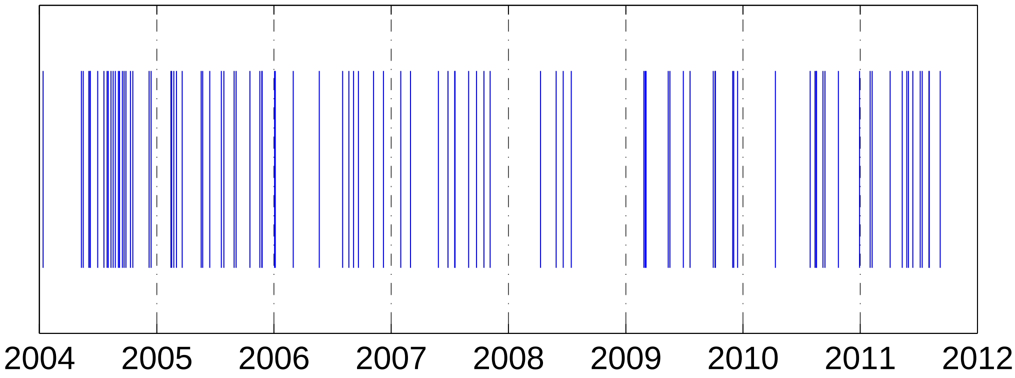
The first step in the empirical analysis is to determine the existence of jumps in the Indian market. Table 2 reports the descriptive statistics of the two daily volatility measures RV and BV of the CNX500 and Figure 1 depicts the occurrence of jump days detected using the BNS test in the market index throughout the sample period 2004 – 2012.

Table 2: Volatility measures for Indian market during the sample period 2004 – 2012

Descriptive	Daily		Monthly	
Statistics	$\sqrt{RV}$	$\sqrt{BV}$	$\sqrt{RV}$	$\sqrt{BV}$
Mean	0.00921	0.00881	0.04705	0.04404
Median	0.00792	0.00752	0.03822	0.03641
Std. Dev.	0.00644	0.00604	0.02607	0.02201
Maximum	0.09633	0.07384	0.16732	0.12823

Within our sample period from 2004 to 2012, we find 105 jump days out of 2,165 trading days in the market index, that is in 4.85% of our sampled trading days. This percentage is

Figure 1: The occurrence of jump days detected with the BNS test in the CNX500 index



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. (2014) who apply the same test statistic in (8) to the US market. We can not 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 108 months in our sample, 64 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 in the last three years in our sample period (9, 12 and 9 days, respectively); see Figure 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. (2014) 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.

5.1. Betas for the Indian banks

Table 3 shows 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).[2] 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 eight banks, AXBK, BOI, DCBA, DENA, ICBK, IDBI, SBI and VJBK 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 0.09. Standard Chartered Bank is the only foreign bank in our data set, which can be a reason why it is more resilient to movements in the domestic Indian market.[3]

Of the 41 banks in our sample, 37 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

Table 3: Average continuous and jump betas for listed Indian Banks

Banks	β_i^c		β_i^d		Difference (%)
ADBK	0.83	[0.75,0.91]	1.35	[1.34,1.37]	62.36
ALBK	0.82	[0.74,0.90]	1.44	[1.42,1.45]	75.68
AXBK	1.04	[0.96,1.12]	1.43	[1.41,1.45]	37.48
BMBK	0.49	[0.41,0.58]	1.22	[1.21,1.24]	147.82
BOB	0.94	[0.86,1.02]	1.52	[1.50,1.54]	61.21
BOI	1.11	[1.02,1.19]	1.66	[1.64,1.67]	49.47
CBI	0.80	[0.71,0.88]	1.46	[1.44,1.48]	82.90
CNBK	0.96	[0.88,1.04]	1.60	[1.58,1.61]	66.66
CRBK	0.38	[0.29,0.47]	1.15	[1.13,1.17]	203.33
CTBK	0.36	[0.27,0.45]	1.08	[1.06,1.11]	200.50
DCBA	1.18	[1.09,1.27]	1.92	[1.90,1.94]	63.38
DENA	1.05	[0.96,1.13]	1.68	[1.67,1.70]	60.86
DNBK	0.43	[0.32,0.53]	0.99	[0.96,1.02]	131.60
FED	0.61	[0.53,0.69]	1.30	[1.29,1.32]	113.98
HDBK	0.67	[0.59,0.74]	1.16	[1.15,1.17]	74.24
ICBK	1.02	[0.94,1.09]	1.49	[1.48,1.50]	46.87
IDBI	1.17	[1.09,1.25]	1.74	[1.72,1.76]	48.65
INBA	0.66	[0.57,0.75]	1.33	[1.31,1.35]	101.56
INBK	0.94	[0.85,1.03]	1.68	[1.67,1.70]	78.73
IOBK	0.80	[0.71,0.88]	1.45	[1.43,1.47]	82.10
JKBK	0.27	[0.18,0.36]	0.95	[0.93,0.97]	250.30
KARU	0.23	[0.15,0.32]	0.81	[0.79,0.83]	247.34
KBNK	0.75	[0.66,0.83]	1.56	[1.54,1.58]	108.28
KTKM	0.87	[0.79,0.96]	1.43	[1.40,1.45]	62.95
LVLS	0.39	[0.29,0.48]	1.12	[1.10,1.14]	190.69
ORBC	0.83	[0.74,0.91]	1.51	[1.49,1.53]	82.75
PNBK	0.90	[0.82,0.98]	1.47	[1.46,1.49]	64.01
PUNA	0.28	[0.20,0.36]	1.12	[1.12,1.13]	302.26
SBI	1.01	[0.94,1.08]	1.44	[1.43,1.45]	42.82
SBKB	0.22	[0.14,0.31]	1.13	[1.11,1.14]	401.77
SBKM	0.14	[0.05,0.24]	1.08	[1.07,1.09]	649.07
SBKT	0.22	[0.13,0.31]	1.24	[1.24,1.25]	461.71
SBNK	0.94	[0.86,1.03]	1.69	[1.68,1.71]	79.09
SIBK	0.48	[0.39,0.57]	1.19	[1.17,1.21]	149.17
STNCy	0.09	[0.00,0.17]	0.63	[0.62,0.64]	631.51
UBOI	0.54	[0.45,0.63]	1.36	[1.35,1.37]	153.14
UCBK	0.97	[0.88,1.05]	1.55	[1.53,1.56]	59.91
UNBK	0.91	[0.82,1.00]	1.58	[1.56,1.60]	73.77
VJBK	1.00	[0.92,1.08]	1.58	[1.57,1.60]	58.67
VYSA	0.29	[0.19,0.38]	1.10	[1.08,1.13]	285.77
YESB	0.91	[0.83,1.00]	1.49	[1.47,1.50]	62.58

very low continuous beta, followed by KARU (0.81).

The jump betas of all banks are on average 151% percent higher than their continuous betas, and the columns of average confidence intervals of continuous and jump betas in Table 3 show that there is no overlap between the confidence intervals of $\hat{\beta}_i^c$ann $\hat{\beta}_i{}^d$ for any bank. This supports the hypothesis that the continuous and jump betas in the augmented CAPM specification of equation (2) differ, and that a single factor CAPM model may miss information which is important for effective portfolio diversification and pricing. As an exemplar consider the confidence intervals for the average continuous and jump beta for all banks depicted in Figure 2, and for the State Bank of India, the largest Indian bank, in Figure 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 2012 for SBI, while the jump beta has both higher values and relatively higher variability than the continuous beta in both figures.

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

$$dp_{i,t} = \delta + \phi_h \hat{\beta}_{i,t}^h + v_{i,t}, \tag{14}$$

which we extend to incorporate the separation of market returns into continuous and jump components below:

$$dp_{i,t} = \delta + \phi_c \hat{\beta}_{i,t}^c + \phi_d \hat{\beta}_{i,t}^d + \omega_{i,t}, \tag{15}$$

where dp_i indicates stock returns, $\hat{\beta}_i^h$ in equation (14) is the estimated single factor CAPM beta, and $\hat{\beta}_i^c$, and $\hat{\beta}_i^d$ in equation (15) denote the estimated continuous and jump betas, respectively. The models should produce a constant value, δ, equal to the risk free rate, and

Figure 2: Confidence interval of average monthly $\hat{\beta}_i^c$ and $\hat{\beta}_i^d$ of all banks

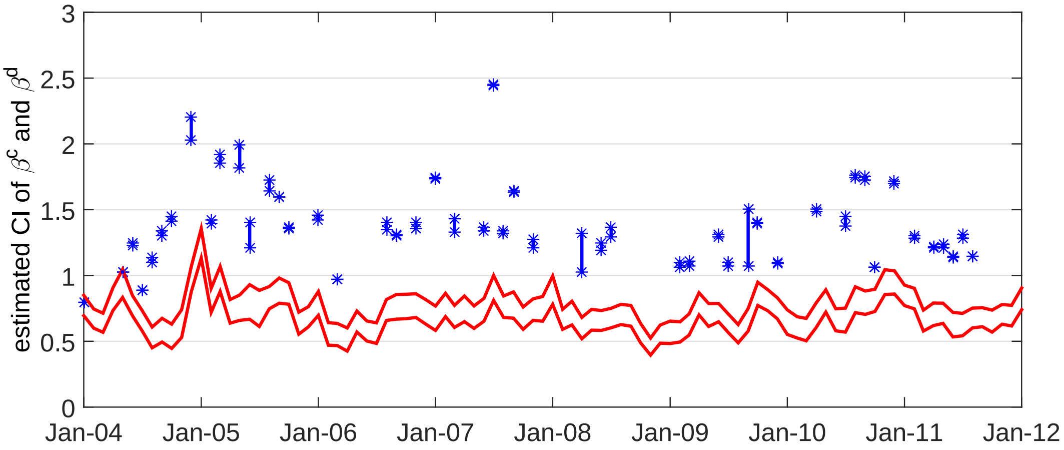
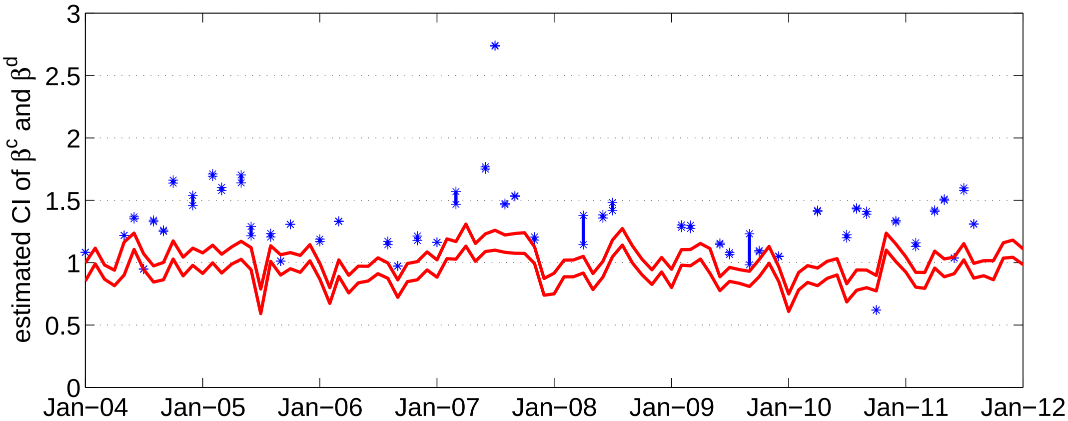


Figure 3: Confidence interval of monthly $\hat{\beta}_i^c$ and $\hat{\beta}_i^d$ of SBI from 2004 to 2012



the coefficients on the beta estimates, ϕ'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 average values of the estimated standard CAPM betas $\hat{\beta}_{i,t}^h$ for Indian banks are shown in Table 4. 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 0.87, while the average continuous beta is 0.69 and average jump beta is 1.36.

Table 4: Average monthly continuous, jump and standard CAPM betas for Indian banks

Bank	$\hat{\beta}_i^c$	$\hat{\beta}_i^d$	$\hat{\beta}_i^h$	Bank	$\hat{\beta}_i^c$	$\hat{\beta}_i^d$	$\hat{\beta}_i^h$
ADBK	0.83	1.35	1.03	KARU	0.23	0.81	0.33
ALBK	0.82	1.44	1.01	KBNK	0.75	1.56	0.96
AXBK	1.04	1.43	1.18	KTKM	0.87	1.43	1.03
BMBK	0.49	1.22	0.67	LVLS	0.39	1.12	0.55
BOB	0.94	1.52	1.13	ORBC	0.83	1.51	1.04
BOI	1.11	1.66	1.30	PNBK	0.90	1.47	1.07
CBI	0.80	1.46	0.98	PUNA	0.28	1.12	0.47
CNBK	0.96	1.60	1.16	SBI	1.01	1.44	1.14
CRBK	0.38	1.15	0.54	SBKB	0.22	1.13	0.42
CTBK	0.36	1.08	0.51	SBKM	0.14	1.08	0.31
DCBA	1.18	1.92	1.40	SBKT	0.22	1.24	0.39
DENA	1.05	1.68	1.25	SBNK	0.94	1.69	1.19
DNBK	0.43	0.99	0.60	SIBK	0.48	1.19	0.63
FED	0.61	1.30	0.79	STNCy	0.09	0.63	0.16
HDBK	0.67	1.16	0.78	UBOI	0.54	1.36	0.74
ICBK	1.02	1.49	1.16	UCBK	0.97	1.55	1.19
IDBI	1.17	1.74	1.36	UNBK	0.91	1.58	1.13
INBA	0.66	1.33	0.84	VJBK	1.00	1.58	1.21
INBK	0.94	1.68	1.15	VYSA	0.29	1.10	0.43
IOBK	0.80	1.45	1.01	YESB	0.91	1.49	1.09
JKBK	0.27	0.95	0.39				

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 (14) and (15) are reported in Table 5. We find positive and significant coefficients of continuous, jump and CAPM betas in univariate regressions shown in models (1), (2) and (3). However, when we regress the stock returns on continuous and jump betas together as shown in model (4), although jump beta remains significant, the continuous beta no longer has a significant coefficient. [4]

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

Table 5: Impact of continuous and jump beta on stock returns

Variables	(1)	(2)	(3)	(4)
Constant	-0.022 (0.1097)	-0.20 (0.1204)	-0.049 (0.1371)	-0.21 (0.1300)
$\hat{\beta}_i^c$	0.28* (0.1226)			0.012 (0.1393)
$\hat{\beta}_i^d$		0.29** (0.0715)		0.28** (0.0815)
$\hat{\beta}_i^h$			0.26* (0.1229)	
Adjusted R^2	0.0036	0.014	0.0036	0.013
F-stat	5.03	20.81	6.03	10.40
DW stat	2.04		2.04	2.04

[a] Significance levels: † : 10%, ∗ : 5%, ∗∗ : 1%. Standard errors are displayed in parentheses below the coefficients.
[c] All models are estimated using pooled OLS regression with the dependent variable monthly stock returns. The number of banks included cross section is 23. The number of periods is 64. The total number of observations is 1472 after adjusted in each model for missing data.

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:

$$\hat{\beta}_{i,t} = \alpha + \sum_{i=1}^{m} \gamma X_{i,t} + u_{i,t}, \tag{16}$$

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, 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 6.

Table 6: Summary statistics of firm characteristics

	CAR	Lev	RoA	Size	RV
Mean	8.68	1.30	1.90	4.29	0.0105
Median	8.54	0.96	1.85	4.18	0.0077
Maximum	19.11	24.43	6.32	7.48	0.1877
Minimum	0	0.01	0.71	0.70	0
Std. Dev.	3.30	1.48	0.67	1.28	0.0120

[a] 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.

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 of equation (16) takes the following form:

$$\hat{\beta}_{i,t} = \alpha + \gamma_1 CAR_{i,t} + \gamma_2 Lev_{i,t} + \gamma_3 RoA_{i,t} + \gamma_4 Size_{i,t} + \gamma_5 Private_{i,t} + \gamma_6 RV_{i,t} + u_{i,t}, \qquad (17)$$

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 7 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 7 show that relationship between continuous beta and leverage is positive and significant, at the 10% significance level, while the relationship of continuous beta with CAR is negative and and significant at the 5% level. A decrease of one unit in the leverage ratio is estimated to lead to a decrease of 0.04 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 1.2 to 1 resulting in a decrease in continuous beta of 0.008. 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 8.6 to 9.6 results in a small 0.02 decrease in continuous beta.

Table 7: Relationship between firm characteristics and the betas

Variables	cont. beta	jump beta
Constant	0.42** (0.1316)	1.57** (0.1121)
CAR	-0.024** (0.0067)	-0.019** (0.0070)
Lev	0.047* (0.0217)	0.057** (0.0195)
RoA	-0.06* (0.0286)	-0.13** (0.0454)
Size	0.14** (0.0185)	0.055* (0.0242)
Private	-0.045 (0.0581)	0.07 (0.0658)
100RV	0.045** (0.0138)	-0.029 (0.0236)
AR(1)	0.76** (0.0253)	
Adjusted R^2	0.65	0.02
F-stat	478.30	5.04
DW stat	2.32	1.62

Significance levels: † : 10%, $*$: 5%, $**$: 1%. 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 108 for models of $\hat{\beta}^c_{i,t}$, and 64 for models of $\hat{\beta}^d_{i,t}$.

Profitability (RoA), size and volatility all have significant effects on continuous beta. The negative coefficient of RoA and positive coefficient of market capitalization indicate that banks of larger size but less profitability show higher sensitivities towards continuous market movements. 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 has no significant relationship with beta.

Each of the explanatory variables, leverage, CAR, RoA and size also have significant effects on jump beta – volatility, however, does not. The signs are the same as those for the continuous beta estimates; increased CAR and RoA reduce jump beta, while decreased leverage and size increase jump beta. The effects of CAR are slightly smaller than in the continuous case, 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. Interestingly the jump beta of more profitable firms is twice that of the continuous betas – profitability reduces the reaction to market discontinuities – providing evidence for the case that profitability provides a better buffer against these events. At the same time, the coefficient on size almost halves for jump betas compared with continuous betas. While in both continuous and jump beta cases larger, less profitable firms have lower betas than their comparator firms, in the continuous beta case this effect is mainly due to size effects (supporting the hypothesis that larger firms are less able to diversify away from the market) and in the jump beta case the effect is mainly due to RoA (supporting 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. (2014).

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.

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 small existing literature for the US in Todorov and Bollerslev (2010) and Alexeev et al. (2014) estimate higher jump beta than continuous beta. This paper confirms 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 2004-2012 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 4.85% 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 151%, 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 paper is correct the required reduction in leverage or increase in capital to produce a 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.

Notes

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

[2]Although we have calculated both daily and monthly time varying betas, in common with Todorov and Bollerslev (2010) and Alexeev et al. (2014) we find that the volatility in the daily beta estimates favours the use of the monthly betas for analysis.

[3]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.

[4]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.

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