Reserve Bank of India

OCCASIONAL PAPERS

Vol.38 - No. 1&2 2017

ISSN 0972 - 7493

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Price : Inland : ₹ 200
₹ 250 (inclusive of postage)
Foreign : US $ 18 (inclusive of air mail courier charges)

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Nowcasting Real Estate Activity in India using Google Trend Data

Pratik Mitra, Anirban Sanyal, Sohini Choudhuri*

Despite the real estate sector being among the major drivers of economic growth in India and contributing about 11 per cent to Gross Value Added(GVA) growth since 2011-12, non-availability of data in a timely manner hinders an objective assessment of the sector's performance. This paper attempts to bridge this gap by employing Big Data Analytics to nowcast the sales growth of real estate companies using Google search data. The paper concludes that the search intensity information improves precision relative to other benchmark approaches while nowcasting the current quarter sales.

JEL Classification : C32, C53, C55, C81

Keywords : Nowcasting, google trend, composite indicator, real estate

Introduction

In most emerging market economies (EMEs), the real estate sector has been an engine of growth and employment with both backward and forward linkages. In India, the growth of the real estate sector has averaged 14.8 per cent from 2011-12 to 2016-17, compared to 6.7 per cent average growth of GVA. Therefore, a fairly accurate assessment of the current state of the sector and its outlook assumes importance in policymaking. As the hard data are published with a considerable lag, information relating to the current quarter and sometimes even the previous quarter is not available at the time of, say, monetary policy meeting, let alone the union/state budget formation.

In India, the data on quarterly aggregate supply, measured by Gross Value Added (GVA), are released with a lag of sixty days after the end of the quarter. The data compilation process relating to quarterly GVA follows a

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benchmark indicator approach in which the available economic indicators are tracked to gauge the state of activity in different sectors. In the case of real estate, corporate results of listed companies are used by the Central Statistics Office (CSO) as coincident indicators (Central Statistics Office 2017).

In this context, the technique of 'nowcasting' assumes critical importance. It typically exploits either soft data like forward looking survey results or 'hard' indicators released at higher frequencies than the target variable of interest. With regard to the real estate sector, quarterly corporate results are reliable indicators for nowcasting real estate activities, but they face the same challenge of time lag as quarterly financial statements of corporates that are generally available with a lag of around forty-five days. Against this background, this paper explores the possibility of bridging the gap by introducing nowcasting sales growth of real estate companies using Google Search.[1]

From 2009, Google started disseminating search intensity data through the public interface of Google Trends. Following the seminal work of Choi and Varian (2012), a new branch of econometrics using Google Trends data has proliferated and examined the value added by Google Trends data while nowcasting labour market conditions, consumer sentiment, consumption outlook, housing market conditions, sales growth and inflation. Although advanced economies, especially the United States (US), have been the front runner in this context, research using Google search data for macroeconomic analysis and projections in the context of EMEs is scarce (Carrière-Swallow and Labbé, 2011). This paper seeks to correct this imbalance and is, to the best of our knowledge, a first in the Indian context. The paper demonstrates that the performance of nowcasted sales growth of the real estate sector improves[2] when search data are used in the analysis. Further, 'noise' in search data was found creating volatility in the predictor space, thereby highlighting the importance of keyword selection in the domain of Big Data Analytics.

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[1] The wide usage of Google has led to the word 'Google' being formally inducted as a synonym of searching in the English dictionary. It is the major internet search engine across countries. According to Internet Live Stats, more than 54,000 queries were fired every second over Google in 2016, each appending new data on search intensity across different keywords, thereby creating an information repository in the sphere of Big Data Analytics (Choi and Varian, 2012).

[2] The forecast precision has been assessed from the root mean square error (RMSE) of rolling forecast. Diebold-Mariano test for relative forecast accuracy has not been used due to small number of instances of rolling windows.

In this paper, we have used the dynamic factor model (DFM) to nowcast real estate sector growth. This kind of framework has been extensively employed in short-term forecasting since the early 1980s. The DFM, an extension of factor models, popularised by Gweke (1977) and Sargent and Sims (1977), is well equipped for extraction of the factors from a larger set of economic indicators that spans the information set into a lower dimensional space. Such a dimensionality reduction approach works well on an information set with a balanced panel. However, in reality, the data of different economic indicators are released at different point of time during a month, making it an unbalanced data set. Further, each data release also involves revision of the earlier released data points. Hence, the information set keeps getting updated with every data release. The jagged edge[3] in the information set can pose considerable challenges to the framework. Giannone *et al.,* (2008) extended this standard framework for nowcasting macroeconomic indicators by introducing the Kalman smoother based factor updation approach suitable for non-synchronous data releases of high frequency economic indicators. The novelty of this approach, therefore, lies in the easy adaptability for nowcasting major macroeconomic indicators when relevant data are released at different time points (dates in a month) with considerable time lag. The framework was first used to nowcast the Gross Domestic Product (GDP) of the US (Giannone *et al.,* 2008). They predicted real GDP growth using a large jagged edged information set and observed that DFM produced more precise forecast in short horizon compared to other benchmark models, including the *Survey of Professional Forecasts*. Subsequently, Angelini *et al.,* (2011) introduced a similar framework for the European Central Bank (ECB) where it was observed that the short-term pooled forecast performance of the factor model using bridge equation improves the forecast accuracy. Also, Altissimo *et al.,*(2001), Schumacher (2010) and D'Agostino *et al.,* (2008) introduced this framework in Banca d'Italia, Deutsche Bundesbank and Central Bank of Ireland, respectively, signifying its wide acceptance in the central banks of developed countries. Barhoumi *et al.,* (2008) compared the forecast performance of such DFM *vis-à-vis* the purely quarterly model (auto regression, vector auto regression and bridge equations) for select European countries. Liebermann (2012) applied nowcasting using a large set of monthly macroeconomic data for Ireland and observed significant improvement in short-term forecast precision over other model-based forecasts suggesting robustness in performance of

[3] Jagged edge refers to the fact that data are released in a non-synchronous manner with different degrees of lag. The time period for the last available information, therefore, varies from series to series.

the DFM framework among competing models. Extending the footprint in EMEs, Kabundi *et al.,* (2016) carried out nowcasting of real GDP growth for South Africa and observed that this nowcasting framework provides a more precise forecast of real GDP than other benchmark models. Sanyal and Das (2017) used this framework for nowcasting sales growth of listed manufacturing companies in India. Further, Chakravartti and Mundle (2017) used the automatic leading indicator-based approach in the DFM framework for forecasting aggregate and sectoral growth of GDP for 2016-17.

The rest of the paper is organised as follows: Section II summarises the adaptation of search data in the available literature on Big Data Analytics; Section III outlines the empirical framework used for identifying suitable keywords and the Section IV discusses data used for analysis and stylized facts. The empirical findings are evaluated in Section V. Section VI concludes highlighting the limitations and the scope for future research.

Section II
Use of Google Search Data for Nowcasting and Economic Research

Increasing internet penetration and the overwhelming acceptability of Google as a search platform are cited as the drivers of Big Data and analytics thereon (Choi and Varian, 2012). This seminal work has been extended to harness the information content of Google search data to provide improved assessments of employment conditions; retail, house and car sales; tourism and consumer confidence (Choi and Varian, 2012).

An intertwining stream in the literature has corroborated the utility of search intensities using Google search data to assess private consumption, leading to the development of a new index of consumer sentiment that was found to be more precise in predicting consumption growth than the University of Michigan Consumer Sentiment Index and the Conference Board Consumer Confidence Index (Penna and Huang, 2009; Vosen and Schmidt, 2011).

The application of these data has been extended to predict the different aspects of economic activity, *viz.*, tourism growth in Hong Kong (Gawlik, *et al.,* 2011); the unemployment rate for Denmark (Zimmermann and Askitas, 2009), the US (D'Amuri and Marcucci, 2010, 2013), and for the UK (McLaren and Shanbhogue, 2011); housing market conditions (McLaren and

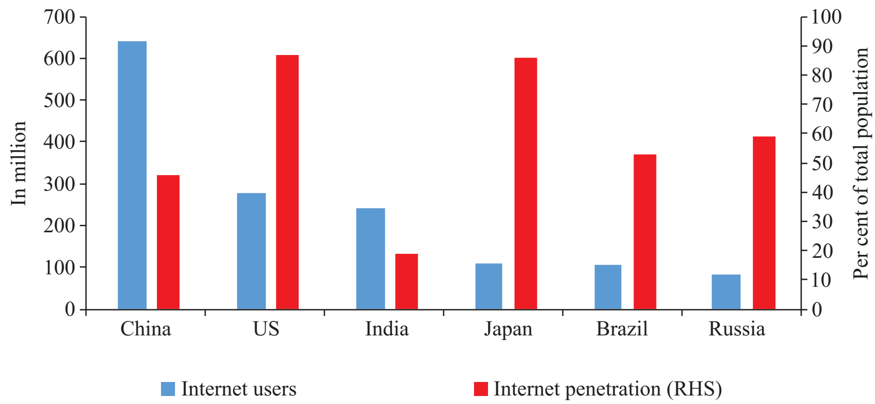
Shanbhogue, 2011), to name a few. Suhoy (2009) conducted a business cycle analysis using Google search data for Israel and observed that the search data successfully identifies the business cycle turn around point. Koop (2013) used the dynamic model selection (DMS) in time varying framework on Google search data to forecast key macroeconomic indicators of the US, namely inflation, wages, unemployment, term spread, financial condition index, industrial production and money supply growth. He observed that DMS with Google search data improves forecast precision. Carrière-Swallow and Labbé (2011) developed an index of online propensity to buy cars and used that index to nowcast car sales growth for Chile. They observed that the use of this index significantly improves the forecast precision for both in-sample and out-of-sample forecasts. Google trend data has also been used to analyse the volatilities in currency markets (Smith, 2012). The practice of using Google search data for macroeconomic assessment and forecasting was formally adopted by the ECB and Bank of England in 2013. Beyond the realm of macroeconomics, Google search data has also been used in other areas such as tracking the flu status in the US (Yang *et al.,* 2015).

Notwithstanding the burgeoning literature on the use of internet search-based big data for nowcasting in the developed world, there is a dearth of similar studies in the context of emerging economies like India. This is primarily due to the lack of internet penetration and skewed usage of internet across the country. It is estimated that 19 per cent of India's total population is extensively using the internet, with the majority being the youth (PwC, 2015). Despite poor infrastructure, internet usage in India has advanced exponentially and has, in turn, powered e-commerce, even at a relatively lower level of penetration (87 and 86 per cent in the US and Japan, respectively) (Chart 1).

Internet users in India surged from 60 million in 2009 to 200 million in 2014 with a forecast of 580 million in 2018 (BCG and RAI[4], 2017). The majority of the population contributing to internet usage is predominantly the urban young middle- and upper-income class with the knowledge of, and accessibility to, the internet. Although internet penetration in rural area has increased manyfold in recent years, infrastructure, especially connectivity, still remains a binding constraint. With increase in internet usage and awareness, internet-based search engines have gradually emerged as primary sources

[4] BCG stands for The Boston Consulting Group and RAI stands for Retailers Association of India.

Chart 1: Internet Penetration Cross-Country Experience (as in 2014)



of information. The information on internet searches can be suitably used to understand the demand conditions in a particular sector of the economy. However, the spread of the internet, at present, is skewed-concentrated in urban areas-and hence the search pattern would represent pre-dominantly urban demand. The suitability of selecting the real estate sector lies in the fact that the real estate activities are heavily concentrated in urban areas and therefore internet searches on real estate are likely to reflect the demand condition of the sector.

Section III
Methodology

The steps followed in this paper begins with compilation of search intensity data in the first stage and then moving to nowcasting. The empirical exercise comprises the following steps:

Step 1	Identification of keywords relating to real estate search
Step 2	Repeated sampling scheme
Step 3	Shortlisting keywords based on their information content
Step 4	Consolidation of search intensity across keywords to derive a search propensity indicator
Step 5	Exposition of nowcasting framework
Step 6	Selection of other economic indicators to facilitate nowcasting
Step 7	Evaluating forecasting performance using rolling forecast

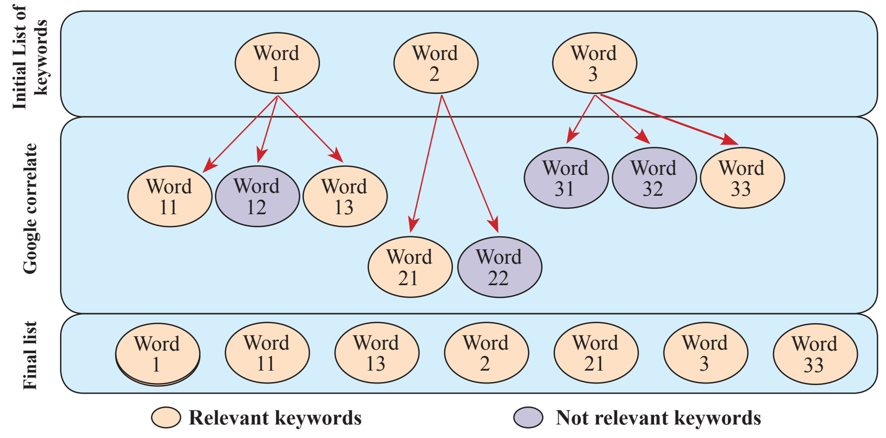
Identification of Keywords Related to Real Estate Search

The choice of keywords plays a crucial role in determining the precision of the nowcasting exercise. Internet searches are often led by subjectivity that varies across users. The choice differs from time to time and user to user according to convenience and familiarity with words. Hence, the usefulness of the search intensity is contingent upon finalising a list of keywords representative enough to capture the real estate sector demand across regions and in different time periods. Following Choi and Varian (2012), Kholodin *et al.,* (2010), we begin with an initial long list of keywords deemed relevant for the real estate sector. 'Google Correlate', a tool on 'Google Trends', provides a suggestive list of keywords with a similar search pattern. This suggestive list, after pruning down the unrelated words by manual screening, was added to the set of keywords. The initial list of keywords along with such suggested search words constitutes an ensemble representative set of the population keywords. An illustrative mechanism followed for creating such representative set is provided in Chart 2.

Once the keywords were identified, the search intensity indices of these keywords were collected from Google Trends every month. The trend index represents a scaled version of search intensity, derived from the ratio of the total number of searches containing a particular keyword to the total number of searches during that time. Further, the relative intensity during a period is scaled from [0,100] scale in the following manner:

$$G: R \rightarrow [0,100] \ni R_t = \frac{S_t}{Max\ S_t} \times 100\ \&\ S_t = \frac{n_t}{N_t} \tag{1}$$

Chart 2: Keyword Selection Framework



where S_t is the relative search intensity. n_t and N_t represent the number of searches on a specific keyword 'X' and total number of searches during that time, respectively. The novelty of this relative scaling is that any increase in number of users is taken care of.

Repeated Sampling Scheme

Since Google uses a sampling approach to gather search intensity data, making inference based on a single observation of search intensity would be inappropriate. The problem can be mapped with the typical sampling problem in statistics where the population search intensity is unknown and hence should be estimated based on sample observations. It has been observed that search intensity index extracted using Google Trends within a day remains the same, whereas samples drawn on different dates are found to vary. Accordingly, the information on search indices against the same set of keywords was collected on a daily basis for thirty days to understand the variation in search intensity. Further, the sample-resample scheme, popularly known as bootstrapping, was applied using these thirty samples to derive credible estimates of population parameters.

Bootstrapping is defined as a metric which is derived based on the random samples drawn from a population with replacement. Bootstrapping is extensively used in statistics to derive a more precise estimate of population parameters. However, the underlying assumption of independence of sample members should be ensured for an unbiased estimate of population parameters. Bootstrapping can be of two types-parametric and non-parametric. Parametric bootstrapping is one where the underlying distribution of the population is known; its non-parametric counterpart extends the resampling mechanism under a non-parametric domain without assuming any particular form of distribution of the population.

In this paper, a thousand instances of sample size of thirty were drawn, with a replacement for each keyword for every month. The median search intensity was calculated from each of these thousand bootstrapped samples for every time point. Due to the statistical regularity condition of the bootstrap procedure, the estimated median estimate is expected to provide a precise estimate of population search intensity. Further, the estimate of population average and standard deviation of the search intensity were derived from these bootstrapped samples for each keyword.

Shortlisting Keywords Based on Information Content

The first stage of shortlisting keywords from the long list was carried out based on the information content of these individual keywords about the demand conditions of the real estate sector. Higher search intensity is expected to indicate higher demand in the sector and is thereby likely to indicate higher sales growth. However, some users may search just to cross-check price movement or for any other purposes which may not translate into actual activity in the sector. Therefore, a judicious view needs to be taken to extract the information content from such an ensemble list and validate the same against realised growth figures.

Autoregressive distributed lags (ARDL) technique was used to check the search momentum against target variable (*i.e.,* sales growth). The ARDL framework can be illustrated as:

$$\Delta Sales_t = \alpha_0 + \alpha_1 \, \Delta Sales_{t-1} + \alpha_2 \, S_{it} + \epsilon_{it} \tag{2}$$

where S_{it} is the year-on-year (y-o-y) growth of search intensity corresponding to ith keyword and $\Delta Sales_t$ is the real sales growth of real estate companies. The real sales growth has been derived by deflating the nominal sales growth by WPI headline inflation.

The specification in equation (2) regresses sales growth on its own lag and the search intensity; it ignores the impact of other macroeconomic factors. Hence, robust standard error has been used to take care of heterogeneity in the residual structure. The coefficient is expected to be significant with a positive sign for those keywords where higher search volume translates into higher sales growth. Accordingly, all those keywords, for which the above condition is satisfied, have been shortlisted in the first stage.

In the second stage, we selected only those keywords where the news content of search intensity was found to be higher. The noise in the search intensity indices can offset the information and therefore should be removed from the analysis. This paper validates the level of noise content of each keyword. If the inter-sample variation of the search intensity is found to be higher, the news content of the keyword search intensity can be lower than the noise component. Thus, this paper incorporates another level of filtration of keywords using an equivalent measure of news-to-noise ratio. Following Carrière-Swallow and Labbé (2011), the inter-sample variation has been measured in terms of ratio of average to standard deviation (*i.e.,* inverse of coefficient of variation, also called Rose criteria). A higher value of Rose criteria would indicate higher news-to-noise ratio. A threshold of (+/-) 5[5] has been used on Rose criteria to determine the significant keywords exhibiting higher news content.

Consolidation of Search Intensity Across Keywords to Derive a Search Propensity Indicator

After finalizing the keywords pool, the next task is to derive a composite indicator of search intensity. As different keywords may be used to search for a particular activity in the sector by different users, inference drawn using a single keyword may not capture search intensity completely. At the same time, the problem of degrees of freedom creeps in when more keywords are used in the empirical models. An optimal trade-off between these two extremes can be achieved using a single indicator of search intensity which reflects the aggregate effect of the selected keywords. Such a composite indicator is useful to augment the information set of nowcasting framework bypassing the degrees of freedom problem.

The composition of search intensities has been derived using three different approaches, namely:

a) **Simple average approach:** In this approach, search intensities of all selected keywords are aggregated using equal weightage as follows:

$$SC_t = \frac{1}{N}\sum_{i=1}^{N} R_{it} \tag{3}$$

Here R_{it} is the scaled search intensity of ith keyword at time point t.

b) **Weighted average approach:** One of the major drawbacks of using equal weightage is the assumption that every keyword contributes equally to the index. However, in reality, the search index of each keyword can exhibit different statistical properties and hence should be combined using a weighting diagram. While there could be many weighting pattern to choose from, inverse of variation seems to be a credible choice of the same. The significance of inverse variation is that, volatility, being a measure of noise, will reduce variation

5 Following Carrière-Swallow and Labbé (2011).

in a composite indicator. Inverse of the variation, therefore, can be considered as a measure of news. Using this approach, the composite search propensity indicator can be derived as:

$$SC_t = \frac{1}{\sum_{i=1}^{N} W_i} \times \sum_{i=1}^{N} (R_{it} \times W_i) \tag{4}$$

where $W_i = \frac{1}{\sigma_i}$ and σ_i is the sample estimate of variation of i^{th} keyword, measured over time horizon.

c) **Principal Component Analysis (PCA):** The dependence structure of search intensities across keywords, reflected in the correlation matrix, can be suitably transformed to reduce the dimensionality in such a manner that there is minimum loss of information. PCA provides an effective mechanism to extract orthogonal factors from the larger information set in such a manner that top factors explain the majority of variability in the information domain. However, inclusion of just one factor is likely to be sub-optimal as loss of information remains a major threat. The composite indicator, therefore, can be calculated as:

$$SC_t = \frac{1}{\sum_i^k v_i} \times \sum_i^k (v_i \times G_{it}) \tag{5}$$

where G_{it} is the estimated i^{th} factor at time t and v_i is the proportional variability explained by i^{th} factor.

Nowcasting Framework

Following Giannone *et al.,* (2008), nowcasting of real estate sales growth has been devised where the high frequency economic indicators are augmented with the composite google search index in the regressor set. Any typical nowcasting problem starts with projecting the target series (real estate sales growth in this paper) using the available information set.

$$\boldsymbol{Forecast(R_v^q | \Theta_n^v)}$$

where R_v^q denotes the quarterly real estate sales growth observed at month v, and Θ_n^v is the available information set. Θ_n^v can be thought of as a collection of information sets spanning the days within month v. The suffix 'n' indicates the total number of variables covered where $n = n_1 + n_2$; n_1 being number of economic indicators and n_2 being number of the Google-based composite indicator. Here, $\Theta_n^v = (\Theta_{n_1}^v, \Theta_{n_2}^v)$ where $\Theta_{n_1}^v$ is the data on economic indicators (including soft and hard data) and $\Theta_{n_2}^v$ is the Google-based composite indicator.

Let us consider the information set at any date j of month v as:

$$\Theta_n^{v_j} = \{Y_{it}|v_j, t = 1(1)T_{iv_j}, i = 1(1)n\} \quad (6)$$

where T_{iv_j} is the last point of data availability for i[th] indicator and for every j, $\Theta_n^{v_j}$ can be considered as vintage data at j[th] date of month v. As new data comes in, $\Theta_n^{v_j} \supseteq \Theta_n^{v_{j-1}}$ and it enriches information content of $\Theta_n^{v_j}$ because of two reasons (i) Y_{iv_j} is a new observation for at least one $i \in \{1, 2,..., n\}$ and (ii) old data often get revised, *i.e.*, $Y_{it-k}|v_j \neq Y_{it-k}|v_{j-1}$ for $k > 0$[6].

Now, in order to forecast the target variable (which is real estate corporate sales growth), another difficulty arises as the corporate sales growth data are available at quarterly frequency while the indicators are available at monthly frequency. Thus there is a need to deal with such a mixed frequency scenario. For this, let us assume that quarterly corporate sales growth is tagged at the last month of the quarter which means that q=3m; (3m-2) and (3m-1) are the two other months within the same quarter. Having assumed that, the next step is to consider the different data vintages $\Theta_n^{v_j}$ as the monthly data releases create multiple number of data vintages depending upon the date of release. Given these notations, the nowcasting exercise boils down to:

$Proj\left(\widetilde{R_{v_j}^{3k}}\middle|\Theta_n^{v_j}\right) = E(R_{v_j}^{3k}|\Theta_n^{v_j}\ for\ v_j \in [(3k-2);3k], Model)$ where expectation is taken over latest available information vintage using a suitable model and forecast precision is calculated as inverse of uncertainty which is defined as:

$$Uncertainty_{v_j}^{3k} = E\left[\left(\widetilde{R_{v_j}^{3k}} - R^{3k}\right)^2\middle| Model\right] \quad (7)$$

As more and more monthly data are released, $\Theta_n^{v_j}$ expands and provides more information base to the forecasting process. Hence, we can expect the precision of the forecast to improve with release of more data.

Giannone *et al.,* (2008) suggested using DFM for nowcasting. One of the major advantages of DFM is that the curse of dimensionality can be dealt with using the factor setup where the factor estimates are updated at each point of data release.

[6] As old data gets revised, the estimates firm up and the chance of future revision of data becomes less likely.

Dynamic Factor Model (DFM)

The factor models are typically expressed as follows:

$$Y_{it|vj} = \mu_i + \lambda_i F_t + \epsilon_{it|vj} \tag{8}$$

for i=1(1) N

where μ_i is the intercept part indicating common level and F_t (*Order*:$k \times 1$) is the factors spanning the information set $\{Y_t\}$. Also $\lambda_i F_t$ and $\epsilon_{it|vj}$ are assumed to be independent.

Equation (8) can be written as:

$$Y_{t|vj} = \mu + \Lambda F_t + \mathrm{E}_{t|vj} \tag{9}$$

The significance of F_t lies in the fact that the components of F_t span the information set $\{Y_{t|vj}\}$ and reduce the dimensionality problem. The idiosyncratic component $E_{t|vj}$ is the unexplained part of $Y_{t|vj}$ and consists of variable specific shocks primarily attributed by exogenous impact and possible revisions in macroeconomic variables.

Due to changing dynamics among different macroeconomic variables, the dynamics of the common factor plays an important role. For the sake of simplicity, the dynamics of the common factors F_t can be expressed as AR (1) process as follows:

$$F_t = \mathrm{AF}_{t-1} + B\eta_t \tag{10}$$

where A is AR(1) coefficient matrix of $k \times k$ order and B (*Order:*$r \times q$) represents a structural relationship between common factors. The shock to common factors η_t is white noise process. Forni *et al.,* (2005a) advocated for a larger set of common factors than idiosyncratic shocks in order to capture the lag-lead relationship among the variables $\{Y_t\}$ along business cycle movement.

Since the data release calendar of different variables within the information set $\{Y_t\}$ differs, the chance of getting an unbalanced panel cannot be ruled out. For that, we assume:

$$E\left(\epsilon^2_{it|v_j}\right) = \tilde{\phi}_\iota = \begin{cases} \phi_i & where \quad Y_{it|v_j} \text{ is available} \\ \infty & where \quad Y_{it|v_j} \text{ is not available} \end{cases} \tag{11}$$

Here $E\left(\epsilon^2_{it|v_j}\right) = \infty$ ensures that no weight would be assigned to the variables having missing data at information vintage Θ_{vj}.

Thus, from equation (11), we get:

$$E\left(\epsilon_{t|v_j}\,\epsilon'_{s|v_j}\right) = \begin{cases} diag\left(\tilde{\phi}_i, i = 1(1)N\right) \; if \;\; t = s \\ 0 \;\; if \;\; t \neq s \end{cases} \tag{12}$$

Also $E(\epsilon_{t|vj}\eta_{s|vj}) = 0$ for all s indicating independence between idiosyncratic shocks and shocks to common factor. Once the coefficients of equations (9) and (10) are estimated, the factors are estimated based on the latest available vintage Θ_{vj} and estimated coefficients.

Nowcasting using bridge model

Once the factor estimates are available, the factors are linked with the target variable (*i.e.,* quarterly sale growth of real estate companies) using the following bridge equation which can be used to forecast the sales growth of real estate companies using the latest available estimate of the factors.

$$R_t^Q = \alpha_0 + \sum_{i=1}^{k} \alpha_i \,\phi(L) F_t + \eta_t \tag{13}$$

Here, the bridge equation is first estimated using the complete panel of observations; the estimates of the parameters help in assessing the impact of information on analysing the past growth pattern. Once the bridge equation is estimated, the estimated factor values are used for determining the quarterly sales growth projection of real estate companies.

Selection of other Economic Indicators to Facilitate Nowcasting

Apart from the search intensity data, the nowcasting exercise also needs to consider information on other economic variables influencing the growth of the real estate sector. Stock and Watson (2002a, 2002b) suggested the inclusion of a comprehensive set of economic indicators within the DFM framework. DFM has been developed on the principle of extracting information set (also called factors) from large number of variables which represent the common dynamics explaining the variability of the data. Thus, the information content of each variable should be cross-checked before being selected in the final pool. One of the most commonly accepted methods to check the nature of dependency is to perform a cross-correlation test. It not only tests the significance of cross-correlations at various lags, but also provides the nature of dependency using the sign of correlation coefficients. In this context, the variables which have significant cross correlation at

0 to 4 lags and have appropriate signs comprise the first-hand selection of pool of variables. However, high cross-correlation affirms a co-movement among the series but does not address one of the major aspects of a business cycle, *i.e.,* the regime switching process, identified as the most critical property of any business cycle indicator by Burns and Mitchell (1946). In view of this, Lahiri and Yao (2006) used turning point analysis using the Bry-Boschan (1971) algorithm. The turning point analysis of the target variable and other economic indicators provides sufficient insights about the different phases of business cycle movement observable in each series. Though Lahiri and Yao (2006) proposed the statistical coherence test for identifying regime changes, for implementation it requires sufficiently large number of observations which were not available for majority of the series. So we rely on visual inspection of regime switches in the target variable and explanatory variables. Any variable (or regressor) having recession and boom regimes during different periods than that of the target series will not be able to predict the turnaround points of target variable efficiently. Hence, the cross-correlation test along with regime switching behaviour would provide sufficient screening of regressors to be selected for nowcasting. Adding up variables based on the above criteria defines a larger pool of variables.

However, as identified by Boivin and Ng (2005), adding more and more variables into the data set may not result in improvement of forecasting performance, as some of the variables may be correlated with other variables and may not impact the target variable. Also, if the idiosyncratic components are large and correlated with each other, adding further variables may not result in better accuracy in forecasting. Thus, pre-selection of variables pose crucial challenge for forecasting. Marie (2013) used an elastic net framework using least-angle regression using elastic net (LARS-EN)[7] for selecting the regressor. The LARS-EN algorithm typically uses sequential backward selection of variables using the ARDL model for checking the explanatory power of regressors and penalizing L1 and L2 norm[8] of regression coefficients. The ARDL framework can be written as:

$$S_t = \alpha + \beta_1 S_{t-1} + \beta_2 S_{t-2} + \cdots + \beta_k S_{t-k} + \gamma X_t + \zeta_t \qquad (14)$$

[7] LARS and EN stand for Least Angle Regression and Elastic net respectively. LARS-EN is an algorithm for elastic net regularisation and variable selection.

[8] L1 norm represents least absolute deviation of predicted values and actual observations whereas L2 norm minimises the squared deviation between predicted and actual values.

EN[9] criteria is represented as:

$$\min_{\beta} \sum_{t=1}^{T}(S_t - \widehat{S_t})^2 + \lambda_1 \sum_{i=1}^{N}|\gamma_i| + \lambda_2 \sum_{i=1}^{N}\gamma_i^2 \tag{15}$$

where λ_1 and λ_2 are the penalty parameters of L1 and L2 norms of regression coefficients.

Evaluating Forecast Performance Using Rolling Forecast

The forecast performance of the nowcasting model was measured following the rolling forecast mechanism. In this approach, the training data set was first determined by truncating the time horizon of the study up to a certain point of time. The model is first estimated on the training data set and the fitted model is then used for forecasting one period ahead forecast. The forecast value was then compared against the actual realisation of the target series (sales growth) using a squared error loss function. In the subsequent steps, one observation was augmented with the training data set and the forecast was made for the immediate future time point using re-estimated model. The process is continued till the end of the time horizon under consideration. The rolling root mean square error (RMSE) was estimated as:

$$RMSE = \left[\left(\frac{1}{M}\right) \times \sum FE_t\right]^{\frac{1}{2}} \ where\ FE_t = \left(\widehat{R_t^q} - R_t^q\right)^2 \ for\ t = 1(1)M \tag{16}$$

where M is total number of iterations in rolling forecast.

In order to benchmark forecast performance, the nowcasting framework has been evaluated against linear and non-linear time series models which are generally used for short-term forecasting. These time series models, also called naïve models, were used under similar rolling forecast mechanism. Better forecast performance of nowcasting model, however, does not necessarily establish value addition of Google search intensity data in forecasting performance. Therefore, similar nowcasting framework, without using Google as one of the regressors, was framed and a similar rolling forecast mechanism was adopted. The forecast performance of nowcasting models with and without a Google-based index was compared to validate the usefulness of Google search data towards better forecast precision.

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[9] Basically EN criteria is a combination of Least Absolute Shrinkage and Selection Operator (LASSO) and Ridge regression which Zou and Hastie (2005) suggested as more efficient than LASSO and Ridge. So we resort to LARS-EN algorithm for final selection of pooled regressor.

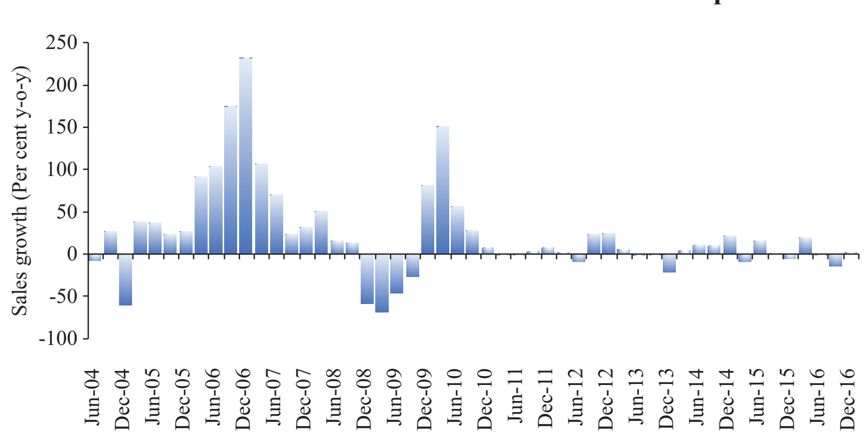
Section IV
Data

The data on target series, *i.e.,* year-on-year (y-o-y) sales growth of real estate companies, is sourced from quarterly financial statements of listed real estate companies that have been considered in the analysis. Since Google Trends provides the search intensity data since 2004, the sales data have been taken from Q1: 2004-05. Due to limited coverage of the real estate companies in the initial period, the data exhibit high volatility till the end of 2010, creating hurdles for empirical exercise (Chart 3).

Google Keywords

As indicated in the previous section, a total of 78 different keywords were considered for the analysis at the initial stage. Monthly search data were obtained from Google Trends. The monthly search data on these 78 keywords was analysed in terms of their inter-sample movements,[10] which showed presence of between-sample volatility across the sample period and therefore indicates the possibility of high noise component *vis-à-vis* news content (Annex 3). The final set of keywords, selected after completing all the steps as discussed above, includes 'building', 'construction', 'land', 'plot', 'independent house', 'apartment', 'real estate', 'property for sale', 'flat' and 'house in Chennai'.

Chart 3: Nominal Sales Growth of Real Estate Companies



[10] Only those keywords having positive search intensity over the period of consideration have been included in the study.

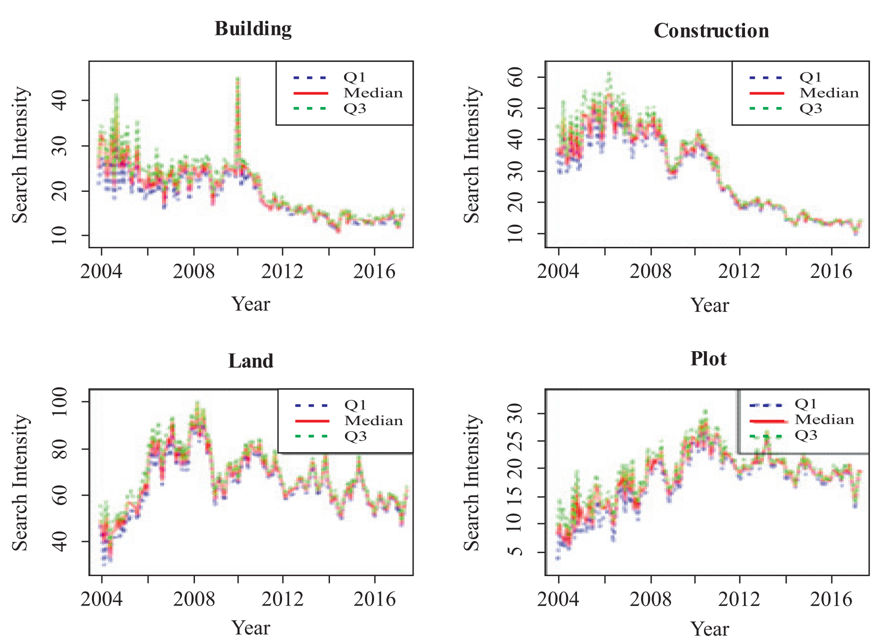
Section V
Empirical Findings

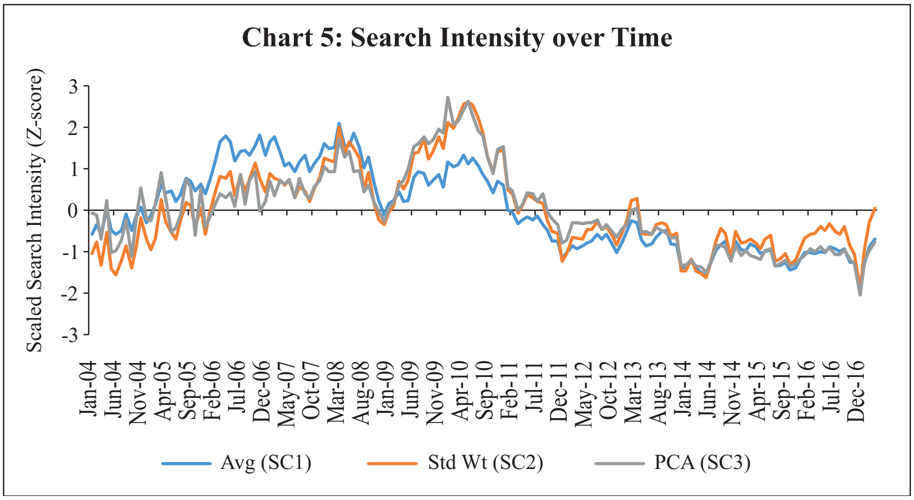
Google Search Intensity Across Keywords

Once the keywords are selected, non-parametric bootstrapping of search intensity was carried out using 1,000 replications. The bootstrapped median estimate, an estimate of 'population' search intensity, indicated that the search volumes varied over time. Further, it was found that inter-sample variation of keyword searches was stable, indicating robustness in the search intensity over time (Chart 4).

The momentum of search intensities was found to vary across keywords. The search volume attained peak levels at different time points for different keywords. The changing pattern of search intensity was found to be a reflection of the preferential shift of internet users towards some particular keywords. In this paper, we use a simple and weighted average of search intensities with weights being inverse of variation in the individual search intensities. The inter-quartile range has been used as measure of variation

Chart 4: Median Search Intensity and its Variation across Keywords





across search intensities in view of the presence of outliers. Apart from the average, the composition methodology was extended to Principal Component Analysis (PCA) harnessing the correlation structure of search intensity across keywords. The first three principal components explaining around 96 per cent of total variation were used for deriving the composite indicators with weights being proportional to variation explained by each factor.

The composite search intensity indicator represents the generalised momentum across selected keywords and, therefore, overcomes the problem of preferential shifting towards any particular keyword. It is, therefore, prudent to analyse the momentum observed in the composite indicator across the time span to draw an inference about the underlying demand conditions of the real estate market. The z score of the composite search intensity derived from simple average, weighted average and PCA approach (say, SC_1, SC_2, and SC_3, respectively) are plotted in Chart 5. All three composite indicators exhibited similar momentum in search intensities. Further, it was observed that the volatility of search volumes moderated and remained range bound since 2011.

Nowcasting Sales Growth

The composite indicator from all three approaches was used for nowcasting real estate sales growth. Apart from Google search data, other high frequency indicators were also used to augment search intensity for the nowcasting exercise. The list of such economic indicators is furnished in Annex 2. Nowcasting exercise was carried out on the information set comprising Google data in the first instance and without Google information in the second stage. Initially the Google indicator using simple average approach was used which was later substituted by weighted average and PCA-based indicators for forecast performance comparison.

Using Google Search Intensity

Following Giannone *et al.,* (2008), factor models with 2, 3 and 4 factors were used for assessing the nowcast performance of target variables for each type of search composite indicator[11]. The performance using SC_1 (*i.e.,* simple average) was evaluated in term of the rolling window approach, extending window length by one quarter after each iteration. It has been observed that the real sales growth has stabilised since 2010 as the coverage of corporates firmed up. Hence, the in-sample fit was carried out using a training set comprising quarterly observations from June 2004 up to March 2013. The framework was used to nowcast the immediate next quarter, *i.e.,* Q1:2013-14. The forecast deviation was calculated by comparing the forecast value of sales growth with the actual observation in Q1:2013-14. Next, the training sample was augmented with one additional observation and nowcasting was carried out for the immediate next quarter, *i.e.*, Q2:2013-14. This process was repeated till the last quarter of 2016. Such an augmentative approach was adopted to utilise the maximum information available till the end of the training data set. Using this rolling forecast mechanism, the forecast values from each of the models were assessed *vis-à-vis* the actual realisation. The rolling forecast indicated weak performance of 2 and 3 factor models[12] compared to the four factor model since 2014-15 for all type of search indicators. The four factor dynamic factor model performed most precisely and was able to track the turn around points of the target variable. Hence, the four factor model is recommended for nowcasting sales growth of real estate companies in the Indian context (Chart 6).

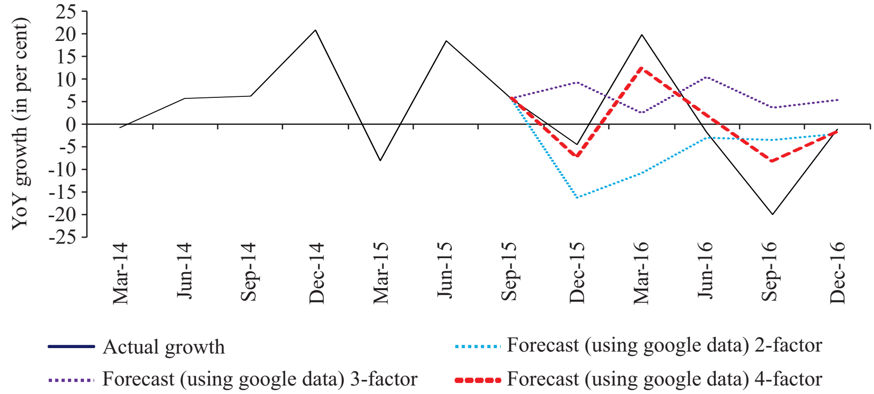
Improvement in Forecast Performance due to Google Search

With a view to ascertain the utility of Google search intensity, a nowcasting exercise was done using the economic indicators while excluding

[11] Three types of composite indicators were used, namely simple, weighted average and PCA-based indicators (as explained earlier in the paper).

[12] In terms of rolling forecast performance.

Chart 6: Rolling Forecast Performance of Different Factor Models



Google search data. The bridge equation comprising four factors was used in both frameworks to assess the relative improvement in nowcasting due to Google search data. The rolling forecast exercise indicated that the nowcasting framework using Google search intensity performs more precisely in one quarter ahead forecast compared to nowcasting model without Google information particularly since Q1:2016-17 (Chart 7).

Comparative Analysis of Forecast Performance

The rolling forecast performance using simple average and weighted average composite indicators followed a similar pattern during time horizon

Chart 7: Rolling Forecast Performance with and without Google Data

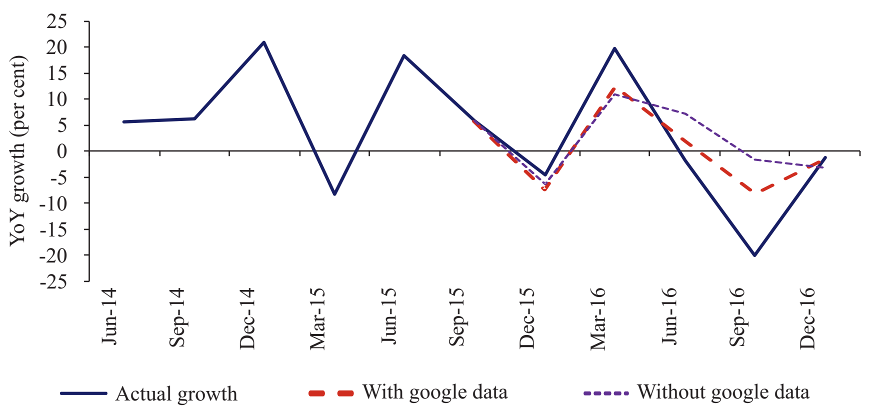


Table 1. Rolling Forecast Performance of Different Models

Models	**Average RMSE**		
	Simple average	**Weighted Average**	**PCA**
Using Google Data			
2-factor model	17.8	17.1	21.1
3-factor model	15.5	15.1	23.1
4-factor model	**9.7**	**9.0**	16.5
Without using Google Data			
2-factor model	18.2	18.0	22.0
3-factor model	16.7	16.5	24.2
4-factor model	12.5	11.5	17.2

from Q1:2013-14 onwards. However, the forecast performance of the PCA-based composite indicator was found to be imprecise compared to the other two methods (Table 1).

The performance of the nowcasting model (using weighted average composite indicator) was also assessed against naïve models. Following the better forecast performance, the four factor model was used for validating any improvement in forecast precision using Google data. The forecast precision of the nowcasting framework was found to be better than the naïve models (Table 2).

Table 2. Rolling RMSE of Nowcasting Model with Naïve Models

Models	**Average RMSE**
Using Google Data	
2-factor model	17.1
3-factor model	15.1
4-factor model	**9.0**
Naïve Models	
ARIMA	18.5
SETAR	17.6
LSTAR	17.8
Neural network	17.2

Section VI
Concluding Remarks

The internet has emerged as a major medium of information search in the last decade in India. As users take recourse to internet searches for various kinds of information, the search intensities are likely to exhibit demand conditions of the concerned sector. The seminal paper by Choi and Varian (2012) unveiled the potential of the search data for nowcasting-related economic activities. The approach was later extended to nowcast different macroeconomic variables by different researchers across countries. However, the majority of such studies were confined to advanced economies. This paper, the first in the Indian context to the best of our knowledge, is an attempt to explore and apply the information content of these search intensities, to assess the current state of economy of a particular sector. As the majority of EMEs lack adequate availability of high frequency data for tracking economic activities, Google search data is likely to provide a possible solution. This paper observes that search intensities provide valuable insight in terms of assessing the current state of the economy. Further, the performance of the nowcasting framework using Google data showed improvement over naïve models and can, therefore, be suitably used to bridge the data gap for policy formulation. However, the nature of the sampling scheme used by Google to create the index, being unknown, may pose challenges in assessing the volatility of the search data. Therefore, this paper suggests incorporating bootstrapping to control the inter-sample variation.

Google search data is found to provide real time insights to the policy makers. However, the utility of using such data depends on other preconditions, namely, internet penetration, user base volume and representativeness of the user base in terms of spatial diversity. These factors are critically important, particularly for EMEs, where the use of internet has gained considerable volume only in recent times. Another major challenge in using Google data lies in the fact that the search queries are dictated by behavioural dynamism and therefore differ across users. Bootstrapping addresses such variability estimation using statistical techniques, but behavioural patterns remain mostly untraceable. Hence, the news-to-noise ratio of a search would be difficult to assess, particularly during various turning points in the economy. Extracting noise out of the search data remains an open area of research.

References

Altissimo, F., A. Bassanetti, R. Cristadoro, M. Forni, M. Hallin, M. Lippi, L. Reichlin (2001). 'EuroCOIN: A real time coincident indicator of the Euro area business cycle', No. 3108, CEPR Discussion Papers. Available at: https://cepr.org/active/publications/discussion_papers/dp.php?dpno=3108 (last accessed June 29, 2018).

Angelini, E., Camba-Mendez, G., Giannone, D., Reichlin, L. and Rünstler, G. (2011). 'Short-term forecasts of euro area GDP growth', *Econometrics Journal*, Volume 14 Issue 1 Pages C25–C44.

Askitas, Nikolaos and Klaus F. Zimmermann (2009), 'Google Econometrics and Unemployment Forecasting', IZA DP No. 4201, June 2009.

Baffigi, A., Golinelli, R., and Parigi, G. (2004). 'Bridge models to forecast the euro area GDP', *International Journal of Forecasting*, 20(3): 447–60.

Bai, J. (2003). 'Inferential theory for factor models of large dimensions', *Econometrica*, 71(1): 135–71.

Bai, J., and Ng, S. (2002). 'Determining the number of factors in approximate factor models', *Econometrica*, 70(1): 191–221.

Banbura, M., Giannone, D., Modugno, M. and Reichlin, L. (2013). 'Nowcasting and the real-time data flow', No. 1564, Working Paper Series, European Central Bank.

Barhoumi, Karim *et al.,* (2008). 'Short-term forecasting of GDP using large monthly data sets – A pseudo real-time forecast evaluation exercise', Occasional Paper Series, No. 84, European Central Bank.

Bates, B.J., Plagborg-Moller , M., Stock, J. H., Watson, M. W. (2013). 'Consistent factor estimation in dynamic factor models with structural instability', *Journal of Econometrics,* Volume 177, Issue 2, December 2013, Pages 289-304.

Bhattacharya, R., Pandey, R. and Veronese, G. (2011). 'Tracking India growth in real time', *Working Paper* No. 2011–90, National Institute of Public Finance and Policy.

Boivin, J. and Ng, S. (2005), 'Understanding and comparing factor-based forecasts', *International Journal of Central Banking*, vol. 1, Issue 3, pp. 117–151.

The Boston Consulting Group (BCG) and Retailers Association of India (RAI) (2017). 'Decoding the digital opportunity in retail'. Available at: http://image-src.bcg.com/BCG-RAI-Decoding-the-Digital-Opportunity-in-Retail-Feb-2017_tcm9-145420.pdf (last accessed June 27, 2018).

Carrière-Swallow, Yan, and Labbé, Felipe (2011). 'Nowcasting with Google Trends in an emerging market', *Journal of Forecasting,* 32(4): 289-98.

Central Statistics Office (2011), "Methodology of Compiling Quarterly GDP Estimates", http://mospi.nic.in/sites/default/files/press_releases_statements/Methodology_doc_for_compilation_of_Quarterly_GDP_28july17.pdf

Chakravartti, P., and Mundle, S. (2017). 'An automatic leading indicator based growth forecast for 2016–17 and the outlook beyond', Working Paper No. 193, National Institute of Public Finance and Policy.

Choi, H., and Varian, H. (2012). 'Predicting the present with Google trends', *Economic Record,* 88(1), Issue s1, pages 2-9.

Chow, G.C., Lin, A. (1971). 'Best linear unbiased interpolation, distribution, and extrapolation of time series by related series', *The Review of Economics and Statistics*, 53(4): 372–75.

Croushore, D., and Stark, T. (2001). 'A real-time data set for macroeconomists', *Journal of Econometrics*, 105(1): 111–30.

D'Agostino, A., and Giannone, D. (2006). 'Comparing alternative predictors based on large-panel dynamic factor models', Working Paper Series 680, European Central Bank.

D'Agostino, A., Giannone, D. and Surico, P. (2006). '(Un) predictability and macroeconomic stability', Working Paper Series 605, European Central Bank.

D'Amuri, Francesco and Marcucci, Juri, (2012), The predictive power of Google searches in forecasting unemployment, No 891, Temi di discussione (Economic working papers), Bank of Italy, Economic Research and International Relations Area.

Della Penna, N., and Huang, H. (2009). 'Constructing consumer sentiment index for U.S. using Google searches', Working Papers 2009-26, Department of Economics, University of Alberta.

Doz, C., D. Giannone and Reichlin, L. (2011). 'A step-step estimator for large approximate dynamic factor models based on Kalman filtering', *Journal of Econometrics, Volume 164, Issue 1, September 1, 2011, Pages 188-205*.

Eichler, M., Motta, G. and Sachs, R. von (2011). 'Fitting dynamic factor models to non-stationary time series', *Journal of Econometrics, Volume 163, Issue July 1, 2011, Pages 51-70.*

Evans, M. D. D. (2005). 'Where are we now? Real-time estimates of the macro economy', *International Journal of Central Banking*, 1(2): 127–75.

Fondeur, Y., and Karame, F. (2013). 'Can Google data help predict French youth unemployment?', *Economic Modelling, Volume 30, January 2013, Pages 117-125.*

Forni, M., Giannone, D., Lippi, M. and Reichlin, L. (2007). 'Opening the Black Box: Structural factor models with large cross-sections', Working Paper Series, no 712 / January 2007, ECB.

Gawlik, E., Kabaria, H., & Kaur, S. (2011). Predicting tourism trends with Google Insights. http://cs229.stanford.edu/proj2011/GawlikKaurKabaria-PredictingTourismTrendsWithGoogleInsights.pdf.

Geweke, J. (1977), "The Dynamic Factor Analysis of Economic Time Series," in Latent Variables in Socio-Economic Models, ed. by D.J. Aigner and A.S. Goldberger, Amsterdam: North-Holland.

Giannone, D., Reichlin , Lucrezia and Small, David (2005). 'Nowcasting GDP and inflation: The real-time informational content of macroeconomic data releases', Finance and Economics Discussion Series, Divisions of Research & Statistics and Monetary Affairs, Federal Reserve Board, Washington, D.C.

Giannone, D., Reichlin , Lucrezia and Small, David (2008). 'Nowcasting: The real time informational content of macroeconomic data', *Journal of Monetary Economics,* Volume 55, Issue 4, May 2008, Pages 665-676.

Huang, Jih-Jeng, Gwo-Hshiung Tzeng,Chorng-Shyong Ong (2006). 'A novel algorithm for dynamic factor analysis', *Applied Mathematics and Computation*, *Volume* 175; Issue 2: Pages 1288–1297.

Humphrey, B. D. (2011). 'Forecasting existing home sales using Google search engine queries', Ph.D thesis, Duke University.

Kabundi, Alain, Nel , Elmarie and Ruch, Franz (2016), "Nowcasting Real GDP growth in South Africa", *ERSA working paper 581, Economic Research Southern Africa.*

Kitchen, John & Monaco, Ralph (2003). "Real-Time Forecasting in Practice: The U.S. Treasury Staff's Real-Time GDP Forecast System", *MPRA Paper 21068, University Library of Munich, Germany, revised Oct 2003.*

Koenig, E. F., Dolmas, S. and Piger, J. (2003). 'The use and abuse of real-time data in economic forecasting', *The Review of Economics and Statistics*, 85(3): 618–28.

Lahiri, K., Yao, V. W. (2006). 'Economic indicators for the US transportation sector', *Transportation Research Part A*, *Volume 40, Issue 10, December 2006, Pages 872-887.*

Lahiri, K., and Monokroussos, G. (2011). 'Nowcasting US GDP: The role of ISM business surveys', *International Journal of Forecasting, Volume 29, Issue 4, October–December 2013, Pages 644-658.*

Liebermann, Joelle (2012), "Real-time forecasting in a data-rich environment", MPRA Paper No. 39452, posted June 14, 2012.

Bessec, M. (2013). 'Short-term forecasts of French GDP: A dynamic factor model with targeted predictors', *Journal of Forecasting, Volume* 32, Issue 6, 500–511.

Marcellino, M., Stock, J. H. and Watson, M. W. (2003). 'Macroeconomic forecasting in the Euro area: Country specific versus area-wide information', *European Economic Review*, 47(1): 1–18.

McLaren, Nick and Shanbhogue , Rachana (2011), 'Using Internet Search Data as Economic Indicators', *Bank of England Quarterly Bulletin No. 2011 Q2.*

Negro, M. D., and Otrok, C. (2008). 'Dynamic factor models with time-varying parameters: Measuring changes in international business cycles', Staff Report, Federal Reserve Bank of New York.

Orphanides, A. (2002). 'Monetary-policy rules and the great inflation', *American Economic Review*, 92(2): 115–20.

Runstler, G., and Sedillot, F. (2003). 'Short-term estimates of Euro area real GDP by means of monthly data', *Working Paper Series 276,* European Central Bank.

Sargent, T.J., and Sims, C.A. (1977), "Business Cycle Modeling Without Pretending to Have Too Much A-Priori Economic Theory," in New Methods in Business Cycle Research, ed. by C. Sims *et al.*, Minneapolis: Federal Reserve Bank of Minneapolis.

Sanyal, A., and Das, A. (2017). 'Nowcasting sales growth of manufacturing companies in India', *Applied Economics, Volume* 50, Issue 5, 510–526.

Silvia, J. E., and Lahiri, K. (2011). 'Transportation indicators and business cycles', *Business Economics,* 46(4): 260–61.

Stock, J. H. and Watson, M. W. (2002a). 'Forecasting using principal components from a large number of predictors', *Journal of the American Statistical Association*, 97(460): 147–62.

— (2002b). 'Macroeconomic forecasting using diffusion indexes', *Journal of Business and Economics Statistics*, 20(2): 147–62.

Suhoy, T. (2009). 'Query indices and a 2008 downturn: Israeli data', Discussion Paper No. 2009-06, Bank of Israel.

Varian, H. R. (2014). 'Big data: New tricks for econometrics', *Journal of Economic Perspectives*, *Volume 28, Issue 2, Spring 2014, pp 3-28*

Vosen, S., and Schmidt, T. (2011). 'Forecasting private consumption: Survey-based indicators vs. Google Trends', *Journal of Forecasting*, 30(6): 565–78.

Zou, H., and Hastie, T. (2004). 'Regularization and variable selection via the elastic net', *Journal of Royal Statistical Society, Series B, Volume 67, Issue 2, pp 301-320.*

Annex : 1
Queries used in Google Trends

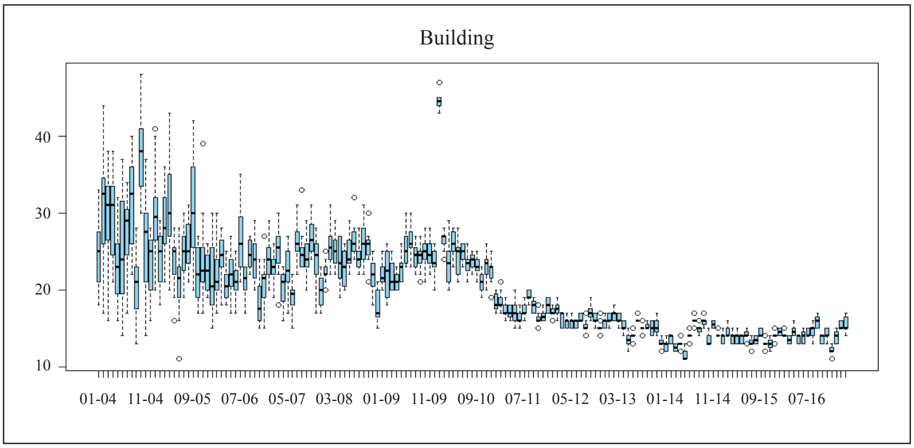
independent house	www.magicbricks.com	BHK flat
Building	www.sulekha.com	1 BHK
construction	www.99acres.com	2 BHK
Flat	estate agents	3 BHK
apartment	property dealers	1 RK
land	independent house in Mumbai	housing society
land for sale	independent house in Bangalore	brokerage
real estate	independent house in Chennai	SRA
property sale	independent house in Kolkata	lease
property	independent house in Delhi	storey building
property for sale	flat in Chennai	farm house
house	flat in Mumbai	real estate in Mumbai
house for sale	flat in Bangalore	real estate in Chennai
home	flat in Delhi	real estate in Bangalore
home for sale	flat in Kolkata	real estate in Kolkata
home loans	plot in Mumbai	real estate in Delhi
plot	plot in Chennai	property in Mumbai
plot for sale	plot in Bangalore	property in Chennai
mortgage	plot in Kolkata	property in Bangalore
north facing	plot in Delhi	property in Kolkata
furnished	house in Mumbai	property in Delhi
fully furnished	house in Chennai	land in Mumbai
partially furnished	house in Bangalore	land in Bangalore
south facing	house in Kolkata	land in Kolkata
east facing	house in Delhi	land in Chennai
west facing	India property	land in Delhi

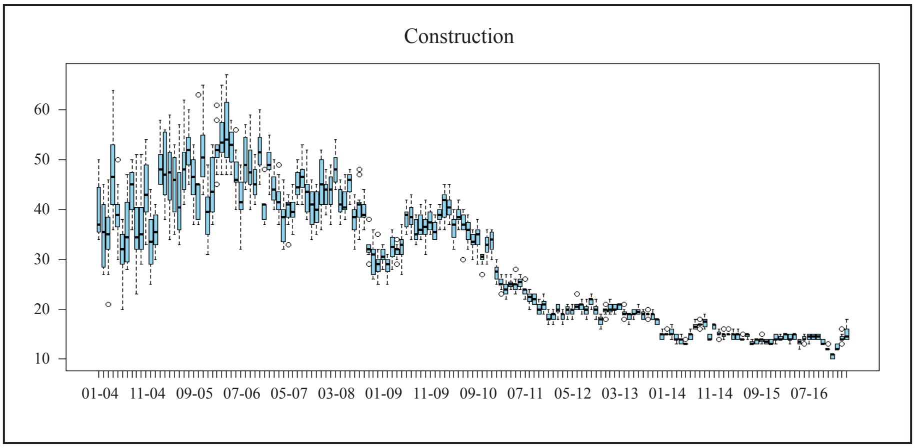
Annex : 2
Economic Indicators used for Nowcasting

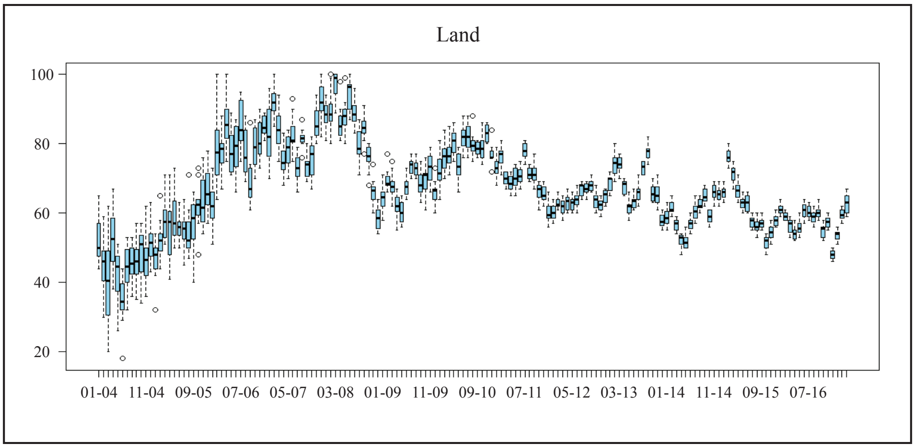
Index of Industrial Production (IIP)	IIP Manufacturing
IIP Basic Goods	IIP Electricity
IIP Capital Goods	IIP Consumer Durables
IIP Intermediate Goods	IIP Consumer non-durables
IIP Manufacturing NIC-2 digit level	Cement Production
Steel Production	Eight Core Industries
Baltic Dry Index	Cargo handled at major ports
Commercial Motor Vehicle Production	Commercial Motor Vehicle Sales
Passenger Car Production	Passenger Car Sales
Three wheeler Production	Three wheeler Sales
Two wheeler Production	Two wheeler Sales
Air Traffic (Passenger)	Air Traffic (Cargo)
Foreign tourist arrival	Railway freight
WPI Headline Inflation	WPI Core Inflation
Merchandise export	Non-oil Import
Non-oil Non-gold import	Aggregate deposit
Bank credit	Currency in circulation
Currency with public	Demand deposits
Reserve money	Narrow money
Broad money	Non-food credit
Call money rate	10 year G-Sec yield
PMI Manufacturing	PMI Services
PMI New order (Mfg)	PMI output (Mfg)
PMI input price (Mfg)	PMI Output price (Service)

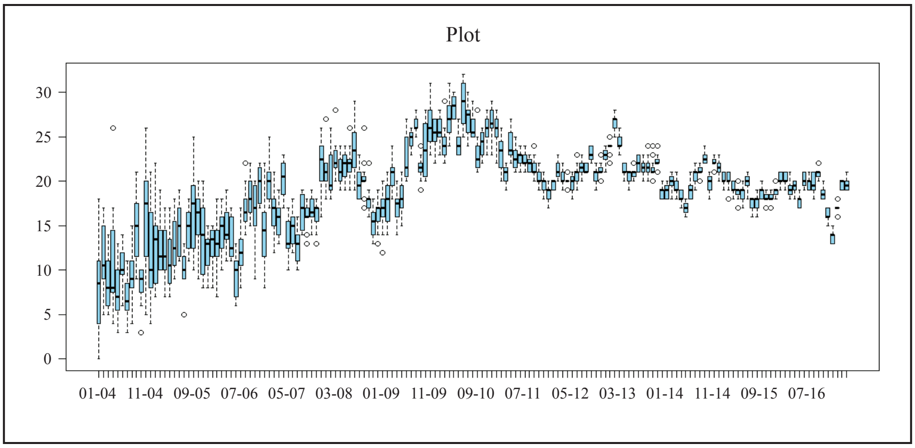
Annex : 3

Inter-sample Variation of Keyword Search Intensity








Plot
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Reserve Bank of India Occasional Papers
Vol. 38, No. 1&2, 2017

Volatility Spillovers between Forex and Stock Markets in India

Sudarsana Sahoo, Harendra Behera and Pushpa Trivedi*

This paper investigates the price and volatility spillovers between the Indian foreign exchange (forex) and stock markets over the sample period April 4, 2005 to March 31, 2017 using bivariate asymmetric BEKK-GARCH(1,1) model. The whole period is divided into five sub-periods, which include two distinct phases of heightened exchange rate volatility. The empirical results establish unidirectional price spillovers from the stock market to the foreign exchange market during the full sample period. The volatility spillovers between the two markets are found only during the two sub-sample periods with very high exchange rate volatility, *i.e.,* bidirectional spillovers during the second sub-sample period and unidirectional spillovers from the stock market to the forex market during the fourth sub-sample period. The response of the foreign exchange market to volatility spillovers from stock markets is asymmetric, *i.e.,* negative shocks from the stock markets resulted in higher volatility in the forex market *vis-à-vis* the positive shocks. The evidence on volatility spillovers during highly volatile periods indicates possible 'contagion' impact that amplifies the volatility and exacerbates the stress in the financial system.

JEL Classification : F31, G12, G15, C58

Keywords : Exchange rate, stock price, volatility, spillover, MGARCH

Introduction

Volatility spillover refers to the process and magnitude by which instability in one market affects other markets. An understanding of inter-market volatility spillovers can help financial sector regulators in formulating appropriate policies and strategies to maintain financial stability, particularly

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when market-specific stress gets transmitted to other markets to pose the risk of systemic instability. It also helps international investors and portfolio managers in pricing of securities and deciding appropriate strategies for trading and hedging/diversification of their investment portfolios (Mishra, Swain and Malhotra, 2007). The existence of significant volatility spillovers between stock prices and exchange rates may increase the non-systemic risk for international investors which results in reduced benefits from international diversification (Kanas, 2000). Exchange rate volatility contributes to the increase in uncertainty of the rate of returns, expressed in home currency, of the unhedged foreign investments (Eun and Resnick, 1988).

Internationalisation of financial markets has resulted in greater level of integration characterised by almost instantaneous flow of information across markets, resulting in rapid volatility transmission from one financial market to another. Agénor (2003) observed that the increasing incidence of financial market volatility and contagion effects are the fallouts of greater financial integration. The volatility spillovers causing rapid spread of contagion was evident during the 2008 global financial crisis.

Large investments and portfolio shifts by foreign portfolio investors (FPIs) in cross-border equities have facilitated greater integration between foreign exchange (forex) and stock markets. The FPIs sell foreign currency to obtain local currency for investing in the local stock market. Conversely, at the time of disinvestment, FPIs buy foreign currency using the disinvestment proceeds received in local currency. Large investments by FPIs lead to appreciation of both stock prices and the exchange rate, while large disinvestments lead to depreciation of both.

The process of integration of Indian forex and stock markets has been greatly facilitated by the economic and financial sector reform measures implemented since the early 1990s. The liberalisation of FPI investments in the Indian stock market has played a major role in increasing the integration of both the markets. With this perspective, this study examines the presence of volatility spillovers between these two markets, *i.e.,* the second moment relationship between the exchange rate and stock prices. Though the core focus of the study is to investigate the volatility spillovers between the two markets, we will also report the findings on the return spillovers between them.

The remainder of the paper is organised as follows. Section II discusses the relevant literature, both theoretical and empirical, on the relationship between exchange rates and stock prices. Section III delineates the stylised facts on the phase-wise developments in the Indian forex and stock markets. Section IV describes the data and empirical methodology used in this study. Section V contains analysis of the empirical results. Section VI carries the concluding remarks.

Section II
Review of Literature

Theoretical Overview

There are two main channels through which exchange rates and stock prices interact, *viz.*, the traditional channel and the portfolio channel. The traditional channel (Dornbusch and Fisher, 1980), based on the 'Goods Market' approach of exchange rate, establishes the relationship between real exchange rate and level of economic activity. The appreciation/depreciation of real exchange rate affects international competitiveness of domestic goods and services, with consequential impact on the trade balance and real output of a country. The change in real output impacts current and expected future cash flows of corporates that result in stock price variation. Secondly, changes in the exchange rate impact the indebtedness of the corporates by changing the domestic currency equivalent of their foreign currency debts. Appreciation of the exchange rate results in reduction in debt repayment obligations. This improves cash flows of those corporates that have foreign currency debts, which in turn leads to rise in the market valuation of their stocks, and *vice-versa* in the case of depreciation of the exchange rate.

The portfolio channel (Frankel, 1983; Gavin, 1989), based on the 'Asset Market' approach of exchange rate, establishes the impact of stock price movements on exchange rate. In an open economy framework, aggregate demand driven increase in stock prices results in positive wealth effects and consequently increases the demand for money. Excess demand for money results in a rise in the interest rate which attracts more foreign portfolio investments leading to appreciation of the exchange rate of the domestic currency. Conversely, a fall in stock prices results in negative wealth effects and outflows of foreign portfolio investments, leading to depreciation of the exchange rate. Phylaktis and Ravazzolo (2002) point out that the portfolio balance approach of exchange rate determination provides the basis for volatility spillover between exchange rates and stock prices.

Another channel of volatility spillovers is the market contagion, *i.e.,* a financial market being impacted by movements in another financial market in the same country or in another country beyond what is explainable by economic linkages. King and Wadhwani (1990) point out that the usual behaviour of rational agents drawing information from price changes in other markets provides the channel for the contagion occurring between financial markets. Ito and Lin (1994) described the 'market contagion hypothesis' stating that the agents in one market become risk averse while observing the price fall in another market and, in response, start unwinding their positions resulting in spillover effects.

The magnitude of volatility spillover between financial markets depends on the extent of their integration. Greater the level of integration of financial markets, higher is the extent and speed of flow of information between markets. The fundamental principle behind financial market integration is the 'law of one price' propounded by Cournot (1927). According to the law of one price, in efficient markets with no informational and administrative barriers, assets of identical maturities provide similar risk-adjusted returns.

Empirical Literature

There is a large body of empirical literature available on the relationship between exchange rates and stock prices in their first moment, while research on their second moment relationship is of recent origin and has mainly focussed on developed markets. Regarding the former, some researchers have found unidirectional causality either from exchange rates to stock prices (Abdalla and Murinde, 1997; Smyth and Nandha, 2003; Pradhan, 2006; Kisaka and Mwasaru; 2012), or from stock prices to exchange rates (Ajayi, Friedman and Mehdian, 1998; Granger, Huangb and Yang, 2000; Nath and Samant, 2003; Pan, Fok and Liu, 2007; Kose, Doganay and Karabacak, 2010), while only few studies have found bidirectional causality (Bahmani-Oskooee and Sohrabian 1992; Mok, 1993; Huzaimi and Liew, 2004; Aydemir and Demirhan, 2009). On the other hand, Rahman and Uddin (2009) did not find any evidence of causality in either direction in Bangladesh, India and Pakistan. Mishra (2004) did not find any causal relationship between exchange rate and stock prices in the context of India. Thus, there is no consensus in the empirical literature about the relationship between exchange rates and stock prices, and the evidences vary widely across countries and over time.

The other important aspect is the relationship between these two variables in their second moment, *i.e.,* volatility spillover. One of the early studies focussing on volatility spillover between the two variables is by Kanas (2000), where he examined volatility spillovers between stock prices and exchange rates in six industrialised countries, namely the United States (US), the United Kingdom (UK), Japan, Germany, France and Canada. Employing a bivariate EGARCH model on daily data from January 1, 1986 to February 28, 1998 (till December 7, 1993 for France), he found evidence of unidirectional volatility spillovers from stock returns to exchange rate returns in respect of all the countries except Germany. He attributed Bundesbank's intervention in the forex market as the possible reason for the absence of spillover of stock market volatility to the forex market in Germany. Examining for eleven emerging market economies and five developed countries, Assoe (2001) found evidence of asymmetric volatility spillovers from forex markets to stock markets only for some countries. On the contrary, Yang and Doong (2004) reported unidirectional asymmetric volatility spillovers from stock markets to forex markets in Canada, France, Germany, Italy, and the UK. Wu (2005) examined volatility transmission for seven East Asian countries and reported bidirectional transmission of volatility between stock returns and exchange rate returns for all countries except South Korea. He also reported that the spillovers had increased during the post-Asian crisis recovery period and the spillover effects were asymmetric in most countries.

In the context of advanced economies, Aloui (2007) provided evidence of long-persisting volatility spillovers and causality in the mean and variance between exchange rates and stock prices in the US and five major European countries (Germany, France, Italy, Spain and Belgium). Alaganar and Bhar (2007) provided evidence of unidirectional volatility spillovers from exchange rate returns to World Equity Benchmark Series. Choi, Fang and Fu (2009) found mixed evidence of unidirectional and bidirectional volatility spillovers between stock prices and exchange rates in New Zealand in the pre- and post-Asian financial crisis periods.

Among the studies in the context of Emerging Market Economies (EMEs), Morales (2008) studied volatility spillovers for six Latin American countries, namely Argentina, Brazil, Chile, Colombia, Mexico and Venezuela and found evidence of widespread spillover of volatility from stock prices to exchange rates; the spillovers from exchange rates to stock prices were confined to a few instances. Fedorova and Saleem (2010) covered three emerging Eastern European countries (Poland, Hungary and the Czech Republic) and Russia. Applying bivariate GARCH-BEKK model on the weekly data, they found unidirectional volatility spillovers from the forex market to equity markets in all the countries except for the Czech Republic where bidirectional volatility spillovers were observed. Chang, Su and Lai (2009) found significant asymmetric volatility transmission between exchange rate and stock prices in Vietnam. Xiong and Han (2015) reported bidirectional asymmetric volatility spillovers in China while Rubayat and Tereq (2017) found unidirectional volatility spillovers from stock prices to the exchange rate in Bangladesh. Bonga-Bonga and Hoveni (2011) provided evidence of unidirectional volatility spillovers from equity markets to the forex market in South Africa. They attributed their findings to the usual risk averse behaviour of foreign investors in emerging markets who pull out their investments when the local equity market becomes volatile leading to increased capital outflows and high exchange rate volatility.

There are a few studies undertaken in the context of India. Employing EGARCH model on daily data for the period January 2, 1991 to April 24, 2000, Apte (2001) found bidirectional asymmetric volatility spillovers between CNX Nifty and USD/INR exchange rate and unidirectional volatility spillovers (without asymmetric effect) between USD/INR exchange rate to Bombay Stock Exchange (BSE) Sensex. Mishra, Swain and Malhotra (2007) studied the volatility spillovers between the two markets for the period January 4, 1993 through December 31, 2003 for the Sensex and from June 3, 1996 to December 31, 2003 for the CNX Nifty. They found bidirectional volatility spillovers between the BSE Sensex and the exchange rate. Using data from April 2, 2004 to March 3, 2012 and employing GARCH and EGARCH models, Panda and Deo (2014) studied volatility spillovers between the two markets. They divided the sample period into three phases in context of the global financial crisis, namely pre-crisis, crisis and post-crisis periods. They reported bidirectional asymmetric volatility spillovers between the two markets in the pre- and post-crisis periods and unidirectional volatility spillovers from forex market to stock market during the crisis period. They also stated that the asymmetric spillover effect was more pronounced during the post-crisis period and attributed the impact of positive news from crisis recovery as the possible reason for the same. Majumder and Nag (2015) studied the relationship between the forex and the stock markets in India by employing a VAR-EGARCH model on daily data from April 2003 to September 2013 and found asymmetric unidirectional volatility spillovers from stock market to the forex market. By splitting the period into pre-crisis, crisis and post-crisis periods, they found bidirectional volatility spillovers between the two markets in the crisis and post-crisis periods. The asymmetric effect was observed in the spillover from stock market to forex market, and not the other way. Jebran and Iqbal (2016) found unidirectional asymmetric volatility spillovers from stock markets to the forex market in India. Mitra (2017) found evidence of bidirectional volatility spillovers and a long-term relationship between stock prices and the exchange rate in India.

The review of the literature suggests existence of volatility spillovers between forex and stock markets in many countries including India and other emerging market economies. Our study is different from the previous studies for India in two aspects. First, we have divided the sample into various sub-periods based on the level of volatility observed in the exchange rate in order to undertake a more meaningful analysis of the spillover effects during various sub-periods. In the twelve-year period from April 4, 2005 to March 31, 2017 considered for our study, we have identified two distinct phases when the USD/INR exchange rate exhibited very high volatility:

(a) September 1, 2008 to December 31, 2008: This period was the peak of the global financial crisis which was marked by heightened volatility in financial markets across the globe. The USD/INR exchange rate registered very high daily volatility[1] of 16.1 per cent (annualised) during this period.

(b) May 23, 2013 to September 4, 2013 (Fed Taper Tantrum): The global financial markets witnessed massive volatility post-announcement of tapering of quantitative easing programmes by the US Federal Reserve. The USD/INR exchange rate registered annualised daily volatility of 17 per cent during this period.

[1] Daily volatility is calculated in terms of the standard deviation of the daily log returns of the exchange rate. The daily exchange rate return (in percentage terms) is computed using the following formula: $\ln(S_t / S_{t-1}) \times 100$ where S_t is the spot exchange rate at time t.

These two sub-periods are studied separately with the objective of assessing the extent of volatility spillovers during such periods, amplifying the stress in the financial markets. Such a disaggregated analysis can help the financial sector regulators to understand the nature of spillovers during highly volatile periods and design necessary policy responses for prevention/ effective management of financial instability caused by such spillovers. This can also help the international investors and portfolio managers in formulating appropriate trading/hedging/portfolio diversification strategies to deal with volatile market conditions.

Second, the studies conducted for India so far have mostly used univariate approaches, except Apte (2001) and Majumder and Nag (2015), to investigate volatility spillovers. The univariate GARCH models may not be suitable for studying this kind of interaction in view of the bidirectional linkages between the two markets as established in the empirical literature. We have used Multivariate GARCH (MGARCH) model to examine the simultaneous relationship between the two markets.

Section III

Some Stylised Facts about Indian Forex and Stock Markets

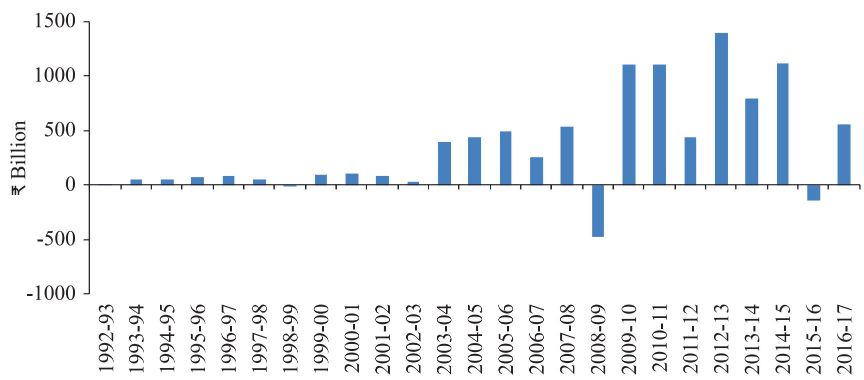
The development of the Indian forex and stock markets was greatly facilitated by the economic and financial sector reforms introduced since the early 1990s. The High Level Committee on Balance of Payments (Chairman: Dr. C. Rangarajan, 1993) constituted in the backdrop of the balance of payment crisis in 1990-91, recommended several reform measures. The major reform in the forex market was the shift to market-determined exchange rate. The Liberalised Exchange Rate Management System (LERMS) involving a dual exchange rate system was introduced in March 1992, which was later replaced by the unified exchange rate system in March 1993. The Expert Group on Foreign Exchange Markets in India (Chairman: O.P. Sodhani, 1995) recommended several measures with respect to trading, participation, risk management and selective interventions by the Reserve Bank of India (RBI) for promoting an orderly development of the Indian forex market. Consequently, the forex market underwent wide-ranging reforms starting January 1996.

Regarding equity markets, the most important reform measure undertaken in the early 1990s was the repealing of Capital Issues (Control)

Act, 1947, which paved the way for market-determined pricing of primary capital issues. Subsequently, the book-building system was introduced to improve transparency and fairness in the pricing of primary issues. Over the years, several measures have been taken for strengthening equity market infrastructure, namely, replacing the open outcry system with screen-based, on-line, order-matching trading platforms; strengthening the settlement system with establishment of depositories; shortening the settlement cycle; and introduction of electronic funds transfer facilities. Trading in derivatives such as futures and options on stock indices as well as individual stocks was introduced to provide more avenues for hedging of equity price risk. The above measures have improved the efficiency of the secondary market leading to greater liquidity and better price discovery. Further, the increased participation of domestic institutional investors has provided greater stability to the Indian stock market from 2016 onwards.

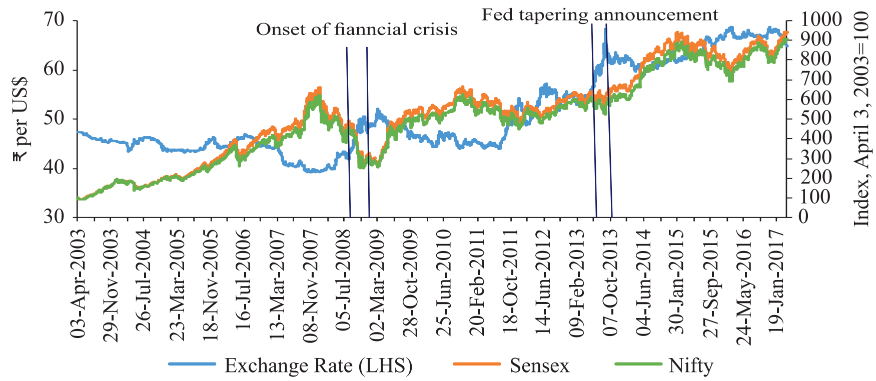
The integration of the Indian forex and stock markets was greatly facilitated by the liberalisation of foreign portfolio investments. FPIs were allowed to invest in Indian equities for the first time on September 14, 1992, but with various restrictions. With gradual liberalisation over the years, only a few restrictions exist currently. The magnitude of capital flows has increased considerably over the period with highest net portfolio equity inflows recorded during 2006-07. As can be seen from Chart 1, net FPI investments in Indian stock markets have picked up in a big way starting 2003-04.

Chart 1: Net Foreign Portfolio Equity Investments



Source: Securities and Exchange Board of India (SEBI) and National Securities Depository Limited (NSDL).

Chart 2: Movement of USD/INR Exchange Rate and Equity Indices



Source: RBI, BSE and NSE.

Increased FPI investments in Indian stock markets have led to their increased participation in the Indian forex market. FPIs participate in the forex market for covering their currency exposures and also for hedging the currency risks in their investment portfolio. The increased FPI activities have facilitated synchronous movements of both markets. The daily movement of USD/INR exchange rates and the equity indices (Sensex and Nifty) during the period 2003-04 to 2016-17 is presented in Chart 2. It shows inverse movements in stock indices and exchange rate, exhibiting a correlation of (-) 0.31 on returns. On the other hand, increased FPI participation in the Indian stock market had a negative effect in terms of rise in volatility in exchange rate and stock indices caused by sudden surge and pause in portfolio flows.

During the period 2003-04 to 2007-08, the Indian forex market witnessed a massive surge in capital inflows, resulting in sharp appreciation of the USD/INR exchange rate with the rupee touching a peak of ₹39.20 per US$ on November 7, 2007. The RBI had undertaken large-scale purchases of US$ during this period to curb volatility induced by sharp appreciation of the exchange rate (RBI, 2007). The foreign exchange reserves increased significantly during this period, from US$ 76.1 billion at end-March 2003 to US$ 309.7 billion at end-March 2008. The surplus rupee liquidity on account of large forex purchases by the RBI was sterilised primarily by issuing of government securities and treasury bills under the Market Stabilisation Scheme (MSS). Subsequently, with the collapse of Lehman Brothers, the exchange rate came under massive depreciation pressure and exhibited heightened volatility as the global financial crisis unfolded with full vigour in September 2008. Though the signs of the sub-prime crisis were visible since 2007, it took the shape of a full-blown crisis after the Lehman failure. The large impact of the crisis on the Indian markets was felt from September 2008 to December 2008. During this period, global risk aversion and deleveraging led to capital flows reversal, especially portfolio investments, from the EMEs. India witnessed large FPI sell-off with concomitant pressures on the USD/INR exchange rate (RBI, 2010). The rupee experienced annualised daily volatility of 16.1 per cent from September 2008 to December 2008. It depreciated sharply from around ₹48 per US$ to exceed the then psychological level of ₹50 per US$ on October 24, 2008 (ibid.). The RBI intervened heavily in the foreign exchange market to contain the sharp fall in the rupee by selling about US$ 18.7 billion in the spot market during October 2008 (RBI, 2009). The RBI also took a number of administrative measures, including, among others, the following: provision of a rupee-US dollar swap facility for Indian banks with branches abroad to mitigate their short-term funding pressure; special window to meet the foreign currency requirements of oil marketing companies; measures to encourage capital inflow, *viz.,* increase in interest rate ceiling on FCNR(B) deposits, relaxation of external commercial borrowings guidelines and permitting housing finance companies and NBFCs to raise foreign currency borrowing. The above extraordinary measures by the RBI could calm down the heightened volatility in the forex market by December 2008.

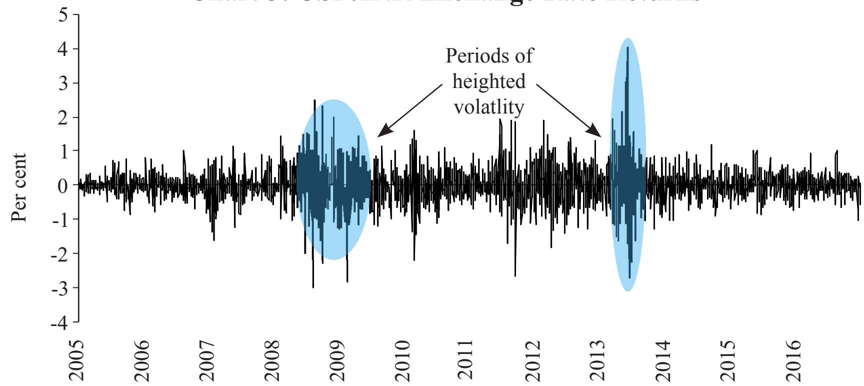
The next episode of very high exchange rate volatility was seen during the period after the announcement of tapering off the quantitative easing (famously known as Fed Taper Tantrum) by the US Federal Reserve on May 22, 2013. US bond yields spiked in response to the announcement resulting in narrower interest differentials with respect to EMEs. This led foreign portfolio investors to pull out their investments, especially debt investments, from EMEs including India. The accelerated capital outflows coupled with the prevailing weak macroeconomic situation led to a sharp fall in the rupee by about 19.4 per cent from ₹55.34 per US$ on May 22, 2013 to the historic low of ₹68.85 per US$ on August 28, 2013. The RBI resorted to several monetary and administrative measures to curb the excessive volatility in exchange rates (Pattanaik and Kavediya, 2015). The RBI sold net US$ 10.8 billion in spot during May-August 2013 and also sold heavily in the forward market thus doubling its forward liabilities to US$ 9.1 billion by end-August 2013 (RBI, 2013). It hiked the overnight Marginal Standing Facility (MSF) rate by 200 basis points; limited the overnight injection of liquidity to 0.5 per cent of banks' net demand and time liabilities; and increased the daily cash reserve maintenance requirement to 99 per cent so as to raise the cost of rupee funding, for banks and non-bank entities, to curb speculative pressure on the rupee. The RBI also took a number of administrative measures such as prohibiting banks to trade in currency futures, curtailing banks' overnight forex open position limits, restricting import of gold, and opening a concessional swap window for attracting FCNR(B) deposits. The annualised daily volatility of USD/INR exchange rate was at a high of 17 per cent during May 23, 2013 to September 4, 2013. The strong measures taken by the RBI coupled with the forward guidance released by the US Federal Reserve in September 2013 could arrest the heightened volatility in the forex market.

The stylised facts described above clearly show the two distinct phases of heightened volatility in the Indian forex market, *viz.*, (a) September to December 2008 - the peak period of the global financial crisis; and (b) May 23, 2013 to September 4, 2013 - the Fed Taper Tantrum period. The comparative descriptive statistics of the daily USD/INR exchange rate returns from April 4, 2005 to March 31, 2017, indicating the two periods of high volatility separately, is provided in Table 1. The daily returns exhibit a wide range of 2.5 to (-)3.0 per cent from September 2008 to December 2008 and 4.0 to (-)1.7 per cent from May 23, 2013 to September 4, 2013. The standard deviation is much higher in both periods compared to the others.

Table 1: Descriptive Statistics of USD/INR Exchange Rate across Different Periods

Item	Apr 4, 2005 - Aug 31, 2008	Sep 1, 2008 - Dec 31, 2008	Jan 1, 2009 - May 22, 2013	May 23, 2013 - Sep 4, 2013	Sep 5, 2009 - Mar 31, 2017
Mean	0.0001	0.1313	0.0129	0.2574	(-)0.0040
Maximum	1.4200	2.4900	1.9900	4.0200	1.5500
Minimum	(-)1.6200	(-)3.0100	(-)2.8200	(-)1.6900	(-)2.6800
Std. Deviation	0.33	1.02	0.56	1.08	0.38
Skewness	0.14	(-)0.33	(-)0.09	0.80	(-)0.81
Kurtosis	5.68	3.36	4.57	4.12	9.11
Jarque-Bera	251.96	1.83	109.54	11.66	1424.13
P-value	<0.01	0.40	<0.01	<0.01	<0.01

Chart 3: USD/INR Exchange Rate Returns



Source: Reserve Bank of India.

A similar observation can be made from Chart 3 showing these two periods with highly volatile movements in the daily exchange rate returns. There was also a spike in volatility during November-December 2011 due to the Eurozone debt crisis, but it was for a short period.

Section IV
Data and Methodology

Data

The objective of this study is to examine volatility spillovers between the Indian forex and stock markets. Accordingly, we use three variables, *viz.,* daily USD/INR exchange rate return (DER), daily return of S&P BSE Sensex (DSENSEX) and daily return of S&P CNX Nifty (DNIFTY) from April 4, 2005 to March 31, 2017 - a total of 2,899 observations. The continuously compounded daily returns, *i.e.,* DER, DSENSEX, DNIFTY are calculated using the formula $R_t = \ln(S_t / S_{t-1}) \times 100$, wherein S is daily spot value of each variable. While the exchange rate refers to the RBI's reference rate of the Indian rupee per US Dollar obtained from the RBI's website, the daily closing prices of Sensex and Nifty were obtained from the websites of BSE and National Stock Exchange (NSE), respectively. The SENSEX and NIFTY are the two major equity indices of India and comprise 30 stocks and 50 stocks, respectively. Though both the indices exhibit strong correlation of 0.99, at levels as well as returns, they sometimes exhibit differential movements in terms of returns and volatility because of differences in their composition and sectoral representation of the Indian economy. Therefore, we have used both the indices as a robustness check of our results.

As mentioned in Section III, the USD/INR exchange rate volatility heightened during September to December 2008 and from May 23, 2013 to September 4, 2013 with severe impacts and unprecedented regulatory responses. These two periods are well-known for their market-wide impacts, and, therefore, we have taken these two periods separately in this study, similar to the approach followed in Wu (2005), Choi, Fang and Fu (2009), Majumder and Nag (2015), and Xiong and Han (2015)[2]. The overall sample period is divided into five sub-periods as given in Table 2.

Table 3 presents descriptive statistics of all the three variables for the full sample period, which suggest that stock markets are more volatile than the forex market. Average daily returns are positive in both the markets and return distributions are positively skewed. Positive skewness indicates that positive returns are more common than negative returns. Kurtosis, a measure of the magnitude of extremes, is substantially higher than 3 and thus leptokurtic for both stock return as well as exchange rate return. Furthermore, the Jarque–Bera test rejected the null hypothesis of normal distribution for all the variables. All these statistics confirm that returns in both markets are not normally distributed. The descriptive statistics of the sub-samples suggest similar findings, except that the Jarque–Bera test did not reject the null hypothesis of normal distribution in sub-sample II, possibly due to small sample size.

Table 2. Details of the Phases

Sub-periods	Features
Period I	Relatively less volatile period (April 4, 2005 to August 31, 2008)
Period II	Peak of the global financial crisis – Highly volatile period (September 1 to December 31, 2008)
Period III	Relatively less volatile period (January 1, 2009 to May 22, 2013)
Period IV	Fed Taper Tantrum- Highly volatile period (May 23 to September 4, 2013)
Period V	Relatively less volatile period (September 5, 2013 to March 31, 2017)

[2] We conducted Bai-Perron structural break tests for three return series and did not find any break in any of the series. Therefore, the division of heighted volatility periods is guided by the well-documented, market-wide impacts during the Lehman-failure-led global financial crisis period and the Fed Taper Tantrum period.

Table 3. Descriptive Statistics

Item	DER	DSENSEX	DNIFTY
Mean	0.01	0.05	0.05
Maximum	4.02	15.99	16.33
Minimum	-3.01	-11.60	-13.01
Std. Dev	0.50	1.50	1.50
Skewness	0.21	0.12	0.004
Kurtosis	8.26	11.63	12.47
Jarque-Bera	3369 (0.00)	9909 (0.00)	10842 (0.00)
LB-Q	22.6 (0.00)	24.5 (0.00)	18.3 (0.00)
LB-Q^2	720.1 (0.00)	443.8 (0.00)	365.5 (0.00)
ARCH-LM	90.6 (0.00)	62.0 (0.00)	51.1 (0.00)
Jarque-Bera (residuals)	2905 (0.00)	8246 (0.00)	10091 (0.00)

DER: USD/INR return; DSENSEX: Sensex return; DNIFTY: Nifty return.

Note: 1. Figures in parentheses are p-values.

2. The statistics provided for Ljung-Box (LB-Q) tests and ARCH langrage multiplier (ARCH-LM) tests have used lag lengths up to 5.

To check stationarity, unit root tests were conducted for all the variables, both for the full sample and all the sub-samples, using Augmented Dicky–Fuller (ADF) and Phillips–Perron (PP) tests. The results confirmed stationarity of all the variables, both in the full sample and all the sub-samples, at 1 per cent level of significance[3]. The regression is conducted for equation (3) separately for three return variables using ordinary least square, and the Ljung-Box Q-statistics for residuals (LB-Q), squared residuals (LB-Q^2) and ARCH langrage multiplier (ARCH-LM) test statistics are reported in Table 3. The rejection of null of serial correlation of squared residuals in LB-Q^2 and ARCH-LM tests and the rejection of normality in the Jarque–Bera test validate the use of ARCH type of models to study the dynamic interdependence of the variables.

Methodology

The dynamic linkages between stock market and foreign exchange market are examined in terms of the conditional second moments of their distributions, termed as volatility spillover. We specify and estimate a

[3] The results of unit root tests are not reported for the sake of brevity.

multivariate model using daily data on stock and exchange rate returns that allows the possibilities of different types and categories of news simultaneously affecting the conditional variances. Before proceeding to estimate volatility spillovers, we employ Granger causality tests (Granger, 1969) to examine the possible endogeneity between these variables[4]. This section describes the specific model employed to examine the spillovers and its econometric properties as well as the estimation strategy.

Granger Causality Test

The Granger causality test involves estimating the following pairs of equations in a vector autoregression (VAR) framework:

$$Y_t = a_1 + \sum_{i=1}^{n} \alpha_i Y_{t-i} + \sum_{i=1}^{n} \beta_i X_{t-i} + \varepsilon_{1t} \tag{1}$$

$$X_t = a_2 + \sum_{i=1}^{n} \gamma_i Y_{t-i} + \sum_{i=1}^{n} \delta_i X_{t-i} + \varepsilon_{2t} \tag{2}$$

where Y_t and X_t are the two variables of interest for testing their causal relationships using up to n lags; a_1, a_2, α_i, β_i, γ_i and δ_i are parameters to be estimated; and ε_{1t} and ε_{2t} are two independent error terms. To test whether X causes Y, the null hypothesis is β_is are jointly zero. A rejection of the null hypothesis confirms that X causes Y. Similarly, a rejection of $H_0: \gamma_1 = \gamma_2 \ldots = \gamma_n = 0$ implies that Y causes X. We have used two different pairs of variables, *i.e.,* (i) DER (exchange rate return) and DSENSEX (BSE Sensex return); and (ii) DER and DNIFTY (CNX Nifty return) to examine the causal relationship between stock prices and exchange rate.

Multivariate GARCH (MGARCH)

A standard VAR is suitable where the residual vector is assumed to be a white noise process with time invariant covariance matrix. However, returns on financial assets typically exhibit 'volatility clustering' which strongly suggests the need for modelling time-varying second-order moments, popularly known as Autogressive Conditional Heteroskedasticity (ARCH). A variant of ARCH, *i.e.*, Generalised Autogressive Conditional Heteroskedasticity

[4] It may be noted that the Granger causality test is not appropriate to determine the endogeneity between variables in the presence of time-variant standard deviation. The results of Granger causality test, though not robust, are reported here to justify our stance on the appropriateness of using MGARCH to examine the volatility spillovers between the two markets.

(GARCH) models are developed to consider time varying second order moments. MGARCH models and their extensions are widely used to examine the relationship between two or more financial variables/financial market volatility in the presence of endogeneity. We estimate a variant of MGARCH model, which also takes into account the asymmetric specifications of Nelson (1991) and the multivariate extension proposed by Kroner and Ng (1998).

The bivariate version of the MGARCH model is used to examine spillovers across two markets as proposed by Engle and Kroner (1995), *i.e.,* a bivariate BEKK-GARCH (1,1) model, where the system of conditional mean equations consists of VAR(p) models (p = 1, ..., n). The specification for conditional mean equation in VAR(p) form is:

$$Y_t = \mu + \sum_{i=1}^{p} \Gamma_i Y_{t-i} + \varepsilon_t \tag{3}$$

where $Y_t = (y_{1t,} y_{2t})$, y_{1t} is exchange rate return (DER) and y_{2t} is stock return (DSENSEX or DNIFTY) at time t. The parameter vector $\mu = (\mu_1, \mu_2)$ represents constants and Γ is a 2×2 matrix of coefficients for autoregressive terms. The own market autoregressive terms (γ_{ii}) are used to eliminate linear dependency in the series whereas the cross market autoregressive terms (γ_{ij}) are used to capture the mean spillover from market *i* to market *j*. The residuals $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t})$ are normally distributed, $\varepsilon_t|\Omega_{t-1} \sim N(0, H_t)$ with its corresponding conditional variance-covariance matrix given by H_t, Ω_{t-1} as an information set at time *t-1*. Selection of lags in the above VAR models was made on the basis Schwartz criteria.

The conditional variance equation is expressed in terms of BEKK specification, which ensures positive semi-definiteness of the conditional variance matrix and is less cumbersome to estimate, with the advantage of estimating less number of parameters:

$$H_t = C'C + A'\varepsilon'_{t-1}\varepsilon_{t-1}A + G'H_{t-1}G \tag{4}$$

To incorporate asymmetric responses of volatility in the variances and covariances, the above model can be further extended as proposed by Kroner and Ng (1998):

$$H_t = C'C + A'\varepsilon'_{t-1}\varepsilon_{t-1}A + G'H_{t-1}G + D'\xi'_{t-1}\xi_{t-1}\mathrm{D} \tag{5}$$

where, ξ_t would be ε_t if it is negative and zero otherwise. The eq. (5) can be written in matrix form as follows:

$$Ht = \begin{bmatrix} C_{11} & 0 \\ C_{21} & C_{22} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\,\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}\,\varepsilon_{1,t-1} & \varepsilon_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$$

$$+ \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix}' \begin{bmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{bmatrix}' \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix}$$

$$+ \begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix}' \begin{bmatrix} \xi_{1,t-1}^2 & \xi_{1,t-1}\,\xi_{2,t-1} \\ \xi_{2,t-1}\,\xi_{1,t-1} & \xi_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix}$$

In the above model, the off-diagonal parameters in matrices A and G measure volatility spillover between markets while the diagonal parameters in those matrices capture the effects of their own past shocks and volatility. The diagonal parameters in matrix D measure the response to own past negative shocks while the off-diagonal parameters d_{ij} show the response of one market to negative shocks in the other market, to be called hereafter as cross-market asymmetric responses. A negative value of D means negative news tend to increase volatility more than the positive news. In case of exchange rate, Nath and Pacheco (2018) define that a negative value of the coefficient implies that a negative shock (the appreciation of the rupee) increases volatility in forex market more than positive shock (the depreciation of the rupee) and a positive value of the coefficient implies that a positive shock (depreciation of the rupee) increases volatility more than the negative shock (appreciation of the rupee).The above BEKK model can be estimated efficiently and consistently using full information maximum-likelihood method (Engle and Kroner, 1995; Kroner and Ng, 1998). The log-likelihood function assuming normally distributed errors can be stated as:

$$L(\theta) = -\frac{Tn}{2}\text{In}(2\pi) - \frac{1}{2}\sum(\text{In}|H_1| + \varepsilon_t^{'}H_t^{-1}\varepsilon_t)$$

where T is the number of observations, n is the number equations and θ represents the parameter vector to be estimated. To obtain the estimates of the parameters, a combination of the standard gradient search algorithm Broyden–Fletcher–Goldfarb–Shanno (BFGS) and simplex algorithm is used.

Section V
Empirical Analysis

Test for Causality

We examined the causal relationship between exchange rate return and stock index return by applying the Granger causality test. The test is conducted using 3 lags based on Schwartz criteria and the results are reported in Table 4. The results show that the F-statistics is significant at less than 5 per cent level in all the cases. Thus, the null of stock return (exchange rate return) does not cause exchange rate return (stock return) is rejected; hence suggesting the presence of bidirectional causality between stock returns and exchange rate returns in India. This indicates the presence of endogeneity between the two variables. Therefore, any type of univariate models to study volatility spillovers may provide biased results. Hence, we used MGARCH model in this study.

Bivariate BEKK-GARCH (1,1) Estimation Results

It is commonly observed that the financial markets exhibit asymmetric effects. Following Apte (2001), Yang and Doong (2004), Wu (2005), Majumder and Nag (2015), and Behera (2017), we tried to capture asymmetric effects in our model. We have estimated the model for both full sample and five sub-samples. The preferred lag lengths for the full sample and all sub-samples are based on Hosking's multivariate Q-test. The estimation is conducted using two groups of variables: (i) DER and DSENSEX and (ii) DER and DNIFTY. The estimates of bivariate asymmetric GARCH(1,1)-BEKK parameters along with various diagnostic test results are reported in Tables 5 through 8. The results for the conditional mean equation and conditional variance equation are reported separately.

Table 4. Granger Causality Test Results

Null Hypothesis	F-Statistics	P-value
DSENSEX does not granger cause DER	48.23	0.00
DER does not granger cause DSENSEX	3.11	0.03
DNIFTY does not granger cause DER	49.67	0.00
DER does not granger cause DNIFTY	3.42	0.02

The results of conditional mean equations in Tables 5 and 6 indicate that the autoregressive coefficients are statistically significant in the case of DER for the full sample and sub-samples 2 and 3, and also in the case of DSENSEX and DNIFTY for the full sample and sub-samples 1 and 5. This establishes that exchange rate returns as well as stock market returns largely depend on their own past values. The off-diagonal parameter (γ_{21}) is found to be statistically significant in the full sample and all sub-samples except for sub-sample 4. However, the γ_{12} coefficient is statistically insignificant in most cases except in sub-sample 5, when DNIFTY is used as a measure of stock return. The results indicate that stock markets do have price spillover effects on the foreign exchange market, but not the *vice-versa*. Further, the negative value of the coefficients indicate negative relationship, *i.e.,* rise in stock price (positive stock returns) leads to appreciation in USD/INR exchange rate (negative exchange rate return) and *vice-versa*.

The main focus of our study is to analyse volatility transmission between forex and stock markets, which can be inferred from the estimated parameters in the conditional variance equations. The results relating to conditional variance equations are provided in Tables 7 and 8. In both the conditional variance equations, the estimated diagonal parameters a_{11} (full sample and all sub-samples except sub-sample 2), a_{22} (full sample and sub-sample 3), g_{11} (full sample and all sub-samples except sub-sample 4) and g_{22} (full sample and all sub-samples) are statistically significant, indicating a strong GARCH(1,1) process, which establishes that volatility in stock and forex markets is driven by their own past shocks and volatility. The large magnitudes of g_{11} and g_{22} indicate strong volatility persistence. The coefficient g_{11} is found to be insignificant in sub-sample 4, suggesting that exchange rate volatility was not persistent during that period.

The a_{12} is statistically significant in 2nd, 4th and 5th sub-samples in the case of DSENSEX and in 4th and 5th sub-samples in the case of DNIFTY, indicating shock spillover from forex market to stock markets mainly during the high volatile periods, *i.e.,* 2nd and 4th sub-samples. The coeffecient g_{12} is statistically significant in the 2nd sub-sample in the case of DSENSEX and in the 1st and 2nd sub-samples in the case of DNIFTY. The results establish the existence of volatility spillovers from the forex market to stock markets mainly during the 2nd sub-sample period - the peak of the global financial crisis. We did not find shock/volatility spillovers from forex market to stock markets in the full sample period. The volatility spillovers from forex market

Table 5. Estimated Asymmetric MGARCH-BEKK Model - Mean Equation (Sensex)

Variables	Full Sample (Apr. 1, 2005 to Mar. 31, 2017)		Sub-Sample 1 (Apr. 1, 2005 to Aug. 31, 2008)		Sub-Sample 2 (Sept. 1, 2008 to Dec. 31, 2008)		Sub-Sample 3 (Jan. 1, 2009 to May 22, 2013)		Sub-Sample 4 (May 23, 2013 to Sept. 4, 2013)		Sub-Sample 5 (Sept. 5, 2013 to Mar. 31, 2017)	
	Dependent Variable: DER											
DER_{t-1}	-0.04	-(1.95)**	-0.01	-(0.23)	-0.19	-(1.87)*	-0.07	-(2.31)**	-0.17	-(1.48)	-0.06	-(1.40)
DER_{t-2}	-0.04	-(2.39)**									-0.02	-(0.51)
$DSENSEX_{t-1}$	-0.04	-(8.65)***	-0.03	-(4.87)***	-0.12	-(4.09)***	-0.09	-(7.46)***	-0.11	-(1.13)	-0.06	-(4.13)***
$DSENSEX_{t-2}$	-0.01	-(1.53)									0.003	(0.22)
Constant	0.01	(1.02)	0.003	(0.39)	0.11	(1.08)	0.01	(0.61)	0.20	(1.92)*	0.01	(0.48)
	Dependent Variable: DSENSEX											
DER_{t-1}	-0.05	-(1.16)	-0.05	-(0.39)	-0.14	-(0.40)	0.01	(0.12)	0.24	(1.50)	-0.15	-(1.42)
DER_{t-2}	-0.02	-(0.49)									0.06	(0.61)
$DSENSEX_{t-1}$	0.05	(2.64)***	0.10	(2.95)***	0.02	(0.14)	0.02	(0.87)	0.08	(0.69)	0.08	(1.91)*
$DSENSEX_{t-2}$	-0.03	-(1.43)									-0.06	-(1.34)
Constant	0.05	(2.80)***	0.12	(2.87)***	-0.46	-(1.29)	0.03	(1.02)	-0.19	-(1.30)	0.04	(1.30)

,,***: Indicates significant at 10 per cent, 5 per cent and 1per cent levels, respectively.

Note: Figures in parentheses are t-statistics.

Table 6. Estimated Asymmetric MGARCH-BEKK Model - Mean Equation (Nifty)

Variables	Full Sample (Apr. 1, 2005 to Mar. 31, 2017)		Sub-Sample 1 (Apr. 1, 2005 to Aug. 31, 2008)		Sub-Sample 2 (Sept. 1, 2008 to Dec. 31, 2008)		Sub-Sample 3 (Jan. 1, 2009 to May 22, 2013)		Sub-Sample 4 (May 23, 2013 to Sept. 4, 2013)		Sub-Sample 5 (Sept. 5, 2013 to Mar. 31, 2017)	
	Dependent Variable: DER											
DER_{t-1}	-0.04	-(2.05)**	-0.01	-(0.32)	-0.19	-(1.85)*	-0.08	-(2.65)***	-0.17	-(1.54)	-0.06	-(1.37)
DER_{t-2}	-0.04	-(2.61)***					-0.05	-(1.97)**				
$DNIFTY_{t-1}$	-0.04	-(10.10)***	-0.03	-(4.79)***	-0.13	-(3.94)***	-0.09	-(7.61)***	-0.12	-(1.31)	-0.06	-(4.36)***
$DNIFTY_{t-2}$	-0.01	-(1.75)*					-0.02	-(1.46)				
Constant	0.005	(0.97)	0.002	(0.30)	0.12	(1.18)	0.01	(0.64)	0.19	(1.92)*	0.01	(0.61)
	Dependent Variable: DNIFTY											
DER_{t-1}	-0.06	-(1.49)	-0.08	-(0.52)	-0.15	-(0.43)	0.03	(0.51)	0.24	(1.53)	-0.18	-(1.75)*
DER_{t-2}	-0.02	-(0.37)					0.05	(0.99)				
$DNIFTY_{t-1}$	0.04	(2.29)**	0.10	(2.79)***	0.03	(0.25)	0.03	(0.94)	0.08	(0.78)	0.07	(1.82)*
$DNIFTY_{t-2}$	-0.02	-(1.18)					0.04	(1.29)				
Constant	0.05	(2.90)***	0.12	(2.68)***	-0.43	-(1.30)	0.03	(0.91)	-0.25	-(1.70)*	0.04	(1.36)

,,***: Indicates significant at 10 per cent, 5 per cent and 1 per cent levels, respectively.

Note: Figures in parentheses are t-statistics.

Table 7. Estimated Asymmetric MGARCH-BEKK Model - Variance Equation (Sensex)

Coefficients	Full Sample (Apr. 1, 2005 to Mar. 31, 2017)		Sub-Sample 1 (Apr. 1, 2005 to Aug. 31, 2008)		Sub-Sample 2 (Sept. 1, 2008 to Dec. 31, 2008)		Sub-Sample 3 (Jan. 1, 2009 to May 22, 2013)		Sub-Sample 4 (May 23, 2013 to Sept. 4, 2013)		Sub-Sample 5 (Sept. 5, 2013 to Mar. 31, 2017)	
a_{11}	0.35	(16.85)***	0.51	(13.09)***	-0.13	(1.58)	0.33	(6.78)***	-0.39	-(2.26)**	0.22	(3.92)***
a_{12}	-0.04	-(0.83)	0.08	(0.45)	-0.70	-(1.75)*	0.01	(0.26)	0.66	(2.96)***	-0.26	-(2.12)**
a_{21}	-0.01	-(1.28)	0.02	(1.87)*	0.01	(0.17)	-0.01	-(0.82)	-0.14	-(0.94)	0.01	(0.86)
a_{22}	0.15	(7.13)***	-0.01	-(0.17)	0.03	(0.24)	0.12	(3.39)****	0.23	(1.51)	-0.06	-(0.78)
g_{11}	0.93	(123.80)***	0.84	(35.23)***	0.84	(7.75)***	0.92	(34.11)***	0.19	(0.79)	0.96	(54.67)***
g_{12}	-0.001	-(0.17)	-0.13	-(1.30)	-1.21	-(2.48)**	-0.01	-(0.28)	-0.28	-(1.09)	0.03	(0.72)
g_{21}	0.001	(0.82)	0.002	(0.60)	0.08	(2.88)***	-0.01	-(1.40)	-0.38	-(2.75)***	0.001	(0.13)
g_{22}	0.95	(158.91)***	0.86	(44.55)***	0.72	(10.52)****	0.98	(160.43)***	0.67	(4.52)****	0.94	(50.66)***
d_{11}	-0.06	-(1.41)	-0.08	(0.66)	-0.04	-(0.26)	-0.04	-(0.51)	-0.05	-(0.18)	0.08	(1.00)
d_{12}	0.02	(0.23)	-0.03	-(0.11)	-0.04	-(0.05)	-0.06	-(0.76)	-0.04	-(0.06)	0.10	(0.79)
d_{21}	-0.01	-(1.79)*	0.04	(4.73)***	0.18	(3.63)***	0.01	(0.61)	0.72	(3.85)***	-0.04	-(1.66)*
d_{22}	0.33	(12.35)***	-0.61	-(11.19)***	-0.51	-(2.10)**	0.24	(7.00)***	0.25	(1.32)	0.33	(6.27 ***
N	2897		834		76		1057		72		854	
Log-likelihood	-6000		-1579		-295		-2441		-211		-1329	

,,***: Indicates significant at 10 per cent, 5 per cent and 1per cent levels, respectively.

Note: 1. Figures in parentheses are t-statistics.

2. Subscripts 1 and 2 of each parameter represent forex and stock markets, respectively.

Table 8. Estimated Asymmetric MGARCH-BEKK Model - Variance Equation (Nifty)

Coefficients	Full Sample (Apr. 1, 2005 to Mar. 31, 2017)		Sub-Sample 1 (Apr. 1, 2005 to Aug. 31, 2008)		Sub-Sample 2 (Sept. 1, 2008 to Dec. 31, 2008)		Sub-Sample 3 (Jan. 1, 2009 to May 22, 2013)		Sub-Sample 4 (May 23, 2013 to Sept. 4, 2013)		Sub-Sample 5 (Sept. 5, 2013 to Mar. 31, 2017)	
a_{11}	0.35	(16.28)***	0.52	(13.31)***	-0.13	-(1.00)	0.34	(6.83)***	0.39	(2.19)**	0.20	(3.66)***
a_{12}	-0.04	-(0.89)	0.12	(0.75)	-0.63	-(1.58)	0.001	(0.01)	-0.70	-(3.06)***	-0.26	-(1.74)*
a_{21}	-0.01	-(1.22)	0.02	(2.39)**	0.01	(0.24)	-0.01	-(0.56)	0.12	(0.86)	0.01	(1.03)
a_{22}	0.16	(7.60)***	-0.02	-(0.39)	0.05	(0.35)	0.12	(4.28)***	-0.22	-(1.50)	-0.05	-(0.62)
g_{11}	0.93	(119.49)***	0.84	(36.53)***	0.83	(7.51)***	0.91	(32.88)***	0.20	(0.78)	0.97	(57.91)***
g_{12}	-0.001	-(0.08)	-0.15	-(2.05)**	-1.22	-(2.70)***	-0.004	-(0.18)	-0.28	-(1.03)	0.01	(0.30)
g_{21}	0.001	(0.82)	-0.00001	-(0.003)	0.09	(3.22)***	-0.009	-(1.80)	-0.35	-(2.52)**	0.01	(0.72)
g_{22}	0.95	(155.01)***	0.84	(39.91)***	0.72	(9.33)***	0.98	(137.9)***	0.68	(4.25)***	0.92	(41.89)***
d_{11}	-0.07	-(2.10)**	0.02	(0.17)	0.04	(0.22)	-0.05	-(0.61)	-0.05	-(0.21)	-0.07	-(0.75)
d_{12}	0.02	(0.24)	0.03	(0.08)	0.18	(0.24)	-0.05	-(0.61)	-0.06	-(0.11)	-0.13	-(0.90)
d_{21}	-0.01	-(1.71)*	-0.03	-(3.73)***	-0.19	-(3.51)***	0.02	(0.87)	0.68	(3.86)***	0.05	(2.35)**
d_{22}	0.33	(12.28)***	0.64	(11.18)***	0.48	(1.88)*	0.26	(6.72)***	0.22	(1.09)	-0.36	-(6.75)***
N	2897		834		76		1056		72		855	
Log-likelihood	-6029		-1587		-292		-2446		-213		-1340	

,,***: Indicates significant at 10 per cent, 5 per cent and 1 per cent levels, respectively.

Note: 1. Figures in parentheses are t-statistics.

2. Subscripts 1 and 2 of each parameter represent forex and stock markets, respectively

to stock market during highly volatile periods is possibly due to presence of many export oriented heavy weight companies like Infosys, TCS, Wipro, and Sun Pharma in the Sensex/Nifty indices which are highly sensitive to exchange rate movements.

In both DSENSEX and DNIFTY, the a_{21} is found to be significant in 1st sub-sample, whereas g_{21} is found to be significant in both 2nd and 4th sub-samples. We did not find shock/volatility spillovers from stock market to forex market when the full sample period was considered. The results suggest that the volatility spillover from stock market to the forex market was restricted to the high exchange rate volatility periods, *viz.,* 2nd and 4th sub-samples. Unlike the price spillovers from stock market to forex market, which was found to be a common phenomenon across the full sample period, the volatility spillovers from stock market to forex market was more of a specific phenomenon observed only during the high exchange rate volatility periods.

The asymmetry parameter d_{12} is not statistically significant in respect of both DSENSEX and DNIFTY. The parameter d_{21} is found significant for the full sample as well as all sub-samples except for the 3rd sub-sample in respect of both DSENSEX and DNIFTY. These findings confirm asymmetric responses of the foreign exchange market to negative shocks in stock markets in the full sample period.

Section VI
Conclusion

The bivariate BEKK-GARCH analysis suggests that there is one way price spillovers from stock markets to forex market in India. This implies the dominance of the portfolio channel in the price relationship between the exchange rate and stock prices in India. The volatilities in both the markets are found to be highly persistent and are driven by their own past shocks and volatility.

With regard to volatility spillovers, unlike the price spillovers, we did not find any volatility spillover effects between these two markets when the full sample period was considered. The volatility spillovers were found to be more of a specific phenomenon, observed mainly during the periods of high exchange rate volatility. The volatility spillovers from stock markets to the forex market were evident during the 2nd and 4th sub-sample periods, while that from the forex market to stock market was observed mainly during the 2nd sub-sample period. The 2nd and 4th sub-sample periods represent the onset of the global financial crisis and the Fed Taper Tantrum, respectively-marked as heightened volatility periods. The results also establish asymmetric responses of the forex market to negative shocks in the stock market.

The findings justify our approach of conducting sub-period analysis. The evidence of volatility spillovers between both the markets during highly volatile periods points to the possible 'contagion' impact, apart from the volatility transmission caused by the large FPI investment/disinvestment actions. This observation is in line with the evidence provided by King and Wadhwani (1990) regarding the existence of high contagion effects during volatile market conditions in their study on transmission of volatility between stock markets. The market contagion amplifies volatility and exacerbates stress in the financial system as a whole.

The findings of this paper may help financial sector regulators to devise appropriate policies and strategies to proactively deal with the volatility spillover effects when the USD/INR exchange rate exhibits high volatility. These findings may also help international investors and portfolio managers to formulate suitable trading/hedging/portfolio diversification strategies to deal with the impact of volatility spillovers during stressful market conditions.

References

Abdalla, I.S.A., and V. Murinde (1997). 'Exchange rate and stock price interactions in emerging markets: Evidence on India, Korea, Pakistan and the Philippines', *Applied Financial Economics*, 7(1): 25–35.

Agénor, P. (2003). 'Benefits and costs of international financial integration: Theory and facts'. *The World Economy,* 26(8): 1089–1118.

Ajayi, R. A., J. Friedman and S. M. Mehdian (1998). 'On the relationship between stock returns and exchange rates: Tests of Granger causality', *Global Finance Journal*, 9(2): 241–51.

Alaganar, V. T. and R. Bhar (2007). 'Empirical properties of currency risk in country index portfolios', *The Quarterly Review of Economics and Finance,* 47:159–74.

Aloui, C. (2007). 'Price and volatility spillovers between exchange rates and stock indexes for the pre- and post-euro period', *Quantitative Finance*, 7(6): 1–17.

Apte, P. (2001). 'The interrelationship between stock markets and the foreign exchange market', *Prajnan*, 30: 17–29.

Assoe, K. (2001). 'Volatility spillovers between foreign exchange and emerging stock markets', *CETAI,* Cahiers de recherché, 2001-04.

Aydemir, O., and E, Demirhan. (2009). 'The relationship between stock prices and exchange rates: Evidence from Turkey', *International Research Journal of Finance and Economics*, 23(2): 207–15.

Bahmani-Oskooee, M. and A. Sohrabian. (1992). 'Stock prices and the effective exchange rate of the dollar', *Applied Economics*, 24(4): 459–64.

Behera, H. (2017). 'Spillover effects of foreign institutional investments in India', *International Journal of Bonds and Derivatives,* 3(2): 132–52.

Bonga-Bonga, L., and J. Hoveni (2011). 'Volatility spillover between the equity market and foreign exchange market in South Africa', *Working Paper 252*, University of Johannesburg.

Chang H. L., C. W. Su and Y. C. Lai (2009). 'Asymmetric price transmissions between the exchange rate and stock market in Vietnam', *International Research Journal of Finance and Economics,* 23: 104–13.

Choi, D. F. S., V. Fang and T. Y. Fu (2009). 'Volatility spillovers between New Zealand stock market returns and exchange rate changes before and after the 1997 Asian financial crisis", *Asian Journal of Finance and Accounting*, 1(2): 107–17.

Cournot, A. (1927). *Researches into the mathematical principles of the theory of wealth*, trans. Nathaniel T. Bacon, New York: Macmillan.

Dornbusch, R. and S. Fisher (1980). 'Exchange rates and the current account', *American Economic Review,* 70: 960–71.

Engle, R. F., and K. F. Kroner (1995). 'Multivariate simultaneous generalized ARCH', *Econometric Theory*, 11: 122–50.

Eun, C. S., and B. G. Resnick (1988). 'Exchange rate uncertainty, forward contracts, and international portfolio selection', *Journal of Finance*, 43: 197–215.

Fedorova, E. and K. Saleem (2010). 'Volatility spillovers between stock and currency markets: Evidence from emerging Eastern Europe', *Finance a úvěr-Czech Journal of Economics and Finance*, 60(6), 519-533.

Frankel, J. A. (1983). 'Monetary and portfolio-balance models of exchange rate determination', in *Economic Interdependence and Flexible Exchange Rates*, ed. J. Bhandari and B. Putnam, Cambridge, MA: MIT Press, pp 84–114.

Gavin, M. (1989). 'The stock market and exchange rate dynamics', *Journal of International Money and Finance*, 8(2): 181–200.

Granger, C. W. (1969). 'Investigating causal relations by econometric models and cross-spectral methods', *Econometrica*, 37: 424–39.

Granger, C. W., B. N. Huangb and C. W. Yang (2000). 'A bivariate causality between stock prices and exchange rates: Evidence from recent Asianflu', *The Quarterly Review of Economics and Finance,* 40(3): 337–54.

Huzaimi, H., and V. K. Liew (2004). 'Causal relationships between exchange rate and stock prices in Malaysia and Thailand during the 1997 currency crisis turmoil'. Available at: http://129.3.20.41/eps/if/papers/0405/0405015.pdf.

Issam S. A. Abdalla and V. Murinde (1997). 'Exchange rate and stock price interactions in emerging financial markets: Evidence on India, Korea, Pakistan and the Philippines', *Applied Financial Economics*, 7(1): 25–35.

Ito, T. and W-L. Lin (1994). ‘Price volatility and volume spillovers between the Tokyo and New York Stock Markets’, in *The internationalization of equity markets*, ed. J. A. Frankel, University of Chicago Press, Chicago, pp. 309–343.

Jebran, K. and A. Iqbal (2016). ‘Dynamics of volatility spillover between stock market and foreign exchange market: Evidence from Asian Countries’, *Financial Innovation*, 2(3): 1-20.

Kanas, A. (2000). ‘Volatility spillovers between stock returns and exchange rate changes: International evidence’, *Journal of Business Finance and Accounting,* 27(3&4): 447–67.

King, M. and S. Wadhwani (1990). ‘Transmission of volatility between stock markets’, *The Review of Financial Studies*, 3(1): 5–33.

Kisaka, S. E., and A. Mwasaru (2012). ‘The causal relationship between exchange rates and stock prices in Kenya’, *Research Journal of Finance and Accounting,* 3(7): 121-131.

Kose, Y., M. Doganay and H. Karabacak (2010). ‘On the causality between stock prices and exchange rates: Evidence from Turkish financial market’, *Problems and Perspectives in Management*, 8(1):127-135.

Kroner, K., and V. Ng (1998). ‘Modelling asymmetric comovements of asset returns’, *The Review of Financial Studies,* 11(4): 817–44.

Majumder, S. B., and R.N. Nag (2015). ‘Return and volatility spillover between stock price and exchange rate: Indian evidence’, *International Journal of Economics and Business Research,* 10(4): 326-340.

Mishra, A. K. (2004). “Stock Market and Foreign Exchange Market in India: Are they Related?”, *South Asia Economic Journal*, 5(2): 209-232.

Mishra, A. K., N. Swain and D. K. Malhotra (2007). ‘Volatility spillovers between stock and foreign exchange markets: Indian evidence’, *International Journal of Business*, 12(3): 344–59.

Mitra, P. K. (2017). ‘Dynamics of volatility spillover between the Indian stock market and foreign exchange market return’, *Academy of Accounting and Finance Studies Journal,* 21(2): 1-12.

Mok, H. M. (1993). ‘Causality of interest rate, exchange rate and stock prices at stock market open and close in Hong Kong’, *Asia Pacific Journal of Management*, 10(2): 123–43.

Morales, L. (2008). 'Volatility spillovers between equity and currency markets: Evidence from major Latin American countries', Cuadernos de Economica, *Latin American Journal of Economics,* 45 (November): 185–215.

Nath, G. and G. P. Samanta (2003). 'Integration between Forex and Capital Markets in India: An EmpiricalExploration',Available at: https://ssrn.com/abstract=475822.

Nath, G. and M. Pacheco (2018). 'Currency futures market in India: An empirical analysis of market efficiency and volatility', *Macroeconomics and Finance in Emerging Market Economies*, 11(1): 47–84.

Nelson, D. B. (1991). 'Conditional heteroskedasticity in asset returns: A new approach', *Econometrica*, 59(2): 347–70.

Pattanaik, S., and R. Kavediya (2015). 'Taper talk impact on the rupee: Preconditions for the success of an interest rate defence of the exchange rate', *Prajnan*, XLIV(3): 251-277.

Pan, M. S., R. C. W. Fok and Y. A. Liu (2007). 'Dynamic linkages between exchange rates and stock prices: Evidence from East Asian markets', *International Review of Economics & Finance*, 16(4): 503–20.

Panda, P. and M. Deo (2014). 'Asymmetric and volatility spillover between stock market and foreign exchange market: Indian experience', *The IUP Journal of Applied Finance*, 20(4): 69-82.

Phylaktis, K. and F. Ravazzolo. 2002. 'Stock prices and exchange rate dynamics', Cass Business School Working Paper.

Pradhan, C. P. (2006). 'The dynamic relationship between the stock price and exchange rate in India', The IUP *Journal of Monetary Economics*, IV: 26–36.

Rahman, M. L., and J. Uddin (2009). 'Dynamic relationship between stock prices and exchange rates: Evidence from three South Asian countries', *International Business Research*, 2(2): 167–74.

Reserve Bank of India (2007). *Report on Currency and Finance 2005–06*, 31 May.

— (2009). *Annual Report 2008–09*, 27 August.

— (2010). *Report on Currency and Finance 2008–09*, 1 July.

— (2013). *Reserve Bank of India Bulletin – October 2013,* 10 October.

Rubayat, S. and M. Tereq (2017). 'Volatility spillover between foreign exchange market and stock market in Bangladesh', *11th International Conference on Management Science and Engineering Management*, June.

Smyth, R., and M. Nandha (2003). 'Bivariate causality between exchange rates and stock prices in South Asia', *Applied Economics Letters*, 10(11): 699–704.

Wu, R. (2005). 'International transmission effect of volatility between the financial markets during the Asian financial crises', *Transition Studies Review*, 12(1): 19–35.

Xiong, Z. and L. Han (2015). 'Volatility spillover effect between financial markets: Evidence since the reform of the RMB exchange rate mechanism', *Financial Innovation (a Springer Open Journal),*1(9):1-12.

Yang, S. and S. Doong (2004). 'Price and volatility spillovers between stock prices and exchange rates: Empirical evidence from the G-7 countries', *International Journal of Business and Economics*, 3(2): 139–53.

Reserve Bank of India Occasional Papers
Vol. 38, No. 1&2, 2017

Inter-temporal Calculative Trust Design to Reduce Collateral Need for Business Credits

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Credit rationing arising out of informational asymmetry and lack of collateral is a well-recognised economic constraint in the credit market. These constraints get magnified for small businesses. This paper attempts to capture the dimension of trustworthiness (calculative trust) by designing a multi-period, incentivised payment structure that will induce economic agents to reveal the existence of private information about any projects or true intentions of paying up the credit that is going to fund the project. The model dynamically estimates the collateral needed by taking into account the truthfulness of the borrower. The proposed design is compared with the benchmark model - credit scoring-based model. Randomised simulations are carried out for the *ex ante* solution for the borrower. We find that the proposed design outperforms from the perspective of lenders when the probability of default of any project is less than 80 per cent. Our simulation result also finds that building trust helps small business owner to significantly reduce the need for collateral.

JEL Classification : M21, R51, G21

Keywords : Calculative trust, collateral

Introduction

Creation of jobs is one of the most important political/economic issues facing developing economies. The progress of Small and Medium Enterprises (SMEs) is imperative for employment growth because, across developing economies, SMEs are a key employment generation sector (Chu, Benzing and McGee, 2007; Lee, 1998; Lin, 1998). This sector grows when entrepreneurs invest in new projects. Retained earnings may not be sufficient to meet the

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capital needed for growth and therefore additional capital may need to be raised in the form of debt. However, small businesses encounter financial constraints while raising capital to fund their growth (Panda and Dash, 2014; Thampy, 2010).

Constraints faced by small businesses are more binding due to the perceived credit risks associated with them. Credit risk can arise from two sources. First, risk arising from the inability of the project to pay back the loan, and, second, risk arising from unwillingness of the business owner to pay back the loan. There is a well developed risk mitigation strategy for a project's inability to pay back the loan, driven by intermediaries such as credit rating agencies, credit bureaus, and internally-developed scorecards. On the other hand, the risk mitigation strategy with respect to unwillingness of a business owner to pay back the credit is not well developed. This is the grey area in the underwriting processes followed by lending institutions.

Willingness to pay back can be traced to trustworthiness of the business owner. This kind of trustworthiness can be visualised as calculative trust as discussed in Lewicki *et al.,* (2006). One can argue that any economic relationship will start with a principal (lending institution) calculating the trustworthiness of the agent (borrower) on the basis of the perceived credit risk associated with dealing with an agent. As the principal deals with the agent over time, set of information with the principal expands, and the trustworthiness of the agent in the eyes of the principal changes. These inter-temporal changes in calculative trust have not been adequately captured in the available literature. Besides, they have not been modelled in a way to understand the risk arising out of an unwillingness to pay back the loan.

The inter-temporal dimensions of the perceived credit risk can also be looked at from a perspective of private information available with a business owner. This asymmetry of information between borrower and lender will lead to adverse selection (*ex ante*), and the creation of a moral hazard (*ex post*) problem. To deal with the asymmetric information problem, lending institutions will demand collateral from all types of borrowers (including the good ones). Non-availability of sufficient collateral may in turn result in non-availability of credit to the potentially good quality borrower. This is the classical credit rationing problem put forward by Stiglitz and Weiss (1981). The asymmetry of information problem is particularly binding in the case of SMEs, as they also face lack of collateral. Therefore, one can argue that small business owners are likely to face acute credit rationing.

This paper develops an incentivised metrics, which induces the small business owner to reveal certain amount of private information so that the lender can assess the risk associated with the borrower's unwillingness to pay back the loan. The paper does not address the credit risk arising out of genuine risk of failure of the project due to external socio-economic and political circumstances. The paper assumes that these kinds of genuine risks can be taken care of by credit default scores, and pricing of credit. The paper is organised into five sections. Section II provides a review of the literature. Section III discusses the model, the *ex ante* solution, and simulation results. Section IV provides the *ex post* solution for the borrower and Section V concludes the paper.

Section II
Literature Survey

Non-availability of financial resources is a major constraint faced by start-ups and SMEs in developing countries (Cook, 2001; Gray, Cooley and Lutabingwa, 1997; Levy, 1993; Peel and Wilson, 1996). It is perceived that SMEs belong to a high risk credit category and hence this sector finds it difficult to raise debt capital to fund its business growth (Thampy, 2010). Stiglitz and Weiss (1981) showed that credit rationing will happen due to the existence of information asymmetry. The principal and agents have different sets of information about the project for which credit is needed. Though both are rational, they might not have sufficient incentives to work towards a common goal (Akerlof, 1970; Ross, 1973). However, the lender solves the problem of information asymmetry through contract and monitoring (Sahlman, 1990).

The purpose of monitoring is to make sure that there is an incentive for compatibility between the borrower and the lender so that the borrower does not take undue risk. The success of the contractual mechanism to reduce the agency risk depends on the completeness of the contract, and its enforcement. However, enforcement of the contract is a challenge, and is costly (Lawton, 2002).

In addition to an appropriate contract, and monitoring, the lender can ask for collateral to reduce the risk due to the failure of a funded project. The need for collateral as a means to reduce credit risk depends on the structure of the credit market (Besanko and Thakor, 1987; Bester, 1985). Chen (2006) showed that the riskier borrowers pledge higher collateral than safe borrowers, and

Jimenez and Saurina (2004) found evidence that highly collateralised loans have higher probability of default. The literature on the relationship between *ex ante* demand for collateral and *ex post* risk associated with the loan is inconclusive. Therefore, taking high amount of collateral may not reduce the credit default *ex post*. Logically, one can argue that the willingness to pay back plays an important role in assessing the risk associated with any borrower. A borrower who has low pledgeable collateral and is willing to pay back the loan is likely to be a safer borrower in comparison to a borrower with highly pledgeable collateral but with an unwillingness to pay back the loan.

An alternative way to addresses the asymmetry of information problem has been looked from the perspective of trust. Das and Teng (1998), Shepherd and Zacharakis (2001), and Vosselman and Van der Meer-Kooistra (2009) argue that the agency risk can be reduced by employing both contractual mechanisms and trust building in a dyadic relationship. Literature on uses of contract and trust can be visualised from three perspectives. First, the presence of a higher trust level will drive lower levels of control and a less stringent contract (Dyer and Singh, 1998). Second, contractual control increases the trust level, hence contractual control and trust are complementary to each other (Leifer and Mills, 1996; Poppo and Zenger, 2002). Third, trust itself is a type of control mechanism, hence both are substitutes (Bradach and Eccles, 1989).

Most of the literature on trust, with respect to the asymmetry of information problem, is discussed in the context of the relationship between venture capitalists and entrepreneurship where there is a greater degree of uncertainty. Panda and Dash (2016) studied different stages of entrepreneurial ventures and found evidence for trust-based control by Indian venture capitalists in the early stage of a firm. They also found a combination of trust and control-based risk mitigation methods adopted by the venture capitalists in the late stages of a firm. The role of trust in building mutually beneficial cooperation has been explored in the case of bank-entrepreneur relationships (Saparito *et al.*, 2004). At present, there is a lack of literature looking at trust in the context of both lender's and borrower's perspectives. This paper attempts to bring trust, which builds over time, to calculate the need for collateral. This model takes the concept of calculative trust, as discussed in Lewicki *et al.,* (2006), to facilitate trust building between a borrower and a lender. The proposed model is an attempt to mitigate the need for collateral by incentivising the borrower to be trustworthy over time. This model has the objective of reducing credit constraints for individuals (non-wilful defaulters) without the availability of hard information. Since many of the credit institutions demand collateral from borrowers, the trustworthy borrowers face credit constraints. The model suggests a methodology to reduce this credit constraint. The model is discussed in the following section.

Section III
The Model

A design in the world of information asymmetry is a procedure to nudge the agent to behave in a pre-specified way, without cohesion. The importance of design can be seen in the Vickrey–Clarke–Groves (VCG) mechanism (Vickrey, 1961; Clarke, 1971; Groves, 1973), where the design helps us to address the following twin objectives: (a) the efficient allocation of public goods among agents which (b) forces them to reveal the true value of these public goods. This is possible by appropriately incentivising the agent to reveal the truth. Our model is inspired by the VCG mechanism to incentivise the borrower to reveal private information about the project for which the loan is sought.

At the time when a borrower seeks a loan for a project, it pays for the borrower to communicate in a way that will positively influence the lender to decide on giving the credit. For example, the borrower may overestimate the project cash flows to show a favourable picture in support of the project. The lender will suffer when a project with inflated cash flows is provided credit, and ultimately the project fails and the lender suffers losses. The proposed model creates a design where the borrower is disincentivised to inflate the cash flow numbers, and will make an attempt to tell the truth about the cash flow of the project (according to the information available with the borrower). Furthermore, our design incentivises the borrower not to deviate from the *ex ante* promises.

Parameters of the Model

The model assumes a rational borrower who has n projects. Each project has a probability of default, which is represented by $\theta_i \in (0,1]$ for $i \in \{1,2,3,...,n\}$. The θ_i is exogenous to our model, and is known to the lender. The borrower approaches the lender. The lender does not have any creditworthiness information about the borrower, and finances one project at a time. Funding of the project is done if a previous loan is paid in full, including interest as per the due date. The borrower's tuple is (B_i,T_i,W_i) for the project $i \in \{1,2,3,...,n\}$, where W_i is the borrower's pledgeable asset, B_i is the amount of loan for project i for a time period T_i. Similarly, the lender's tuple is ($\overline{B}_{i,}$ α_i,r_i), where $\overline{B}_i$ represents the upper bound of the loan sanctioned for the project i, α_i represents fractions of the $B_i(1 + r_i)^{Ti}$ needed as collateral, and r_i is the interest rate of the loan. The interest rate for the project i depends upon the riskiness (θ_i) of the project i. Keeping in mind the credit risk, the sanctioned loan amount for each project is constrained by the expected cash flows from the project and the W_i available at that period.

The Design

Project – i

Loan for project i is sanctioned if all loans availed previously are repaid in full. The borrower has pledgeable asset W_i. The project cash flow is random and distributed uniformly in $[\underline{y}_i, \overline{y}_i]$. The probability of default θ_i for the project i is determined by the lender from its past experience of similar projects. For this project the lender charges interest rate r_i such that:

$$r_i = r_f + r_p(\theta_i),\ r_p(\theta_i) \geq 0,\ \frac{dr_p(\theta_i)}{d\theta_i} > 0$$

where r_f is risk-free rate and $r_p(\theta_i)$ is risk premium which depends upon the probability of the default of the project i. The upper bound for loan amount ($\overline{B}_i$) is decided by the lender for time period T_i by

$$B_i \leq \min\left\{\frac{1}{\alpha_i}\left(\frac{\underline{y}_i + \overline{y}_i}{2} - \overline{C}\right)\sum_{t=1}^{r_i}\frac{1}{(1+r_i)^t}, \frac{1}{\alpha_i}\frac{W_i}{(1+r_i)^{Ti}}\right\} = \overline{B}_i$$

$\alpha_i \in (0,1]$ is percentage of $B_i(1 + r_i)^{Ti}$ that the lender needs to keep as collateral for the project i; $\overline{C}$ is subsistence consumption of the borrower. For project 1, it is assumed to be equal to 1, because the lender wants to mitigate all the risk by demanding 100 per cent of the loan amount, including interest, as collateral. Besides, a binding collateral requirement exists because the lender does not have any prior information of trustworthiness of the borrower. This construct is contrary to Bester (1985), which finds that higher collateral requirements will attract high-risk borrowers. Bester's finding is static, while our model takes an inter-temporal approach. Therefore, in the second period (when the borrower seeks funding for project 2), the collateral needed will be dynamically determined, and will come down if the borrower honours the reported payment schedule for project 1.

- The borrower pays the collateral $\alpha_i B_i (1 + r_i)^{T_i}$ for the project i.
- The borrower is asked to report a payment schedule:

$$P_i = \{(P_{i1}, P_{i2}, \cdots, P_{iT_i-1}, P_{iT_i}) \in \mathbb{R}_+^{T_i}: \sum_{t=1}^{T_i} \frac{P_{it}}{(1+r_i)^t} = B_i\}$$

  for the project i. Here P_{it} represents reported payment for the time period t for the project i, $\mathbb{R}_+$ is the set of non-negative real numbers.

- The borrower pays $P'_{i1} \geq 0$, and this payment is independent of P_{i1} in time 1, pays $P'_{i2} \geq 0$ in time 2, and so on.
- If

$$\sum_{t=1}^{T_i} \frac{P'_{it}}{(1+r_i)^t} < B_i$$

  the lender liquidates the collateral and retains an amount (M_i) from the proceeds from liquidation of the collateral such that

$$\sum_{t=1}^{T_i} \frac{P'_{it}}{(1+r_i)^t} + \frac{M_i}{(1+r_i)^{T_i}} = B_i$$

- Let T'_i be the time period in which the loan amount is fully paid. So T'_i can be less than or equal to T_i.

Taking these into account, we define a term c_{it} that captures the trust-building process between the borrower and the lender in time t for the project i,

$$c_{it} = \begin{cases} 0 & : P'_{it} = P_{it} = 0 \\ \dfrac{P'_{it}(P'_{it} - P_{it})}{P'_{it} + P_{it}} & : Otherwise \end{cases}$$

$\forall\ t \in \{1,2,3,\cdots, T'_i\}$. As c_{it} increases over the period, the trustworthiness increases. We use this to incentivise or disincentivise the borrower depending on the behaviour of the borrower over time. The construct of the incentivising scheme is provided below.

Let n_{it} be the cardinality of the set $S = \{c_{ij} : j = 1,2,3,\cdots, t-1 \ \&\ c_{ij} \geq 0\}$. This, n_{it}, is the number of periods in which the borrower had kept its promise before time for the project.

Let's define the following ***reward–penalty function***:

$$\beta_{it} = \begin{cases} c_{it}^{2(t-n_{it})-1} & : \; c_{it} < 0, n_{it} \geq 0 \\ \\ c_{it}^{\frac{1}{1+n_{it}}} & : \; c_{it} > 0 \end{cases} \tag{1}$$

For $t = 2, 3, 4,...,T_i'$ and $\beta_{i1} = c_{i1}$.

The variable n_{it} plays a very important role in *reward–penalty function* β_{it}. It controls the magnitude of penalty or reward depending on the promised payment schedule and the actual payment schedule. The complexity arises when $n_{it} = 0$, because n_{it} is 0 when the borrower pays everything in the first payment or when the borrower has not kept any promises. The former is trustworthy behaviour which is rewarded in our design and the latter is not trustworthy behaviour and is penalised in our design.

Explanation for β_{it}

Value of β_{it} is directly related to the trustworthiness of a borrower. Calculation of β_{it} depends on the behaviour of the borrower with respect to the promise that is made *ex ante*. While calculating β_{it} we have separated three types of borrowers for rewarding and penalising.

$c_{it} < 0, n_{it} = 0$: These are types of borrowers who historically have not kept any promises, and are not keeping the promise in time period t as well. Borrowers of these kinds are not trusted, and are asked to provide 100 per cent of the loan amount as collateral.

$c_{it} < 0, n_{it} > 0$: These are types of borrower who have kept their past promises at least once, but are not keeping the promise in time period t. Borrowers of these kinds are not trusted fully and are penalised by asking for higher amount of collateral. The degree of penalty depends on the number of times promises are kept.

$c_{it} \geq 0$: This is a type of borrower who is keeping promises at time period t. In this case n_{it} negatively affects the magnitude of reward, and the design incentivises the borrower to pay back the loan as early as possible.

If $c_{it} = 0$, for all $t = 1,2,3,\cdots,T_i'$, the borrower kept the promise and, hence, has to be rewarded. Then the lender asks for collateral $\hat{\alpha} \sim U(0,1)$, *i.e.*, distributed uniformly over (0,1), as a percentage of the amount $B_{i+1}(1 + r_{i+1})^{T_{i+1}}$ for project $i + 1$. However, our objective is to reduce the collateral ratio by incentivising the borrower to prepay the credit by deviating from the promised payment positively. Therefore, we have taken $E(\hat{\alpha}) = 0.5$ as the collateral requirement ratio. In case $c_{it} \neq 0$ for some t, we define

$$\alpha_{i+1} = \frac{1}{\max\{1, 1 + \sum_{t=1}^{T_i'} \beta_{it}\}}$$

For the next project $i + 1$, lender asks for $\alpha_{i+1} B_{i+1}(1 + r_{i+1})^{T_{i+1}}$, as value of collateral.

Implications of the Design

Proposition 1: *It is optimal strategy for the borrower to report payment scheme* 0,0,0,....,0, $B_i(1+r_i)^{T_i}$ *and pay within time period* $T_i' < T_i$.

Proof. Let

$$\Delta_{it} = P_{it}' - P_{it}$$

If the borrower pays the loan amount (no default case) , then

$$\sum_{t=1}^{T_i} \frac{\Delta_{it}}{(1+r_i)^t} = 0 \tag{2}$$

and,

$$c_{it} = \frac{P_{it}' \Delta_{it}}{P_{it}' + P_{it}}, \forall t \in \{1,2,3,\cdots,T_i\}$$

One of the trivial solutions that satisfy Eq. (2), $\Delta_{it} = 0$ for all t. If $\Delta_{ij} < 0$ for some time period $j \in \{1,2,3,\cdots,T_i\}$ then it will increase α_{i+1}. To have each $\Delta_{it} \geq 0$ and to minimise α_{i+1}, the borrower should report to pay 0 till $T_i - 1$. Since $\Delta_{it} \geq 0$ for all $t < T_i - 1$ then $\Delta_{iT_i} < 0$. This will reduce the value of α_{i+1}. Now the borrower thinks of paying the entire credit before T_i, so that the bank will not take $\Delta_{iT_i} < 0$ into consideration for calculation of α_{i+1}. Therefore, the optimal strategy will be to report 0,0,0,....,0, $B_i(1 + r_i)^{T_i}$ and pay within time period $T_i' < T_i$.

Taking optimal reporting from Proposition-1 into account $P_{it} = 0, \forall t < T_i - 1$, therefore

$$c_{it} = \frac{P_{it}'(P_{it}')}{P_{it}'} = P_{it}'$$

Hence,

$$\beta_{it} = c_{it}^{\frac{1}{t}}$$

Ex ante Solution for the Borrower

The Proposition-1 helps us to know the *ex ante* payment schedule of a rational borrower. However, the same rational borrower will minimise *ex post* α_{i+1}. The *ex ante* optimisation problem for the borrower will be

$$\min_{c_{i1},c_{i2},\dots,c_{iT_i-1}} \frac{1}{\max\{1, 1+\sum_{t=1}^{T_i'} c_{it}^{\frac{1}{t}}\}}$$

Such that,

$$\sum_{t=1}^{T_i-1} \frac{c_{it}}{(1+r_i)^t} = B_i$$

$$c_{it} \geq 0$$

Equivalently,

$$\max_{c_{i1},c_{i2},\dots,c_{iT_i-1}} \sum_{t=1}^{T_i-1} c_{it}^{\frac{1}{t}}$$

Such that,

$$\sum_{t=1}^{T_i-1} \frac{c_{it}}{(1+r_i)^t} = B_i$$

$$c_{it} \geq 0$$

Clearly, the function $\sum_{t=1}^{T_i-1} c_{it}^{\frac{1}{t}}$ is a strictly concave function, hence the first order conditions solution will be sufficient for the optimal solution and it will be unique.

Using the Lagrangian multiplier method we can solve the above problem.

Lagrangian of the optimisation problem is given by:

$$\mathcal{L}_1 = \sum_{t=1}^{T_i-1} c_{it}^{\frac{1}{t}} - \lambda_1\left(\sum_{t=1}^{T_i-1} \frac{c_{it}}{(1+r_i)^t} - B_i\right)$$

Here 'λ_1' is the Lagrange multiplier. From the first order conditions, the solution of the above problem will be

$$\lambda_1 = 1 + r_i \qquad (3)$$

The optimal payment scheme for borrower $P^{*'}_{it}$ is given by:

$$P_{it}^{*'} = c_{it}^{*} = \frac{(1+r_i)^t}{t^{\frac{t}{t-1}}}, \forall t = 2,3,4,\cdots,T_i - 1. \tag{4}$$

$$P_{i1}^{*'} = c_{i1}^{*} = B_i - \left(\sum_{t=2}^{T_1-1} \frac{c_{it}^{*}}{(1+r_i)^t}\right)(1 + r_i) \tag{5}$$

The above optimal solution from our design incentivises the individual to create a payment schedule that decreases over time.

Comparison with the Benchmark Model

To showcase the value of the proposed design, we have compared the results of our model with a benchmark model. The benchmark case is where a lender provides loans to projects having probability of default less than *k*. The probability of default is predetermined exogenously. The lender takes collateral before providing the loan. Let the collateral amount be $\phi B_i (1 + r_i)^{T_i}$ for project *i*, where $\phi \in [0,1]$ which is a policy parameter that decides collateral amount. In case of default, the lender recovers some portion of the loan amount by liquidating the collateral. The liquidating factor is δ_i, which lies in [0,1].

Then expected profit π for the risk-neutral lender under the benchmark model can be written as:

$$E(\pi_{\text{Benchmark Model}}) = \sum_{i\in\{j:\theta_j \le k\}} [(1-\theta_i)B_i(1+r_i)^{T_i} + \theta_i\delta_i\phi B_i(1+r_i)^{T_i}]$$

Similarly, in the proposed model, we keep asset as collateral, which has a liquidation factor $\gamma_i \in [0,1]$ for the project *i*. The expected profit for the risk-neutral lender when the proposed model is used can be written as:

$$E(\pi_{\text{Model}}) = \sum_{i=1}^{n} [(1-\theta_i)B_i(1+r_i)^{T_i} + \theta_i\gamma_i\alpha_i B_i(1+r_i)^{T_i}]$$

Taking both expressions into consideration:

$E(\pi_{\text{Model}}) - E(\pi_{\text{Benchmark Model}})$

$$= \sum_{i\in\{j:\theta_j>k\}}(1-\theta_i)B_i(1+r_i)^{T_i} + \sum_{i=1}^{n}\theta_i\gamma_i\alpha_i B_i(1+r_i)^{T_i} - \sum_{i\in\{j:\theta_j\le k\}}\theta_i\phi\delta_i B_i(1+r_i)^{T_i}$$

$$= \sum_{i\in\{j:\theta_j>k\}}(1-\theta_i)B_i(1+r_i)^{T_i} + \sum_{i\in\{j:\theta_j>k\}}\theta_i\gamma_i\alpha_i B_i(1+r_i)^{T_i}$$
$$+ \sum_{i\in\{j:\theta_j\le k\}}\theta_i\gamma_i\alpha_i B_i(1+r_i)^{T_i} - \sum_{i\in\{j:\theta_j\le k\}}\theta_i\phi\delta_i B_i(1+r_i)^{T_i}$$

$$= \sum_{i\in\{j:\theta_j>k\}}[(1-\theta_i)B_i(1+r_i)^{T_i} + \theta_i\gamma_i\alpha_i B_i(1+r_i)^{T_i}] + \sum_{i\in\{j:\theta_j\le k\}}\theta_i B_i(1+r_i)^{T_i}(\gamma_i\alpha_i - \phi\delta_i)$$

By using these equations, we can put down the following proposition.

Proposition 2: *The welfare of a lender (expected profit) will always be higher in the designed model when* $\gamma_i \geq \frac{\phi\,\delta_i}{\alpha_i}$.

Simulation Result

The objective of the simulation is to compare the performance of the proposed model *vis-à-vis* the benchmark model. The performances are measured in terms of two outcomes. First, profit generated by the lender; and second, total amount of collateral needed as a percentage of total loans given. The simulation is done by coding the model in R software, and has been done for 1000 (n = 1000) projects. Each project has a probability of default, which has been generated randomly from a uniform distribution $\theta_i \sim U[0,1]$. The proposed model is applied to generate designed collateral metrics for different projects. The result of the same has been plotted in Chart 1 and Chart 2.

Chart 1: Distribution of α

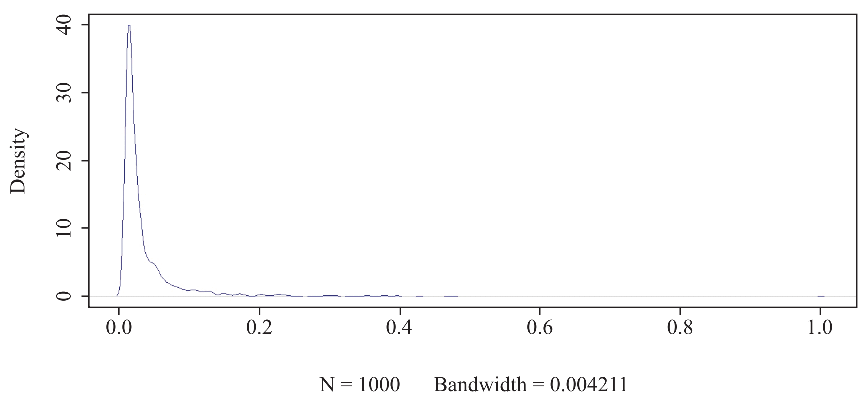


Chart 2: Value of α for Different Projects

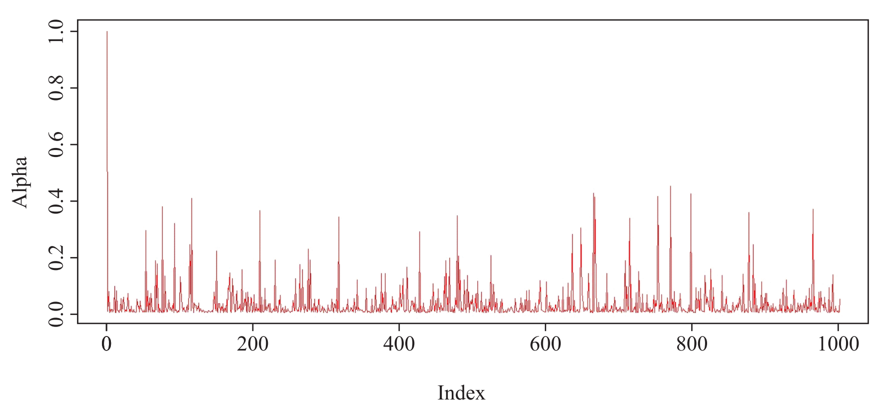


Table 1: Simulation Result

	$E(\pi_{Model}) - E(\pi_{Benchmark})$ for 1000 Replications (with t-test)					
Loan Amount	$k = 0.05$	$k = 0.30$	$k = 0.5$	$k = 0.8$	$k = 0.9$	$k = 0.99$
0–25 lakhs	12493.85***	11348.91***	9155.42***	2528.79***	948.59***	-1820.46***
0–50 lakhs	24982.67***	22667.89***	18299.05***	5220.70***	1963.96***	-3713.25***
0–100 lakhs	49872.13***	45475.22***	36589.55***	10450.63***	3784.37***	-734.23***

Notes: *p - value <0.1; **p - value <0.05; *** p - value<0.01.

In the case of the benchmark model we have taken two cases. In the first case, the collateral requirement depends upon the values of θ_i s, and the amount of collateral required is $\theta_i B_i(1 + r_i)^{Ti}$ where the amount borrowed is B_i (Table 1). In second case, collateral needed is independent of the default risk of the project (Table 2) and depends on φ, which is a policy parameter

Table 2: Simulation Result with Policy Parameter ϕ

	$E(\pi_{Model}) - E(\pi_{Benchmark})$ for 1000 Replications (with t-test)					
Policy Parameter	$k = 0.05$	$k = 0.30$	$k = 0.5$	$k = 0.8$	$k = 0.9$	$k = 0.99$
ϕ=0.01	49748.63***	45647.11***	37804.07***	18457.90***	9851.07***	365.75 ***
ϕ=0.02	50159.46***	45590.56***	37611.09***	18605.34***	9689.72***	256.72***
ϕ=0.03	49787.31***	45720.78***	37709.135***	18214.72***	9706.17***	134.76***
ϕ=0.04	49885.81***	45812.82***	37538.95***	18109.82***	9434.03***	-15.30**
ϕ=0.05	50231.55***	45566.65***	37424.77***	17930.45***	9331.92***	-152.74***
ϕ=0.06	50102.85***	45813.46***	37370.11***	17703.19***	9204.74***	-234.56***
ϕ=0.07	50000.21***	45335.13***	37255.71***	17635.43***	9143.52***	-380.43***
ϕ=0.08	49958.29***	45517.59***	37343.81***	17412.35***	9040.47***	-500.24***
ϕ=0.09	49965.63***	45271.22***	37458.35***	17120.41***	8971.95***	-651.28***
ϕ=0.1	50124.56***	45750.08***	37210.02***	15675.07***	8998.34***	-754.20***
ϕ=0.2	50278.28***	45785.05***	36751.19***	14185.70***	6507.99***	-39672.21***
ϕ=0.3	50114.05***	45476.90***	36716.65***	12611.07***	4624.84***	-6356.89***
ϕ=0.4	50672.44***	44952.48***	35959.41***	10986.27***	2470.28***	-9035.63***
ϕ=0.5	50057.41***	44952.46***	35220.93***	9489.68***	497.98***	-10476.30***
ϕ=0.6	50454.53***	44770.08***	34486.60***	7495.72***	-1731.09***	-13562.17***
ϕ=0.7	50409.29***	44928.74***	33902.88***	6289.84***	-3598.10***	-16547.25***
ϕ=0.8	50129.72***	44042.05***	33995.35***	4643.14***	-5497.62***	-19042.21***
ϕ=0.9	50112.10***	44062.76***	32348.97***	3976.87***	-7861.64***	-21473.02***
ϕ=1	50529.24***	43792.57***	31993.65***	3071.992***	-9744.46***	-23782.32***

Notes: *p - value <0.1; **p - value <0.05; ***p - value<0.01.

as defined before in the model. Liquidating factor δ_i for collateral of the *ith* project is generated randomly from a uniform distribution over support [0,1]. For the designed model, we have assumed a random liquidating factor γ_i which is distributed uniformly over [0,1].

The difference $E(\pi_{\text{Model}}) - E(\pi_{\text{Benchmark Model}})$ has been calculated and the difference between expected profits is tested (one tailed t-test).

$$H_0 : E(\pi_{\text{Model}}) - E(\pi_{\text{Benchmark Model}}) = 0$$

$$H_1 : E(\pi_{\text{Model}}) - E(\pi_{\text{Benchmark Model}}) > 0$$

Table 1 shows that the proposed model does better when a project having a probability of default less than 0.9 is accepted by the benchmark model, and the benchmark model will do better for projects with the probability of default greater than 0.9 (which is an unlikely event). Table 2 shows that the proposed model provides better result than the benchmark model for all values of ϕ where $k < 0.8$. The benchmark model does better when the lender provides loans to very high risk projects, and demands a very high percentage of loan as collateral. The previous two simulations shown in Tables 1 and 2 find the dominance of the proposed model for all projects with a probability of default at 0.8. Table 3 shows the calculated values of collateral needed as a percentage of the total loan amount for the proposed model for different cut-off values of k. We can see that there exists very little difference across the different value of k, which means that the proposed design is independent of the default probability of projects. However, the lender can decide on a cut-off level of k, and after that decide on the collateral need using the proposed model.

Table 3: Collateral Need as a Percentage of Total Borrowing for the Proposed Model

	Collateral Ratio = $\frac{\text{Collateral}}{\text{Amount of Borrowing}}$					
Loan Amount Limits (in ₹ lakh)	$k = 0.05$	$k = 0.30$	$k = 0.5$	$k = 0.8$	$k = 0.9$	$k = 0.99$
0 - 25	8.5	8.1	7.9	8.5	8.0	8.3
0 - 50	7.5	7.0	7.5	8.4	7.4	8.1
0 - 100	8.1	7.9	7.4	7.4	8.0	7.8

Section IV
Ex post Solution for the Borrower

Our *ex post* solution assumes Proposition-1 to hold. Suppose in the first period, the borrower's cash flow is ψ. In case $\psi \geq \overline{C} + P^{*\prime}_{i1}$, the borrower achieves the first best solution as discussed in the *ex ante* solution for the borrower. If not (*i.e.*, $\psi < \overline{C} + P^{*\prime}_{i1}$), then the borrower pays $P^{*\prime}_{i1} = C^{*}_{i1} = \psi - \overline{C}$ and consumes the subsistence amount. In this case the optimisation problem becomes,

$$\max_{c_{i2}, c_{i3}, \ldots, c_{iT_i-1}} \sum_{t=2}^{T_i-1} c_{it}^{\frac{1}{t}}$$

Such that
$$\sum_{t=2}^{T_i-1} \frac{c_{it}}{(1+r_i)^t} = B_i - \frac{P'_{i1}}{1+r_i}$$

$$c_t \geq 0$$

The Lagrangian of the above problem becomes

$$\mathcal{L}_2 = \sum_{t=2}^{T_i-1} c_{it}^{\frac{1}{t}} - \lambda_2\left(\sum_{t=2}^{T_i-1} \frac{c_{it}}{(1+r_i)^t} - B_i + \frac{P'_{i1}}{1+r_i}\right)$$

Solving the first order condition, we have

$$P^{*\prime}_{it} = c^{*}_{it} = \frac{(1+r_i)^t}{(\lambda_2 t)^{\frac{t}{t-1}}} \tag{6}$$

Putting it in the constraint, we have

$$Z(\lambda_2) = \sum_{t=2}^{T_i-1} \frac{1}{(\lambda_2 t)^{\frac{t}{t-1}}} - B_i + \frac{P'_{i1}}{1+r_i} = 0 \tag{7}$$

The function Z(.) has the following characteristics

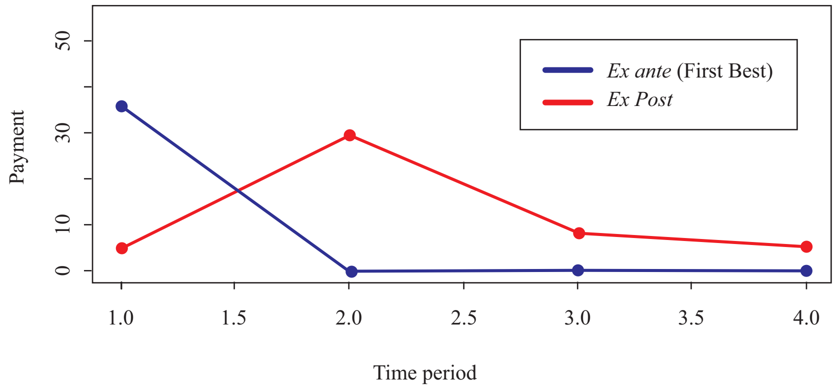
$$\frac{\partial Z}{\partial \lambda_2} < 0, \lim_{\lambda_2 \to 0} Z(\lambda_2) = \infty > 0, \lim_{\lambda_2 \to \infty} Z(\lambda_2) = -B_i + \frac{P'_{i1}}{1+r_i} < 0$$

Thus there exists a unique positive solution for λ_2 of Eq.7.

Since Eq.7 is a non-linear equation, we need computational capabilities to find the optimal payment schedule. We have designed a programme in R to solve for the optimal schedule of the borrower, and the result is shown in Chart 3.

As we can see from Chart 3, in case the borrower is unable to pay the first best optimal payment, then the borrower can find the optimal solution for the remaining periods. The optimal schedule shows the borrower has the incentive to pay more in the next period in case the payment was missed in

Chart 3: *Ex ante* and *Ex post* Payment Schedule



the previous period, which will depend upon the cash flow from the project in the previous period. Thus, the proposed model incentivises the borrower not to default willingly, and pay back the loan as early as possible.

Section VI
Conclusion

The paper attempts to link mainstream literature on the need for collateral and credit rationing with management literature on trust building over time. The model compares the *ex ante* payment promise with *ex post* payment structure for trust building. This is done by creating a design, which incentivises the behaviour of honouring a commitment to a proposed *ex ante* payment schedule. In the proposed design, a small business owner can improve the creditworthiness over time, and can avail higher amounts of credit with a smaller amount of collateral.

The simulation results show that the lending institutions will be able to increase their profit by using the proposed model *vis-à-vis* the benchmark model. The proposed model will always outperform the benchmark model when the probability of default of a project is less than 80 per cent. Besides, with the help of trust building, a small business owner can bring down collateral requirements to as low as 10 per cent of the total borrowing.

The model can be improved by bringing the probability of default into the design, and simulation can be done on real life data of a lending institution.

References

Akerlof, G. A. (1970). ‘The market for “lemons”: Quality uncertainty and the market mechanism’, *The Quarterly Journal of Economics*, 84(3), 488-500.

Benmelech, E., and N. K. Bergman (2009). ‘Collateral pricing’, *Journal of Financial Economics*, 91(3), 339–60.

Berger, A. N. *et al.,* (2011). ‘Why do borrowers pledge collateral? New empirical evidence on the role of asymmetric information’, *Journal of Financial Intermediation,* 20(1), 55–70.

Berger, A. N. and G. F. Udell (1990). ‘Collateral, loan quality and bank risk’, *Journal of Monetary Economics*, 25(1), 21–42.

– (1995). ‘Relationship Lending and Lines of Credit in Small Firm Finance’, *The Journal of Business*, 68(3), 351–381.

Besanko, D. and A. V. Thakor (1987). ‘Collateral and rationing: Sorting equilibria in monopolistic and competitive credit markets’, *International Economic Review*, 28(3), 671–689.

Bester, H. (1985). ‘Screening vs. rationing in credit markets with imperfect information’, *The American Economic Review*, 75(4), 850–855.

Bradach, J. L., and R. G. Eccles (1989). ‘Price, authority, and trust: From ideal types to plural forms’, *Annual Review of Sociology*, 15(1), 97–118.

Chen, Y. (2006). ‘Collateral, loan guarantees, and the lender’s incentives to resolve financial distress’, *The Quarterly Review of Economics and Finance*, 46(1), 1–15.

Chu, H. M., C. Benzing and C. McGee (2007). ‘Ghanaian and Kenyan Entrepreneurs: A comparative analysis of their motivations, success characteristics and problems’, *Journal of Developmental Entrepreneurship*, 12(3), 295–322.

Clarke, E. H. (1971). ‘Multipart pricing of public goods’, *Public Choice*, 11(1), 17–33.

Cook, P. (2001). ‘Finance and small and medium-sized enterprise in developing countries’, *Journal of Developmental Entrepreneurship*, 6(1), 17-40.

Das, T. K., & Teng, B. S. (1998). ‘Between trust and control: Developing confidence in partner cooperation in alliances’, *Academy of Management Review*, 23(3), 491-512.

Dyer, J. H., and H. Singh (1998). 'The relational view: Cooperative strategy and sources of interorganizational competitive advantage', *Academy of Management Review*, 23(4), 660–79.

Gray, K. R., W. Cooleyand J. Lutabingwa (1997). 'Small-scale manufacturing in Kenya', *Journal of Small Business Management*, 35(1), 66-72.

Groves, T. (1973). 'Incentives in teams', *Econometrica: Journal of the Econometric Society*, 41(4), 617–31.

Jimenez, G., and J. Saurina (2004). 'Collateral, type of lender and relationship banking as determinants of credit risk', *Journal of Banking and Finance*, 28(9), 2191–2212.

Lawton, T. C. (2002). 'Missing the target: Assessing the role of government in bridging the European equity gap and enhancing economic growth', *Venture Capital: An International Journal of Entrepreneurial Finance*, 4(1), 7–23.

Lee, C. Y. (1998). 'Quality management by small manufacturers in Korea: An exploratory study', *Journal of Small Business Management*, 36(4), 61-67.

Leifer, R., and P. K. Mills (1996). 'An information processing approach for deciding upon control strategies and reducing control loss in emerging organizations', *Journal of Management*, 22(1), 113–137.

Levy, B. (1993). 'Obstacles to developing indigenous small and medium enterprises: An empirical assessment', *The World Bank Economic Review*, 7(1), 65–83.

Lewicki, R. J., E.C. Tomlinson and N. Gillespie (2006). 'Models of interpersonal trust development: Theoretical approaches, empirical evidence, and future directions', *Journal of Management*, 32(6), 991–1022.

Lin, C. (1998). 'Success factors of small and medium-sized enterprises in Taiwan: An exploratory analysis of cases', *Journal of Small Business Management*, 36(4), 43–56.

Peel, M. J., and N. Wilson (1996). 'Working capital and financial management practices in the small firm sector', *International Small Business Journal*, 14(2), 52–68.

Panda, S., and S. Dash (2014). 'Constraints faced by entrepreneurs in developing countries: A review and assessment', *World Review of Entrepreneurship, Management and Sustainable Development*, 10(4), 405–421.

—(2016). 'Exploring the venture capitalist-entrepreneur relationship: Evidence from India', *Journal of Small Business and Enterprise Development*, 23(1), 64–89.

Plaut, S. E. (1985). 'The theory of collateral', *Journal of Banking* & *Finance*, 9(3), 401–19.

Poppo, L., and T. Zenger (2002). 'Do formal contracts and relational governance function as substitutes or complements?' *Strategic Management Journal*, 23(8), 707–725.

Ross, S. A. (1973). 'The economic theory of agency: The principal's problem', *The American Economic Review,* 63(2), 134–139.

Sahlman, W. A. (1990). 'The structure and governance of venture-capital organizations', *Journal of Financial Economics*, 27(2), 473–521.

Saparito, P. A., C. C. Chen and H.J. Sapienza (2004). 'The role of relational trust in bank-small firm relationships', *Academy of Management Journal*, 47(3), 400–410.

Shepherd, D. A., and A. Zacharakis (2001). 'The venture capitalist-entrepreneur relationship: Control, trust and confidence in co-operative behaviour', *Venture Capital: An International Journal of Entrepreneurial Finance*, 3(2), 129–149.

Stiglitz, J. E., and A. Weiss (1981). 'Credit rationing in markets with imperfect information', *The American Economic Review*, 71(3), 393–410.

Thampy, A. (2010). 'Financing of SME firms in India: Interview with Ranjana Kumar, Former CMD, Indian Bank; Vigilance Commissioner, Central Vigilance Commission', *IIMB Management Review*, 22(3), 93–101.

Vickrey, W. (1961). 'Counterspeculation, auctions, and competitive sealed tenders', *The Journal of Finance*, 16(1), 8–37.

Vosselman, E., and J. Van der Meer-Kooistra (2009). 'Accounting for control and trust building in inter firm transactional relationships', *Accounting, Organizations and Society*, 34(2), 267–283.

Reserve Bank of India Occasional Papers
Vol. 38, No. 1&2, 2017

Global Liquidity and Foreign Portfolio Flows to India: An Empirical Assessment

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This paper examines the role of global liquidity as a driver of external financial flows into India. It finds that foreign portfolio investment flows to India are more sensitive to fluctuations in global liquidity conditions than foreign direct investment and external commercial borrowings. Furthermore, the liquidity channel of transmission of accomodative monetary policies of the advanced economies to India is found to be stronger, while the portfolio balance channel and the confidence channel do not exihibit any statistically significant impact on portfolio flows into India.

JEL Classification : G15, F32, F41

Keywords : Global liquidity, monetary policy, bounds test

Introduction

India opened up its economy to the outside world following the balance of payments (BoP) crisis in 1991. Foreign Institutional Investors (FIIs)[1] were allowed entry into the Indian capital market at the beginning of 1993, and the Foreign Portfolio Investor (FPI) policy has been progressively liberalised thereafter. With the freer movements of FPI flows, the Indian economy has been exposed to spillovers from external shocks.

With the onset of the global financial crisis in 2008, major central banks of the world adopted Unconventional Monetary Policies (UMPs), which were expected to not only stimulate the economy but also keep the asset markets

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The authors would like to express their sincere thanks to Shri Sitikantha Pattanaik, Dr. Rajeev Jain, Dr. Jai Chander, Kumar Rishabh, Soumasree Tewari, Madhuresh Kumar for their comments/inputs on the paper. The authors also express their gratitude for the comments received from the participants of the DEPR Study Circle, an in-house discussion forum in the Reserve Bank of India. The views expressed in this paper and all errors, if any, are to be attributed to the authors only. All the usual disclaimers apply.

[1] FII and FPI are used interchangeably in this study.

alive (Smaghi, 2009). With the large-scale operation of UMPs, balance sheets of major central banks expanded considerably, the liquidity generated moved around the world in search of yields and, in a way, became a key source of spillovers from monetary policies of advanced economies. Sometimes, this liquidity played havoc by making currencies of many EMEs stronger, thus leading to former Brazilian Finance Minister Guido Mantega to call it a *currency war*.[2] Against this backdrop, India witnessed several spells of capital inflows during 2009–2012, given its comparatively higher growth and the better outlook on return on capital.

Things reversed in the aftermath of the statement made by the former Chairman of the Federal Reserve Ben Bernanke (in May 2013) about tapering of quantitative easing (QE) in the United States (US), and the markets across the globe witnessed high volatility. In the case of India, FPI outflows created volatility in the markets, and "*the rupee touched record lows, and there was palpable fear that India was going towards a South-East Asia-crisis style abyss. The situation was rescued only after Reserve Bank of India duly administered tough monetary medicine to ailing bond and currency markets*".[3] The issue of managing the movements in FII flows has become more important after the former chairperson of the Federal Reserve, Janet Yellen, announced reductions in Fed's balance sheet from October 2017. The European Central Bank, too, decided to cut its bond buying programme to €30 billion per month from €60 billion, starting January 2018. Both these measures are likely to affect the level of global liquidity, and in that process flows to EMEs.

There are several studies on the effects of QE and its tapering on EMEs. Some papers (Basu *et al*., 2014; Patra *et al*., 2014, 2016; and Shankar, 2011) address this issue from an Indian perspective. Global liquidity, however, was not assigned much importance in such studies. The objective of this paper is to examine the effect of global liquidity on India's cross-border financial flows. This paper focuses on: (i) whether the FII flows to India are influenced by global liquidity; (ii) how different types of flows respond to global liquidity; and (iii) which financial centre has more influence on the FPI flows to India. Section II reviews the literature on the subject; Section III describes the

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[2] *Financial Times*, September 27, 2010.

[3] Euro Money, October, 2014.

stylised facts on FII flows to India. Section IV contains the methodology and the empirical analysis, and Section V concludes.

Section II
Literature Review

There is a vast literature that has focused on the subject of the determinants of cross-border financial flows. Most of these studies consider global liquidity as a key non-price indicator of cross-border credit supply (Cerutti *et al*., 2014 and Bruno and Shin, 2013). The cross-border bank flows are found to decrease with rise in volatility and increase in the slope of the US yield curve, but increase with a rise in money growth in G4 countries and US dealer bank leverage (asset/equity ratio). Further, banking conditions in other financial centres, particularly the UK and the euro area, captured by bank leverage and, spread between treasury bill rate and government securities yield also drive cross-border bank flows, and sometimes are found to be more important than the US banking conditions. In a way, the global financial cycle is driven by monetary policy in the US, and banking conditions in the UK and euro area. The level and cyclicality of cross-border flows are dependent on host country's policies and characteristics. Flexible exchange rates, capital flow management tools and regulations are useful in managing the cyclicality of cross-border flows. Bruno and Shin (2013) developed a model of gross capital flows for the international banking system that highlights the leverage cycle of global banks as a key driver of the transmission of financial conditions across the globe. They found that global factors play a bigger role than local factors in driving the banking sector capital flows.

Passari and Rey (2015) and Rey (2015) show that large cross-border flows across countries tend to rise in periods of low volatility, and decrease in periods of high volatility. There is a global financial cycle in capital flows, asset prices and credit growth, which co-move with the Chicago Board Options Exchange (CBOE) Volatility Index (VIX) that measures uncertainty and risk aversion in financial markets. Asset markets of countries receiving more credit inflows are more sensitive to the global cycle. With free capital mobility, the global financial cycle poses challenges for national monetary policies. The trilemma in international economics is that with free capital mobility, independent monetary policies are feasible if and only if exchange rates are floating. The global financial cycle has now reduced the trilemma into a dilemma which espouses that independent monetary policies are possible if and only if the capital account is managed (Rey, 2015).

Some studies (Fratzscher *et al*., 2013; Lim *et al*., 2014; Lim and Mohapatra, 2016) attempted to quantify the potential implications of QE policies and their withdrawal on gross flows to developing countries. These studies have identified the transmission mechanism of QE through liquidity channel, portfolio balance channel and confidence channel. There is also evidence of heterogeneity among different types of flows - portfolio flows are more sensitive than foreign direct investment (FDI) to the effects of QE. Global push factors tend to dominate country-specific pull factors, and are reflected in the significance of the fundamental variables that operate at the global level, like abundant liquidity (falling short-term treasury bill rate), portfolio rebalancing away from long-term bonds, and improved confidence for investing in risky assets (a shrinking VIX). The QE measures in the US in the early part of the global crisis of 2008 brought orderliness to the financial markets of the US, and boosted bond and equity prices of the US and further led to the US dollar appreciation for some time after the announcement. The capital flew out of EMEs into US equity and bonds under QE1 (announced in November 2008) but in the opposite direction in QE2 (announced in November 2010) regime. Further, there was heterogeneity in the response of EMEs to Federal Reserve policies. Countries with better institutions and fundamentals and more active monetary policy were less affected. US unconventional monetary measures have contributed to portfolio reallocation as well as repricing of risk in global financial markets. QE1 triggered a churning of portfolio by global investors out of EMEs and into US equity and bond funds, leading to overall appreciation of the US dollar. By contrast, QE2 was largely ineffective in lowering yields worldwide, but witnessed sizeable capital inflows, mainly into EME equities, and a general US dollar depreciation (Fratzscher *et al*., 2013). There are indeed global spillovers and externalities from monetary policy decisions in AEs. The effect of QE3 (announced in September 2012) was very subdued in comparision with the earlier QEs (Patra *et al.,* 2014).

Forbes and Warnock (2011) identified episodes of extreme capital flow movements, and demarcated various episodes of "surges" and "stops", and "flight" and "retrenchment". Global factors such as global risks and contagions are associated with extreme capital flow episodes like sudden stops and retrenchments. Domestic macroeconomic characteristics have less influence on the flow of capital. Capital controls have an insignificant association with the probability of surges or stops of capital flows. Also, global liquidity has no significant relationship with such episodes in capital flow. There is no empirical support to the widespread presumption that changes in global liquidity or interest rates in a major economy are important factors driving surges in capital flows.

Ahmed and Zlate (2013) found that net capital flows to EMEs are determined by factors like growth, interest rate differentials between AEs and EMEs and global risk perceptions - though in the pre-crisis period the growth differential was a more important factor for total inflows, risk aversion was relatively more important for portfolio flows. The application of the pre-crisis model moderately under-predicts the net capital flows in the post-crisis period, but vastly under-predicts portfolio net inflows. This has happened due to the changes in the sensitivity of the flows to some of the explanatory variables. Mostly, the sensitivity of the portfolio flows to policy rate differentials and to risk-aversion seems to have increased during the post-crisis period. Furthermore, capital control measures introduced in various countries appear to have dampened both total and portfolio flows. In the pre-crisis phase, forex interventions by the central banks to counter currency appreciation pressures had increased capital inflows to EMEs, but this phenomenon was absent in the post-crisis phase. There was no statistically significant positive effects of unconventional US monetary expansion on total flows, but it brought in a change in the composition in favour of portfolio flows.

The ‘tapering talk’ by Ben Bernanke in May 2013 had a negative impact on the exchange rates and financial markets in EMEs (Eichengreen and Gupta, 2015). Countries with larger and more liquid markets, and with high inflows of capital in earlier years faced more pressure on their exchange rates, foreign exchange (forex) reserves and equity prices. It appears that EMEs with large appreciation of real exchange rates and high current account deficit (CAD) in the QE period faced the sharpest currency depreciation, reserves losses, and stock market declines after the taper talk. It also showed that good fundamentals and better economic performance were unable to provide the expected degree of insulation. Basu *et al*., (2014) studied the effect of tapering in context of India, and highlighted the fact that the sharp fall in the Indian Rupee was sufficient for the press to make India a special case. The study also pointed out that the reasons for the fall in the Indian markets included the large capital inflows in earlier years, and deterioration in macroeconomic indicators like fiscal deficit and inflation, leading to foreign investors moving away from India at the first hint of rebalancing. The response of the Indian authorities was in the form of hiking the interest rate, establishing a window for swapping Foreign Currency Non-Resident (Bank) dollar funds, cutting down gold imports, reducing the limit for overseas direct investment under the automatic route, and swap window for oil companies. The paper advocates a clear communication policy, and the creation of a medium-term policy framework while retaining maximum space for policy later.

Chandrasekhar (2008) studied the trends in financial flows to developing countries after the South-East Asian crisis and showed that supply side factors rather than financial requirements of developing countries contributed to the surges in capital flows. The globalisation of finance resulted in changes in the financial structure. A small number of centralised financial institutions intermediate global capital flows, and this has implications in terms of accumulation of risk and vulnerability to financial crisis in the markets that have potential for herd behaviour. The supply-side driven surge in capital has three kinds of effects: (i) financial decisions are increasingly made to suit international firms; (ii) it increases financial vulnerability in these countries; and (iii) it brings in macroeconomic adjustments that reduce the fiscal and monetary autonomy in these countries.

The determinants of portfolio flows to India have been studied by Chakrabarti (2001), Mukherjee *et al.*, (2002), Gordon and Gupta (2003), Rai and Bhanumurthy (2004), Kaur and Dhillon (2010), Verma and Prakash (2011) and Dua and Garg (2013). Chakrabarti (2001) studied the nature and determinants of FII flows to India and found that the flows were highly correlated with equity returns in India. The Asian crisis marked a regime shift in the FII flows to India. FIIs do not seem to be at any informational disadvantage in India. Mukherjee *et al.*, (2002) studied the same issue with the help of daily data and concluded that there was no evidence of portfolio diversification benefit for the FIIs in investing in Indian market. Dua and Garg (2013) undertook an empirical investigation keeping the portfolio balance model in sight. The domestic stock market performance, exchange rate and domestic output growth were found to be the predominant determinants of both FII and American Depository Receipts (ADRs)/Global Depository Receipts (GDRs) flows. The output growth influences the ADR/GDR, but not the FII flows. The macroeconomic factors have similar type of influence on the aggregate portfolio flows and FII flows. Verma and Prakash (2011) found that the capital flows, particularly the FDI and FII equity flows to India, are not sensitive to interest rate differentials. Further, stronger growth in the countries of the Organisation for Economic Co-operation and Development (OECD) coincided with a period of larger capital inflows to India. According to Gordon and Gupta (2003), the portfolio flows into India were determined by both domestic factors as well as external factors. Lagged stock return and changes in credit ratings are the domestic factors while London Interbank Offered Rate and emerging market stock returns are external factors driving portfolio flows to India. Rai and Bhanumurthy (2004) found that FII inflows depend on stock market returns, inflation rates and *ex ante* risk. It was also observed that FIIs react with greater sensitivity to bad news than to good news.

Shankar (2011) examined the connection between UMPs and FII inflows into India. FII inflows had declined after the announcement of QE2 by the Federal Reserve. It was explained in terms of the expectations factoring behaviour of market participants and developments in India and abroad. Patra *et al.,* (2014) studied the influence of UMPs, taking the case of QE in the US as well as its tapering, on the Indian economy through an event study analysis and use of generalised method of moments (GMM). QE1 had a higher impact than QE2. Further, the taper announcement had a strong adverse impact than the actual taper. The spillovers to India happened mostly through the portfolio rebalance channel, aided to some extent by the liquidity channel. It also highlighted that the spillovers from QE in the US and its tapering had implications for the conduct of monetary policy in EMEs like India. However, in this study, the liquidity channel was proxied by the short-term interest rate in the US (three-month Treasury Bill yield).

Some important research papers published on FII flows to India are given in Annex I.

Section III
Financial Flows to India - Some Stylised Facts

Before 1991, India was highly dependent on external assistance, NRI deposits and commercial borrowings. However, with rising foreign investment, after 1991, its dependence on external assistance has declined (Tables 1 and 2).

Table 1: Composition of Net Capital Flows to India

(US$ mn)

Item/Year	1991	1992	2001	2011	2015
I. Foreign investment	103	133	5,862	42,127	73,456
II. External assistance	2,204	3,034	410	4,941	1,725
III. Commercial borrowings	2,254	1,462	4,303	12,160	1,570
IV. Rupee debt service	-222	429	-617	-68	-81
V. NRI deposits	1,268	-91	2,316	3,238	14,057
Other capital	1,931	473	292	-12,416	1,109
A. Capital account	7,056	3,915	8,840	63,740	89,286
B. Reserves (increase -/ decrease +)	1,278	-3,384	-5842	-13,050	-61,406

Note: Financial Year (April to March) Basis

Source: Handbook of Statistics on the Indian economy, RBI.

Table 2: Net Foreign Investment to India

(US$ mn)

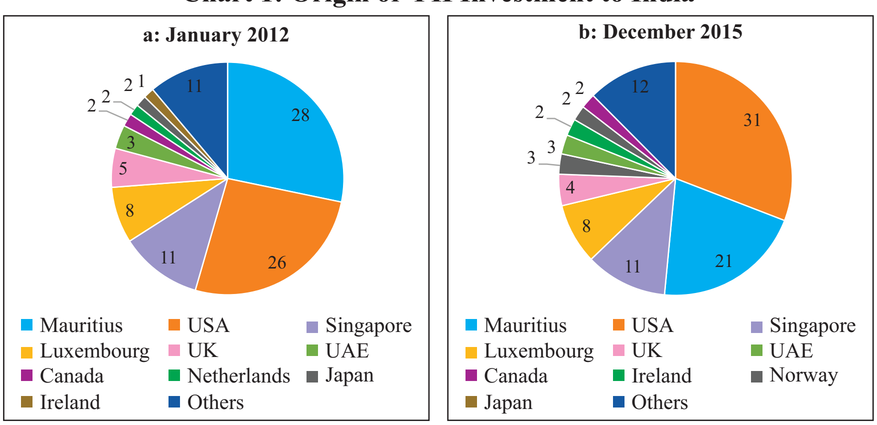
Category	1990	1991	2001	2011	2015
Direct investment	97	129	3,272	11,834	31,251
Portfolio investment	6	4	2,590	30,293	42,205

Note: Financial Year (April to March) Basis

Source: Handbook of Statistics on the Indian economy, RBI.

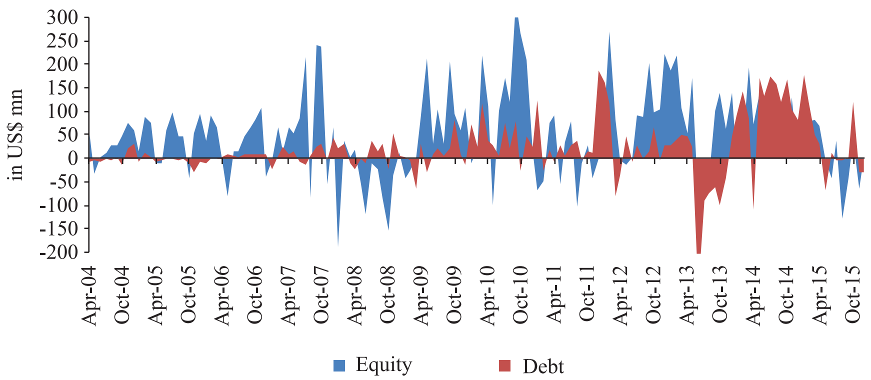
The FIIs flow to India has seen shift in origin over the years. In January 2012, most of the FIIs originated from Mauritius (28 per cent), the USA (26 per cent), Singapore (11 per cent), Luxembourg (8 per cent) and the UK (5 per cent). In December 2015, the share of the US has increased to 31 per cent, while the share of Mauritius has declined to 21 per cent. The shares of other countries have seen either marginal or no variation over the period (Chart 1 a and b). The share of top five countries has remained more than 75 per cent over the period.

Chart 1: Origin of FII Investment to India



Source: National Securities Depository Ltd.

Chart 2: Movement of FII Flows



Source: Bloomberg.

In different instances of market turbulence, financial flows to India were affected differently. When the global financial crisis of 2008 struck, outflow of capital took place mostly from the equity segment of the capital market, but during the financial market volatility generated by taper talk in 2013, outflows were mostly from the debt segment (Chart 2).

Capital flows to EMEs surged after the global financial crisis, but they remained volatile. EMEs have argued that UMPs of AEs were primarily responsible for the huge inflow of capital to these economies (Ahmed and Zlate, 2013). To analyse whether growth in global liquidity generated by the expansionary monetary policies of AEs has affected financial flows to India, one must look at the definition indicated in BIS (2011), which divide global liquidity into official liquidity and private liquidity. The official liquidity is the summation of global monetary aggregates, while the private liquidity is the summation of global credit aggregates. In the present study, the official liquidity indicator, measured based on the methodology prescribed in Baks and Kramer (1999), is used. First, the monthly money supply growth for the G4 countries (the US, euro area, the UK and Japan) is calculated. The growth rate of money supply for each G4 country (in domestic currency terms) is weighted by the respective country's GDP share (taken in US dollars) (Kumar and Sharma, 2014). The annual share is applied across all 12 months. In the second step, the weighted GDP growth is obtained for the G4 countries, at a quarterly frequency, where the quarterly growth rate of nominal GDP (in local currency) for each country is weighed by its GDP share in total GDP of the G4 countries (calculated in US dollars). The weighted money supply growth (annualised) in G4 countries gets subtracted by the weighted nominal

GDP growth (annualised) in these countries to arrive at the global liquidity growth. The data on narrow money (M2) are used to calculate the money supply growth.

The effects of global liquidity are transmitted to EMEs via liquidity, portfolio balance and confidence channels (Lim *et al.*, 2014; Lim and Mohapatra, 2016). First, the liquidity channel operates when the central banks in AEs increase their asset purchases from the market. It operates through both improved availability of liquidity with the banks, as well as lowering of the cost of liquidity in the market. The increased amount of liquidity also reduces the interest rates - many research papers have used the three-month US Treasury Bill yield as an indicator of the liquidity channel. Second, the portfolio balance channel operates through purchase of long duration assets that may alter the demand for financial assets of EMEs, given the possibilities of asset substitution. The difference between interest rate at the long end of the spectrum in a developed country and in India is used as the indicator of this channel. Third, for the confidence channel, sending signals is pertinent. By opting for asset purchases, the central banks try to send signal to the market that the purchase of financial assets can go on till lasting recovery arrives. Hence, the rise in confidence through this process helps in improving the sentiments for investment globally. Here, CBOE VIX is used as the indicator to gauge the market aversion for investment in risky EME assets.

In this context, the recent IMF estimates show that normalisation by the US Fed – raising the policy interest rate and shrinking of the balance sheet – is likely to reduce portfolio inflows to emerging markets by about US$70 billion over the next two years as compared with the average annual inflows of US$240 billion since 2010. It estimates that the reduction in the size of the Fed's balance sheet would cut flows by US$55 billion over the next two years. Flows could fall by an additional US$15 billion if short-term interest rates were to rise in line with the IMF forecasts assuming that the US policy rate would rise to just under 3 per cent by the end of 2019, and that the tightening process would be orderly and would not take a toll on emerging markets growth (IMF, 2017) .

Before examining the relationship between global liquidity growth and FII flows to India, it is useful to look at the charts plotting the FII inflow to India along with global liquidity, interest rate differential and global VIX. It is evident from the charts that in the period before 2012, FII inflows to India did not move in tandem with the rise or fall in global liquidity. However, recently there have been occasions showing some correspondence, an indication that global liquidity may lead to FII inflows to India (Chart 3a). The total capital flows to India also show some correspondence with global liquidity growth in the similar manner.

The FII inflows rise with the fall in VIX, and vice-versa, though the inverse movement between FII inflows and VIX is less visible in the recent period (Chart 3b). The total capital flows do not show similar association with the VIX.

Chart 3c shows that there is no co-movement between FII inflows and interest differentials (id), *i.e.,* difference between the yield on10-year security of the Governmnet of India (GoI) and that of the US.

Chart 3a: Movement of FII Inflow and Global Liquidity

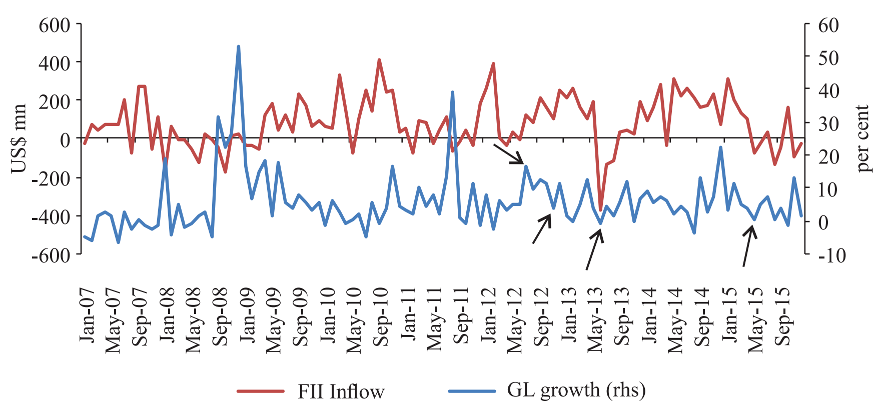


Chart 3b: Movement of FII Inflow and CBOE VIX

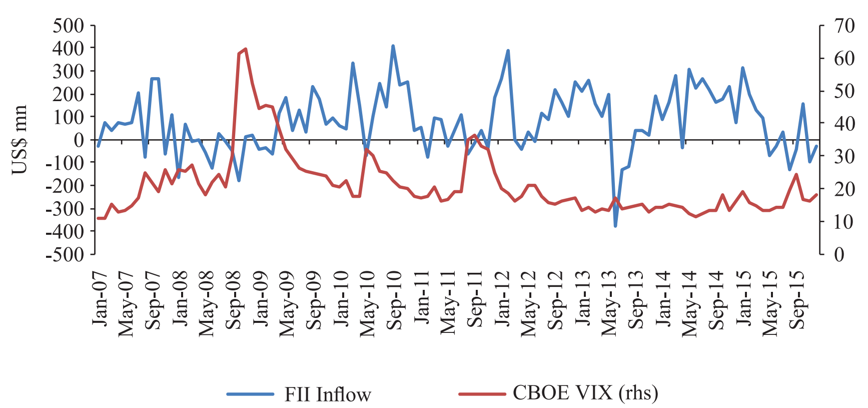
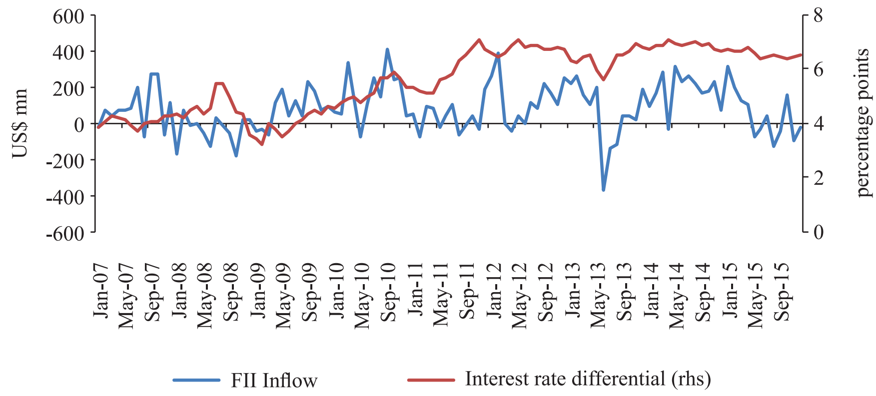


Chart 3c: Movement of FII Inflow and Interest Rate Differential



Section IV
Estimation of the Effects of Global Liquidity on Financial Flows to India

Drawing from the literature on the subject (Cerutti *et al*., 2014; Gordon and Gupta, 2003; Lim *et al*., 2014; Lim and Mohapatra, 2016), which identified the role of global liquidity, risk aversion/uncertainty, and monetary policy in the AEs in affecting financial flows to EMEs, we estimate the following equation:

$$FII_t = c + FII_{t-1} + GL_{t-1} + ID_{t-1} + VIX_{t-1+}\varepsilon_t$$

Net FII flows in the current period is the dependent variable. The independent variables are as follows: (i) FII_{t-1} is FII inflow at one period lag, (ii) GL_{t-1} is the measure of global liquidity at one period lag, (iii) ID_{t-1} is the interest rate differential at one period lag, (iv) VIX_{t-1} is the measure of global risk aversion at one period lag. The interest rate differential is calculated by subtracting the average yield on the 10-year government securities of the G4 countries from the GoI 10-year security yield.

The regression equation indicates that FII flows to India take place through observable global liquidity (GL), portfolio balance (*i.e.*, ID), and confidence (*i.e.*, VIX) channels. Some more variables are also used in the above equation as additional controls, namely, growth in Index of Industrial Prodouction (IIP) in India, inflation in India, and import-cover of forex reserves to obtain more robust regression results. Furthermore, a dummy has been added for the months when the taper announcement was made by the Federal Reserve (from May to November 2013). Variables are taken in lags to avoid any possibility of endogeneity (Gordon and Gupta, 2003).

Data Sources

The relevant data for the estimation are sourced from the RBI website (www.rbi.org.in), Securities and Exchange Board of India website (www.sebi.gov.in), Datastream, Bloomberg and Reuters. The money supply (M2) data of the US, the EU, the UK and Japan were obtained from Datastream. The FII flow data are taken from Central Depository Services Ltd. Government security yield and VIX data are taken from Bloomberg. The IIP data for India are taken from the website of the Central Statistics Office (www.mospi.gov.in). GDP data for the US, the EU, the UK and Japan are taken from the OECD Stat database.

The net capital/portfolio flows are the dependent variables. At the disaggregated level, flows of FDI, FII, and external commercial borrowings (ECBs) are also separately used. Data periodicity is monthly, from January 2012 to December 2015 (48 data points for the study). The FIIs access to the debt segment was very limited until very recently, though they were allowed as early as in 1998. At the end of 2015, the limits on FPI participation in government securities was US$ 25 billion while in corporate bonds it was US$ 51 billion; the corresponding limits at the end of 2011 were US$ 15 billion and US$ 30 billion, respectively.

Empirical Results

Sensitivity to Global Liquidity

Different types of financial flows exhibit varying sensitivity to different channels of transmission. To study this aspect, capital flows are examined for three major types of financial flows, *viz.*, FDI, FII and ECBs. The ADF test results show that the variables considered are stationary, except the interest rate differential (See Annex II, Table A.1). Hence, the auto regressive distributed lag (ARDL) bounds test is applied to examine the presence of any long-run relationship of different types of capital flows with various channels of global liquidity transmission, and longer period data from January 2001 to December 2015 have been used. The results show that FDI flows and ECBs are not co-integrated with global liquidity (see Annex II, Table A.2). In contrast, and as expected, net FII flow is co-integrated with global liquidity. This result is in line with findings of other studies on portfolio flows to EMEs. The literature indicates that since monetary policy is effective in the short run and portfolio flows are generally short-term in nature, it is likely that these get affected by the monetary policy (Lim *et al*., 2014; Lim and Mohapatra 2016). FDI is not sensitive to change in global liquidity as it is more dependent on the long-term growth potential of the country. Similarly, ECBs, subject to various regulatory parameters, are not found to be sensitive to global liquidity.

Determinants of FII Flows

Taking the above approach to a more disaggregated level to empirically examine the determinants of FII flows into India, the same equation is re-estimated while including additional variables – IIP of India (expected sign positive); NEER (expected sign positive); inflation in India (expected sign negative); and, import cover (expected sign positive). Some of the variables are integrated of order one, hence variables in first difference were used to make them stationary. The regressions are estimated by ordinary least square (OLS) with Newey-West heteroskedasticity autocorrelation consistent standard errors and covariance. The regression was estimated using monthly data from January 2012 to December 2015.

The lagged dependent variable is always significant. Furthermore, the results show that global liquidity is a significant factor in explaining FII flows to India (see Annex II, Table A.3). It also turns out to be a significant factor in the regression for equity flows, but not for debt flows. However, the p-value of global liquidity is at the margin of 10 per cent in case of debt flows. Overall, the results suggest that the liquidity channel matters for financial flows to India, which in turn indicates that the normalisation of the Fed balance sheet can reduce portfolio flows into India. Other variables like ID and VIX are not statistically significant implying that the portfolio balance channel and the confidence channel do not significantly influence FII flows. Taper dummy is significant in case of total FII flows as well as debt flows Change in import cover is found to be significantly associated with total FII flows and equity flows, but not with debt flows. In contrast with established perception, inflation is found to be positively associated with equity flows into India, which may be incidental.

The literature suggests that global liquidity predominantly originates from the US (Cerutti *et al*., 2014) . It poses questions on the role of other financial centres in the generation of global liquidity. To examine this aspect, the specification used in Annex II, Table A.3 was modified by substituting global liquidity, interest rate differential, and VIX by the liquidity generated in respective countries, interest rate differential of India *vis-à-vis* the respective country's 10-year Government security yield (10-year US Government security, 10-year German Government security for Euro, 10-year UK Government security and 10-year Japan Government security) and volatility index in the stock market of the respective countries, *viz.,* US (CBOE VIX), UK (FTSE 100 Volatility), Japan (NIKKEI Volatility) and Euro area (DAX volatility). Other variables in the regression equation as well as the structure of the equation remained the same. As shown in Annex II, Table A.4, the coefficient of liquidity generated in the US was the only statistically significant variable, indicating that liquidity generated in the US is a potent factor in steering FII flows to India while the same does not seem to hold for liquidity originating from the UK, the euro area and Japan.

Section V
Conclusion

The global crisis of 2008 resulted in a major disruption in the global financial markets. To keep markets alive and running, major central banks adopted UMPs and, as a result, the balance sheets of major central banks expanded exponentially. Between 2007 and 2015, the balance sheets of the European Central Bank and the Bank of Japan doubled, while that of the Federal Reserve of the US and the Bank of England expanded five times. These policies injected a surfeit of liquidity in the markets of the AEs which led to spillovers in the form of capital flows to the EMEs.

The reversal happened in a major way in 2013 against the backdrop of the announcement by the Federal Reserve on the reduction of bond purchases or the 'beginning of taper'. The recent announcements on balance sheet normalisation by the Federal Reserve and reduction of monetary stimulus by the European Central Bank have made the global liquidity a more prominent factor to drive capital flows to EMEs.

During periods of global market turbulence, financial flows to India have been affected differently. During the period of global financial crisis, an outflow of capital took place, mostly from the equity segment, while during the financial market turbulence generated by the taper talk in 2013, outflows were mostly from the debt segment. Against this backdrop, this paper studied the effects of fluctuations in global liquidity on portfolio flows into India. Empirical findings of this paper point to three broad conclusions:

First, global liquidity has differential effects on different types of capital flows. FDI and ECBs are not sensitive to changes in global liquidity conditions while FII flows are sensitive to policies that affect global liquidity.

Second, the transmission of global liquidity to India happens through the liquidity channel. This paper does not find any statistically significant role of the other two channels of transmission, *i.e.*, the portfolio balance channel and the confidence channel.

Third, the US monetary policy and associated global liquidity conditions exert larger influence on portfolio inflows into India than those of other major central banks.

References

Ahmed, S. and A. Zlate (2013), 'Capital Flows to Emerging Market Economies: A Brave New World?', International Finance Discussion Papers, No. 1081, June, Board of Governors of the Federal Reserve System.

Baks, K. and C. Kramer (1999), 'Global Liquidity and Asset Prices: Measurement, Implications, and Spillovers', *IMF working paper*, No. 168.

Basu, K., B. Eichengreen and P. Gupta (2014), 'From Tapering to Tightening: The Impact of the Fed's Exit on India', *Policy Research working paper, no. WPS 7071, Washington DC, World Bank Group*.

Bank for International Settlements (BIS) (2011), 'Global Liquidity: Concept, Measurement and Policy Implications', Committee on the Global Financial System (CGFS) Papers, No. 45.

Bruno, V. and H. S. Shin (2013), 'Capital Flows, Cross-border Banking and Global Liquidity', Griswold Center for Economic Policy Studies, *working paper, No. 237a*.

Cerutti E. M., S. Claessens and L. Ratnovski (2014), 'Global Liquidity and Drivers of Cross-border Bank Flows,' *IMF working paper,* No.14/69.

Chandrasekhar, C. P. (2008), 'Global Liquidity and Financial Flows to Developing Countries: New Trends in Emerging Markets and their Implications', *G24 discussion paper series*, No. 52.

Chakrabarti, R. (2001), 'FII Flows to India: Nature and Causes', *Money and Finance*, Volume 2, No. 7, October–December.

Dua, P. and R. Garg (2013), 'Foreign Portfolio Flows to India: Determinants and Analysis', Centre for Development Economics, Delhi School of Economics, *working paper, No. 225*.

Eichengreen, B. and P. Gupta (2015), 'Tapering Talk: The Impact of Expectations of Reduced Federal Reserve Security Purchases on Emerging Markets', *Emerging Markets Review,* Volume 25, Pages 1-15.

Forbes, K. J. and F. E. Warnock (2011), 'Capital Flow Waves: Surges, Stops, Flight and Retrenchment', *NBER working paper,* No.17351.

Fratzscher, M., M. L. Duca and R. Straub (2013), 'On the International Spillovers of US Quantitative Easing', *ECB working paper*, No. 1557.

Gordon, J. P. F. and P. Gupta (2003), 'Portfolio Flows into India: Do Domestic Fundamentals Matter?', *IMF working paper,* No. 3/20.

Global liquidity, Credit and Funding Indicators - IMF Policy Paper, 2013 July.

Reserve Bank of India (RBI) *Handbook of Statistics on Indian Economy*, Reserve Bank of India, Mumbai, September 15, 2017.

International Monetary Fund (IMF) (2017), *Global Financial Stability Report.*

Kaur, M. and S. S. Dhillon (2010), 'Determinants of Foreign Institutional Investors' Investment in India', *Eurasian Journal of Business and Economics*, 3(6).

Kumar, R. and S. Sharma (2014), 'Global Liquidity, Financialisation and Commodity Price Inflation', *RBI working paper*, No. 1

Lim, J. J., S. Mohapatra and M. Stocker (2014), 'Tinker, Taper, QE, Bye? The Effect of Quantitative Easing on Financial Flows to Developing Countries', *Policy Research working paper*, No. 6820, World Bank.

Lim, J. J. and S. Mohapatra (2016), 'Quantitative Easing and the Post-crisis Surge in Financial Flows to Developing Countries', *Journal of International Money and Finance*, Volume 68, 331–357.

Mukherjee, P., S. Bose and D. Coondoo (2002), 'Foreign Institutional Investment in the Indian Equity Market: An Analysis of Daily Flows during January 1999–May 2002', *Money and Finance*, Volume 2, No. 9–10.

Patra, M. D., J. K. Khundrakpam, S. Gangadaran, R. Kavediya and J. M. Anthony (2014), 'Responding to QE Taper from the Receiving End', *Journal of Macroeconomics and Finance in Emerging Market Economies*, Routledge, Volume 9, No. 2, 167-189.

Patra, M. D., S. Pattanaik, J. John and H. Behera (2016), 'Global Spillovers and Monetary Policy Transmission in India', *RBI working paper,* No. 3.

Passari, E. and H. Rey (2015), 'Financial Flows and the International Monetary System', *NBER working Paper*, No. 21172.

Pesaran, M. H., Y. Shin and R. J. Smith (2001), 'Bounds Testing Approaches to the Analysis of Level Relationships', *Journal of Applied Econometrics*, 16(3), 289–326.

Rai, K. and N. R. Bhanumurthy (2004), 'Determinants of Foreign Institutional Investment in India: The Role of Return, Risk, and Inflation', *The Developing Economies*, 42(4), 479-493.

Rey, H. (2015), 'Dilemma not Trilemma: The Global Financial Cycle and Monetary Policy Independence', *NBER working paper,* No. 21162.

Shankar, A. (2011), 'QE-II and FII Inflows into India: Is there a Connection?', *RBI working paper,* No. 19.

Smaghi, L. B. (2009), 'Conventional and Unconventional Monetary Policy', Keynote lecture at the International Centre for Monetary and Banking Studies, Geneva, April 28.

Verma, R. and A. Prakash (2011), 'Sensitivity of Capital Flows to Interest Rate Differentials: An Empirical Assessment for India', *RBI working paper,* No. 7.

ANNEX I

Some Important Research Papers Published on FII Flows to India

Authors (Year)	Major Global Variables	Major Domestic Variables	Major Regional Variables	Data Frequency	Indicator for FII Inflow	Methodology Used
R. Chakrabarti (2001)	S&P 500 Index, MSCI World Index	BSE return (both dollar and Rupee), Volatility of daily US dollar return, Short term interest rate, Credit rating	Nil	Mostly monthly	FII flow as proportion of the preceding month's market capitalisation	OLS with Newey-West heteroskedasticity autocorrelation consistent standard errors and covariance
Gordon and Gupta (2003)	IIP in OECD, US stock market return and LIBOR	IIP India, Exchange rate depreciation, Credit rating, Liquidity in BSE, and Seasonal dummies for first four months of the calendar year	MSCI EM Index, IIP in EM	Monthly	FII equity flows in US$ mn, also as a percentage of BSE market capitalisation	OLS corrected through Cochrane-Orcutt two step method
Mukherjee, Bose and Coondoo (2002)	S&P 500 (return and volatility) MSCI WI(return and volatility)	Market capitalisation in stock market, Sensex (return and volatility), Rupee-dollar exchange rate Call money rate and IIP	–	Daily, return in dollar term in competing markets	FII Purchase to previous day's market capitalisation (Mcap), FII Sale to previous day's Mcap, FII Net to previous day's Mcap	OLS
Kaur and Dhillon (2010)	S&P 500 return, PPI in USA, US 3 month Tbill rate	Indian stock market return, BSE stock market turnover, Market capitalisation in BSE, WPI, IIP and Exchange rate	–	Monthly	FII net investment	ARDL Model

(Contd...)

Authors (Year)	Major Global Variables	Major Domestic Variables	Major Regional Variables	Data Frequency	Indicator for FII Inflow	Methodology Used
Dua and Garg (2013)	IIP growth of OECD countries, 3month Libor	Sensex, NEER, Reserve to Import Ratio, IIP growth in India, interest rate differential (3 month Tbill rate-3 month Libor) and NEER volatility	Morgan Stanley Capital International Emerging Markets Net Index (MSCI-EM)	Monthly	Net FPI,FII, ADR Flows	ARDL Model
Rai and Bhanumurthy (2004)	S&P 500 Index, PPI USA	BSE Sensex, Monthly standard deviation of sensex and S&P500 and WPI India	–	Monthly	Net FII Flows	TARCH model
Patra *et al* (2014)	US IIP, 3 month T-Bill rate in US, Global VIX	India IIP, Rupee-USD rate, trade balance, 10 year yield differential between US and India, 3 month yield differential between US and India, Market capitalisation and WPI inflation	–	Monthly	Gross FII flows	GMM model

Note: S&P 500 : Standard and Poor's 500
MSCI world Index: Morgan Stanley Capital International World Index
IIP: Index of Industrial production in India
Libor: London Inter-bank Offer rate
PPI : Producer Price Index in USA
NEER: Nominal Effective Exchange rate

ANNEX II

Table A.1: ADF test

Series	Test statistic	Test Critical value at 5 per cent	Test Critical value at 10 per cent	Result
Global Liquidity	-11.0	-2.88	-2.58	Unit root rejected
VIX	-3.93	-2.88	-2.58	Unit root rejected
ID	-1.10	-2.88	-2.58	Unit root not rejected
FII flow	-5.90	-2.88	-2.58	Unit root rejected

Table A.2: Sensitiveness of Types of Capital Flows to Global Liquidity (ARDL Bounds Test Result for Cointegration)

Variables	F-statistic	Probability	Result
FII (FII/ Global Liquidity, Interest Rate Differential, CBOE VIX)	**4.26**	**0.00**	**Co-integration**
Critical F value@	Lower Bound	Upper Bound	
95% level	2.85	4.05	
90% level	2.43	3.57	
FDI (FDI/ Global Liquidity, Interest Rate Differential, CBOE VIX)	**1.85**	**0.12**	**No-cointegration**
Critical F value@	Lower Bound	Upper Bound	
95% level	2.85	4.05	
90% level	2.43	3.57	
ECB (ECB/ Global Liquidity, Interest Rate Differential, CBOE VIX)	**2.09**	**0.09**	**No-cointegration**
Critical F value@	Lower Bound	Upper Bound	
95% level	2.85	4.05	
90% level	2.43	3.57	

Note:

@: The critical values are obtained from Pesaran *et al.,* (2001).

#: Lag value of 4 was applied on the basis of AIC criterion, ensuring that there is no serial correlation.

$: In case of FII and FDI, data from January 2001 to December 2015 have been used. Due to the difficulty in data collection, data from April 2004 to December 2015 have been used in case of ECBs.

Table A.3: Determinants of Net FII Flows to India during 2012-15

Variables	Net FII Flows		Net Debt Flows		Net Equity Flows	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
Constant	4.53	0.91	13.3	0.49	6.7	0.78
FII(-1)	0.50*	0.01	0.42*	0.02	0.41*	0.08
Basic controls						
IIP growth in India(-1)	-5.08	0.60	-0.42	0.94	-4.85	0.41
Channels of Transmission						
Liquidity channel						
Global liquidity(-1)	8.5*	0.00	3.14	0.10	4.9*	0.00
Portfolio Balance channel						
Change in Interest rate Differential (-1)	79.8	0.49	47.0	0.44	24.9	0.73
Confidence channel						
Change in Global VIX(-1)	1.77	0.88	2.21	0.67	-0.69	0.91
Additional Controls						
Inflation in India(-1)	40.9	0.23	1.01	0.96	38.9*	0.04
Change in NEER(-1)	-10.5	0.55	-8.5	0.42	3.62	0.77
Change in Import Cover(-1)	52.9*	0.06	15.1	0.37	35.7*	0.01
Taper Dummy	-140*	0.02	-105*	0.00	-40.8	0.20
R^2	0.41		0.45		0.36	
Adjusted R^2	0.27		0.32		0.21	
DW statistic	1.82		1.97		1.63	

Note: The regressions are estimated by OLS with Newey-West heteroskedasticity autocorrelation consistent standard errors and covariance.
: Variables are statistically significant.

Table A.4: Role of Monetory Policy of the US and Other Countries as Drivers of FII flows to India during 2012-2015

Variables	US	UK	Euro Area	Japan
Constant	40.9 (0.36)	67.1 (0.08)	55.9 (0.20)	63.3 (0.07)
FII(-1)	0.47 * (0.03)	0.42 * (0.03)	0.40* (0.05)	0.38* (0.04)
Basic controls				
IIP growth in India (-1)	-5.77 (0.55)	-9.25 (0.28)	-10.28 (0.18)	-8.24 (0.29)
Channels of Transmission				
Global Liquidity (-1)	3.73 * (0.02)	0.04 (0.98)	1.72 (0.48)	1.77 (0.38)
Change in Interest Rate Differential (-1)	104.9 (0.39)	119.7 (0.28)	65.6 (0.52)	5.13 (0.52)
Change in VIX(-1)	0.34 (0.98)	0.74 (0.65)	-0.31 (0.87)	0.10 (0.95)
Additional Controls				
Inflation in India (-1)	22.6 (0.50)	24.1 (0.46)	23.3 (0.38)	26.04 (0.47)
Change in NEER (-1)	-11.8 (0.52)	2.37 (0.89)	-0.72 (0.97)	4.51 (0.81)
Change in Import Cover (-1)	50.7 * (0.08)	41.4 (0.14)	44.8 * (0.08)	42.7* (0.09)
Taper Dummy	-140.5* (0.02)	-121.4* (0.06)	-125.5* (0.05)	-121.7* (0.07)
R^2	0.39	0.35	0.34	0.24
Adjusted R^2	0.25	0.21	0.19	0.18
DW statistic	1.90	1.87	1.91	1.87

Note: The regressions are estimated by OLS with Newey-West heteroskedasticity autocorrelation consistent standard errors and covariance. The figures given in the parentheses are the p-values.
: Variables are statistically significant .

Reserve Bank of India Occasional Papers
Vol. 38, No. 1&2, 2017

The Architecture of Collapse: The Global System in the 21st Century by Mauro F. Guillén, Oxford University Press, UK (2015), 240 Pages, £25.00*

The post-crisis global efforts directed at entrenching financial stability do not seem to have adequately recognised the fact that a complex and interconnected financial system is extremely unstable. *'The Architecture of Collapse'* argues that the modern global system has 'become intricate, interconnected, unwieldy and unpredictable', that it has become unstable due to the way it is currently structured. The author, Mauro F. Guillén, is Director of the Joseph H. Lauder Institute at Penn, and also holds the Dr. Felix Zandman Endowed Professorship in International Management at the Wharton School of the University of Pennsylvania. According to Guillén, the broad indicators – demographic, economic, financial, political, social and cultural – suggest a likely persistence of global systemic instability. He highlights the fact that crises and other episodes of abrupt change seem to occur rather frequently. He refers to the 'current structure of global system', as the '*The Architecture of Collapse'* due to its inherent propensity to lead to 'instability, disruption and crisis'. The book contains seven chapters.

Chapter 1 on the global system traces its origin, and compares and contrasts the old and modern global systems using a framework of nodes, network and system. The 'Global System' as an idea has evolved over the years. Guillén alludes to the definition of the global system by Immanuel Wallerstein in his first volume of *The Modern World-System* (1974) as one of hierarchy exhibited by 'core' and 'periphery' countries. Highly industrialised countries form the core and the less industrialised countries, the periphery.

Guillén, drawing from several indicators as well as theories, advances the idea that the global system has indeed collapsed and is a result of several shock waves. He argues, again drawing from well-argued empirical literature, that 'interactive complexity' and 'tight coupling' 'create a situation in which the system cannot easily return to equilibrium if something throws it off balance'.

Guillén effectively uses the network theory to analyse the emerging complexities in growth, structure, dynamics, and functioning of nodes and networks and their mutual interrelationships in the global system so as to identify whether it leads to shock diffusion or shock absorption. A complex network could be shock absorbing as well as shock diffusing. It could be shock absorbing when the structure and pattern of relationships among the different nodes is complex but impervious to the global isomorphic forces, making it difficult to contribute to a contagion. It is shock diffusing when the nodes are complex and tightly coupled with other nodes.

The term 'interactive complexity' refers to many parts moving in an intricate arrangement, interacting with one another in non-linear ways. The term 'tight coupling' refers to the extent to which the parts are tightly related to one another, thus reducing the buffers and/or degrees of freedom, the tolerance, or the margin for error. The author clarifies that two parts may be interdependent but not necessarily tightly coupled.

In Chapter 2, Guillén delves into the complexities of inter- and intra-country interactions. The frequency of currency, inflation, stock market, domestic debt, external debt, and banking crises has significantly increased in recent times. This has been illustrated with the use of several data on economic and financial crises sourced from the works of Reinhart and Rogoff ("This Time is Different: Eight Centuries of Financial Folly", Princeton University Press, 2009), the World Bank, Bank for International Settlements (BIS), United Nations Industrial Development Organization (UNIDO), World Trade Organization (WTO) and International Monetary Fund (IMF).

While analysing complexity and networks, the author views complex networks as generally shock-absorbing while those which are tightly coupled as shock-diffusing. The author also distinguishes between network complexity and node complexity, which together lead to systemic complexity. The network complexity arises due to factors like increase in number of countries in the global system, foreign direct investment, information flows, tourism and migration, and trade in goods and services. The network complexity such as portfolio investments could be shock-diffusing during a crisis. The node complexity arises due to factors such as democracy, size of the state/country, industrial diversification and state failure. The author further explains that network coupling arises due to factors such as current account imbalances, foreign portfolio investment, cross-border banking (can also generate node coupling as in the case of Euro Zone), currency trading, and trade in intermediates, while node coupling takes place on account of factors like population ageing, public debt, wealth inequality, income inequality and urbanisation. The node and network complexities contribute to systematic complexity. Some of the famous instances of coupling-induced troubles (CIT) include France in 1981, Mexico in 1994–95, the Asian Flu of 1997, Argentina in 2001–02 and Euro Zone in 2009. Germany and Europe represent an example of tight coupling since Europe is tightly integrated but is dependent on Germany. Likewise, Germany is dependent on Europe. The coupling has become tighter over time, especially in the wake of the crisis. The implications are that the Euro Zone would remain unstable for the foreseeable future. The United States-China relationship is one of interactive complexity (trade and foreign direct investment) and tight coupling in terms of portfolio investments (government bonds). This, according to Guillén, has serious implications for the global system, impacting trade, capital flows and reserves.

Chapter 3 explains the differences between network and node coupling; and the implications of current account imbalances, international trade, growth of cities, debts of countries, and income inequality that have resulted from structural changes in the global landscape over the last 30 years. Guillén demonstrates that the dynamics of complexity and coupling unfolds not only at the global systemic level but also within the sub-components (e.g. industries and regional trade block). Chapter 4 investigates the recent global crisis of 2008. It demonstrates how interactive complexity and tight coupling at the node level can jointly destabilise one large country like the US and the crisis can spread to other parts of the world depending upon the patterns of complexity and coupling at the network level.

Focusing on case studies of complexity and decoupling, Chapter 5 analyses the relationship between China and the US to illustrate the dynamics of complexity and coupling at the dyadic level, noting how it contributed to the crisis and how it might evolve in the future. Guillén argues that the China-US relationship can be seen as both stabilising as well as destabilising. Chapter 6 compares the European Union (EU) and the Euro Zone in the context of the debt crisis that emerged in 2009. According to the author, the EU is a more complex subsystem but not tightly coupled. On the other hand, the Euro Zone is both complex and tightly coupled, such that it is extremely sensitive to the disruptions and failures originating even from the smallest countries within the zone.

Guillén takes stock of evidence and issues in Chapter 7, charting out specific recommendations to make the global system more predictable, subject to lesser failures and overall safer. The current global system is characterised by spread of practices, crises and events from one country to another and these processes of diffusion tend towards "isomorphism" due to the network complexity and tight coupling at the network and node levels. High levels of state capacity in terms of ability to intervene during normal and crises times, build buffers/firewalls against instability, disruption, crisis and breakdown whether the menace is due to financial, ethnic conflict or natural disaster, he argues, make the adoption of new models more likely in response to normative, mimetic or emulative isomorphism. He adds that the role of state capacity during crisis involves independence of central banks. He illustrates how the independent central banks during the recent global crisis in Europe (debt crisis) and US (political gridlock) were in a better position to act than governments in restoring confidence and accelerating growth. States with more capacity have the means to identify and evaluate alternatives proposed or adopted elsewhere in the world, assess their impact, and conduct follow-up studies after implementation.

This book analyses the stability of the global economy in a different perspective using concepts of network, nodes and the links between them. In the context of financial systems, the nodes of the network represent financial institutions, while the links are created through mutual exposures between banks, acquired in the interbank market by holding similar portfolio exposures or by sharing the same mass of depositors. A network approach to economic and financial systems for assessing macroeconomic and financial stability is insightful. Such an approach can be particularly helpful in capturing the externalities – risk associated with a single country or institution may spread to the entire global system. A better understanding of network externalities may facilitate the adoption of a macro-prudential framework for financial supervision. Regulations that target an individual country or institutions, and those which take into account vulnerabilities emerging from network interdependencies, may prevent a local crisis from becoming global.

With his elegant style of writing, Guillén helps the reader navigate a complicated global landscape by offering clarity on instability and crisis. The resilience of an economy/financial entity can only be improved by (i) enhancing the shock-absorbing components of the system, especially the capacity of states and governments to act, and (ii) by containing the shock-diffusing mechanisms, in particular those related to phenomena such as trade imbalances, portfolio investment, cross-border banking, population ageing, and income and wealth inequality.

In sum, Guillén's book outlines the high-impact risks facing both local and global economies and details how the evolution of interconnected markets designed for efficiency have left many economies exposed. Apart from opinion and analysis, the book also offers a wealth of empirical evidence presented in the form of comprehensible visual displays, graphs and charts. This book promises utility to a wide range of readers who may be interested in today's finance-driven global society and the evolution of nations.

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Reserve Bank of India Occasional Papers
Vol. 38, No. 1&2, 2017

Financial Crisis, Corporate Governance, and Bank Capital by Sanjai Bhagat, Cambridge University Press (2017), US$39.99

The global financial crisis (GFC) has brought to the fore the importance of 'corporate governance' and put a question mark on prevailing practices on dealing with stressed 'too big to fail' (TBTF) banks. Though, there were various factors which led to the crisis, excessive risk taking by the top executives in large financial institutions and the lenient government policies for home buyers could be identified as the two prominent ones. While there are several books available now on the GFC, it is difficult at times to differentiate one from the other in terms of the broad content and key findings. The book by Sanjai Bhagat titled *'Financial Crisis, Corporate Governance, and Bank Capital'*, however, lucidly explains some of the intricate aspects of the GFC while offering a unique approach in terms of an empirical analysis of the relationship between corporate governance and capital requirement in banks. The author, professor at the University of Colorado, having experience of working with the US Securities and Exchange Commission, the US government agencies and Fortune 500 companies, provides insightful details of the crisis and also offers remedies to overcome or minimize the effect of such a crisis in the future.

The book highlights the role of public policies relating to home mortgage in the financial crisis. Prior to 1992, the US government sponsored enterprises - Fannie Mae and Freddie Mac-promoted the growth of sub-prime market and dominated the residential mortgage market with their combined share rising from 40 per cent in 1996 to 56 per cent in 2008. This enabled home ownership by those who could not otherwise afford it. In this process financial institutions played a key role by issuing mortgage backed securities (MBSs). MBSs issued by banks, also known as private label securities (PLS), constituted about 50 per cent of the total MBS issued. Total PLS issued during 2005 and 2006 amounts to more than US$ 1 trillion. As the US real estate prices started to decline in 2005-08, home buyers who had no money started defaulting on payments and the default rate increased to 35 per cent, which eventually affected the US financial system.

The author argues that apart from the lenient government policies for home buyers, excessive risk taking decisions by the top executives in large financial institutions was a major cause of the GFC. The book also contests the notion of ‘too big to fail’ (TBTF): the firm whose size, complexity, interconnectedness, and critical functions make it so important to the overall financial system of a country that, if anything goes wrong, in the larger interest of the economy, the government needs to bail it out. As the TBTF results in uneven playing field for small and big banks, the author proposes a solution which can be implemented only by the intervention of corporate board members and institutional investors in big banks.

The author argues that the pre-crisis compensation packages prevailing in the industry might have led to misaligned incentives. The TBTF bank CEOs were able to realise substantial gains on their common stock sales in the pre-crisis period (2000-07), while during the crisis of 2008 they had to incur large losses. Additionally, stock sales by TBTF bank CEOs were significantly greater than stock sales by other bank CEOs in the pre-crisis period. Finally, different risk-taking measures suggest that TBTF banks were significantly riskier than other banks. The author, based on an empirical analysis of the compensation structure of 100 US financial institutions, provides an alternative to the existing compensation package.

The compensation package proposed by the author is based on simplicity and transparency, and focuses on creating and sustaining long term shareholder value without any need of bailouts. The proposed package, unlike most other executive compensation reform proposals, does not place a ceiling on executive compensation. The author provides four justifications in support of a simple and transparent compensation structure. First, the financial sector is a fast-evolving sector and it is difficult to predict risks that may emerge as products and markets develop. Moreover, in the context of large and interconnected financial institutions and complex financial instruments, banks grapple with ‘unknown’ and ‘unknowable’ risks. The more complicated and opaque an incentive package is, the more difficult it will be to anticipate individual responses and predict what risks will or will not materialise. Second, as shareholders are now required to vote on CEO compensation packages, a simple incentive structure is easier for them to understand and evaluate, reducing the need to rely on third-party vendors of proxy voting advice, the value of which has been the subject of considerable controversy. Third, simplicity and transparency in incentive compensation packages mitigate public scepticism towards high pay of executives. Finally, the focus on creating and sustaining long-term shareholder value would channel management's attention to longer term profitability of an investment or trading strategy. Business and legal scholars posit that managers should act in the best long-term interest of shareholders - what could be the better way to do this than tie management's incentive compensation to long-term share price. The author refers to this as the Restricted Equity proposal, as he proposes that the incentive compensation of bank executives should consist only of restricted equity - restricted in the sense that the individuals cannot sell the shares or exercise the options for one to three years after their last day in office.

The proposal only limits the annual cash payouts an executive can receive. The amount of restricted stock and restricted stock options that can be awarded to a bank manager is essentially unlimited as per the proposal; though, in practice, the award amounts should and need to be anchored to the current practices in a particular company. Also, the focus on creating and sustaining long-term shareholder value would minimise the likelihood of a bailout which would reduce the potential burden on the taxpayers.

Equity-based incentive programs, however, may lose effectiveness in motivating managers to reduce excessive risk-taking when a bank's equity value approaches zero. There is a moral hazard or agency cost of debt arising from shareholders' potential preference to take extreme risks when a firm is close to insolvency. This is because the shareholders gain from the upside of a positive outcome, albeit low in probability, while limited liability leaves the losses, should the gamble fail, on creditors. The moral hazard problem when equity value approaches zero may well be more severe for banks, as their creditors have less interest in monitoring against risk-taking activity because the government not only stands behind retail depositors, but also often bails out other creditors. Suitably aligning management's incentives in this context, therefore, calls for focus on the interaction among bank capital structure, bank capital requirements and bank executive incentive compensation whereas, the extant literature analyses compensation reform in isolation.

The book provides an excellent overview of executive compensation policies by banks and highlights how understanding their interactions with other variables like bank size and bank capital can enhance our assessment of risks and improve regulatory aspects. The author emphasises that banks' shareholders and management at present have fairly limited ability to internalise the consequences of risks. Corporate governance principles ensuring clear allocation of authority, responsibilities and accountability for deterioration in financial soundness parameters of a bank are as much important as the emphasis on higher and better quality control to ensure financial stability.

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Reserve Bank of India Occasional Papers
Vol. 38, No. 1&2, 2017

Doughnut Economics: Seven Ways to Think Like a 21st-Century Economist, Kate Raworth (Random House Business Books, London), 2017; pp 384, £14.99.

The global financial crisis also led to a setback for economics as a subject - in terms of its relevance to the society. Serious limitations of the subject in preventing the crisis and in providing an effective early resolution has necessitated fresh innovative thinking on what economics must teach to stay relevant. '*Doughnut Economics: Seven Ways to Think Like a 21st-Century Economist'* by Kate Raworth, a renowned economist, profound thinker, and prolific writer, is an important contribution in that direction. The book is revolutionary in its approach, and one of its kind in the field of economics. It may restore confidence of the people who lost faith in economics after the global financial crisis, provide credence to the subject itself and give assurance to those who fear that the reputation of this branch of social sciences is at stake. The rebels and dissenters who emerged after the 2008 financial crisis, across the world, can find solace in it.

Raworth has proposed seven path-breaking innovative ways of thinking in her book. In the first chapter, she argues convincingly that pursuing the economic goal of gross domestic product (GDP) growth alone is neither just nor sustainable. We have become so fascinated and addicted to this notion that our only concern is to grow as fast as possible, even beyond the means of our natural resources, hence jeopardising the life supporting system of earth itself. The source of this excessive emphasis on GDP growth lies in the mainstream economic theories – classical economists encouraged more production, economists like Keynes advised consuming more and neoclassical growth economists suggested greater investment. GDP growth was, in fact, considered the panacea for all economic malaise.

According to Raworth, pressure on global climate change, growing inequality, daunting social and economic deprivations, and the unfolding of the 2008 global financial crisis indicate the need to focus on alternative economic goals. Hence, terms like sustainable growth, long-term growth, balanced growth, green growth and smart growth have gained currency. The progress in this direction, however, is not enough and there is an urgent need to reprioritise our goals. Raworth defines this by visualising an American doughnut that has two rings or boundaries. The inner ring represents the 'social and human foundation', *i.e.*, access to the basic, minimum twelve amenities such as health, education, housing, clean water, nutritional food, energy, income, work under social justice, peace, gender equality and political empowerment. Any transgression of this boundary means a shortfall or deprivation of social amenities. The outer ring indicates the ecological ceiling of planetary pressure and any overshooting of this circle would mean excessive air pollution, ozone layer depletion, ocean acidification, biodiversity loss, chemical pollution, and water table depletion. Our aim should be to stay within the area between these two rings, which represents a 'sweet spot' of an appropriate balance of life. The author argues that we have overshot these two circles due to unsustainable growth. Reversion to the 'sweet spot' needs maintaining a 'thriving-dynamic balance' instead of pursuit of growth. This visual representation of the economic goal (to remain within a doughnut) is the main highlight of this book.

In the second chapter, the writer examines the changes, over time, in the role played by institutional agents in shaping society. The 20th century was dominated by neo-liberal principles where market was trusted to be an efficient institutional agent. In a free market environment with least regulations, the business sector played an important role of making innovations and profits. In this scenario, finance was regarded as 'infallible' and trade was considered a 'win-win' activity for all. The role of the state was of lesser significance and it was supposed to not interfere in the functioning of market. The other agents such as the household, the commons, the society, and the earth did not get much attention during this period.

Raworth suggests a change in the priority of various agents in the 21st century and claims that the main protagonist should be the mother earth, which deserves the most respect. The second most important role is for the society, which is 'foundational' and needs to be nurtured. The third could be assigned to economy which needs to be supported by other agents. The value of the contribution made by households, which had an insignificant role in the earlier framework, should be accounted for now. It is important to regulate market, which is a powerful agent, so that the externality could be internalised. According to the author, the commons are 'creative' and their true potential could be realised if they are 'governed by clearly defined communities with collectively active rules and punitive sanctions'. The state can take 'centre stage' by getting a mechanism to fix accountability as markets and commons fail. The role of finance should be to 'serve the society' and not to 'dominate' it. There is a need to define the purpose of the business sector while trade needs to be fair. In this section, the book advocates to shift away from a 'market-contained' economy to an 'embedded' one.

The author discusses the limitations of the rationality assumption, which is the basic tenet of a large chunk of modern literature in economics. This assumption has made human behaviour excessively self-centred, which has led to outcomes that are often not consistent with social goals even though they may appear to facilitate the achievement of individual goals. Raworth, therefore, urges a change in perception from 'I' to 'We' and recommends a transition from a rational man to a 'social adaptable man'. In this context, there is a need to assign a greater role to normative economics rather than depend on positive economics which is bereft of value judgement. The tendency of shying away from judging what is good and bad seems to be a hurdle in the path of creating a just society.

Chapter four is devoted to discussion on growing bias of economics literature towards the approach followed by mathematicians and scientists. By turning the theories into maths, economists have ended up with models that are based on equilibrium, with little capacity to predict and respond to real world booms and busts. Raworth points out that because of the distance from real world problems, no one 'saw the crash coming'. It is, therefore, time to 'ditch the Physics envy and embrace the economic complexity with its spiralling feedbacks, emerging trends and surprised tipping points instead of simple mechanical equilibrium'. All the important economic events like the Great Depression, hyperinflation after the second World War, fall of the Berlin wall, and the sub-prime crisis were not sudden events. They had been gradually in the making and could have been foreseen. There are no 'external' or 'exogenous' shocks to the system – all the shocks are inherently internal and 'endogenous' and 'One can listen to what the system tells us'.

The author debates the widely accepted notion of growth and inequality trade-off, which states that a country has to endure the pain of inequality at the beginning of its economic journey, if it wants to become rich. Economists like Simon Kuznets thought that there exists an inverted U curve relationship between inequality and GDP growth. But the evidence of growth of East

Asian economies and Japan indicates that it is possible to achieve 'rapid economic growth with low inequality'. In this book, the author asserts that rising inequality is a 'policy choice' rather than an unwanted outcome which cannot be controlled. The objective can be achieved more effectively through appropriate distribution of 'sources of income' such as land, enterprise, technology and knowledge rather than focussing on redistribution of income itself. Our laws, rules and regulation should be 'distributive by design'. Drawing reference to the financial crisis of 2008, the author states that the major cause of the crisis was an uneven distribution of credit in the economy. Furthermore, the bailout process could have been more effective, had the central banks channelled new money directly through community-based renewable energy systems.

According to Raworth, our industrial design is 'degenerative'. We take resources from the system, use them and lose them. This cycle contrasts with the natural systems of earth where life support comes from recycling of carbon, nitrogen, oxygen, phosphorous and water. If the current hazardous practice continues, the end of the world may not be very far. There is a need to move from degenerative to regenerative design of industries where we can reuse and recycle resources so that the total resources of the earth do not decrease. The focus should be on inventing industries which can 'inhale' carbon dioxide instead of 'exhaling' it; designing cities where rooftops generate energy from the sun, grow food and shelter wild life; and construct buildings which sequester carbon dioxide, cleanse the air, treat their own sewage and convert them into soil enriching nutrients. The progress in this direction so far is slow. However, a few good developments have taken place in this direction-for instance, a company in California captures methane from dairy farms and converts them into bio plastic and makes products like bottles and office chairs, and firms in South Australia use sea water to grow tomatoes. In fact, Bangladesh, might become the 'first solar-powered nation'.

Underlining the need for adopting a balanced approach, Raworth suggests that we should neither be too obsessed about growth nor completely discard it. It is not possible to eradicate human deprivation without achieving a threshold level of economic growth. The author's approach towards growth is to be 'agnostic' – one should design an economy that 'promotes human prosperity, no matter whether growth is going up, down or steady'. In this book, Raworth advises that GDP growth should be considered along with resource use growth, and not separately. If GDP grows faster than the 'resource use' then it is known as relative decoupling; a path suggested by the author for low income countries. For high income countries, she prescribes absolute decoupling; where GDP growth is not only faster than 'resource use' but also accompanies 'absolute' fall in 'resource use'. Germany's GDP during 2000 to 2013 grew by 16 per cent while its 'consumption based carbon dioxide fell by 12 per cent' and similar are the situations in case of UK and USA. It shows that despite absolute decoupling, these countries' emission levels are not falling fast enough. Some scientists have calculated that the falling rate of emission should be between 7 per cent to 8 per cent whereas in reality it is 1 per cent to 2 per cent. Hence, the author advocates for 'sufficient absolute decoupling' in growth which means a growth that is on a sufficient scale to get back the economy to doughnut.

The ideas and concepts explained in the book could prove to be game changers in the field of economics. Raworth's original work is to visualise economic goal in terms of a doughnut and identify; a sweet spot where every economy must try to reach. She believes that pictures are more influential than text. One of the most important diagrams that we study in macroeconomics is 'circular flow of income' where national income flows between four sectors of the economy. She considers this diagram to be one of the most misleading diagrams in economics, which is also incomplete as it does not include earth's resource-use cycle. No doubt income flows from one sector to the other, but what about the flow of energy and resources? There is no channel to refill the resources obtained from earth. Therefore, the diagram needs to be redrawn which would help to understand the economic system more realistically. Though there is a vast literature available on sustainable development and the failure of markets to provide public goods, this book offers a fresh analytical description of the problem and a way ahead. All these ingenious ideas and brilliant framings suggested by Kate Raworth are highly motivating and have the potential to transform our thought process, but their practical applicability is debatable. If only some of these ideas could be implemented, the world would be a much better place.

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Regd. No. “No. R.N. 37535/80”

Published by Jai Chander for the Reserve Bank of India, Sahid Bhagat Singh Road, Fort, Mumbai-400 001 and printed by him at Jayant Printery LLP, 352/54, Girgaum Road, Murlidhar Compound, Near Thakurdwar Post Office, Mumbai - 400 002.