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Nowcasting Real Estate Activity in India using Google Trend Data

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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.

[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

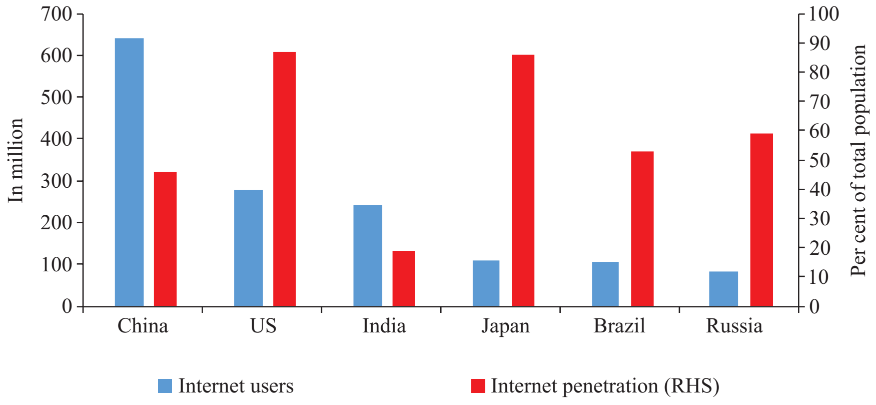
Shanbhogue, 2011), to name a few. Suhoy (2009) conducted a business cycle analysis using Google search data for Israel and observed that the search data successfully identifies the business cycle turn around point. Koop (2013) used the dynamic model selection (DMS) in time varying framework on Google 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

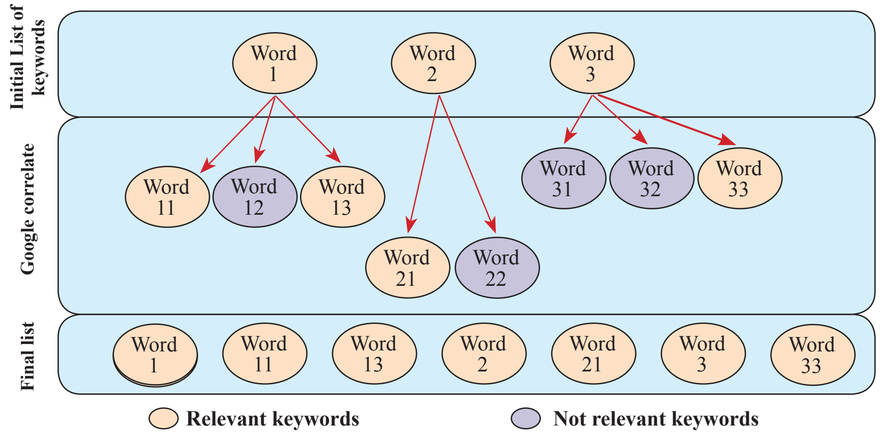
Identification of Keywords Related to Real Estate Search

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:

$$G: R \to [0,100] \ni R_t = \frac{S_t}{Max\ S_t} \times 100\ \&\ S_t = \frac{n_t}{N_t} \qquad (1)$$

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:

$$SC_t = \frac{1}{N}\sum_{i=1}^{N} R_{it} \qquad (3)$$

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 ith 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 ith factor at time t and v_i is the proportional variability explained by ith 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.

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

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, $\Theta^v_n = (\Theta^v_{n_1}, \Theta^v_{n_2})$ where $\Theta^v_{n_1}$ is the data on economic indicators (including soft and hard data) and $\Theta^v_{n_2}$ is the Google-based composite indicator.

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

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

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

$Proj\left(\widetilde{R^{3k}_{v_J}}\middle|\Theta^{v_j}_n\right) = E(R^{3k}_{v_j}|\Theta^{v_j}_n\ for\ v_j\ \in [(3k-2);3k], Model)$ 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:

$$Uncertainty^{3k}_{v_j} = E\left[\left(\widetilde{R^{3k}_{v_J}} - R^{3k}\right)^2\middle| Model\right] \tag{7}$$

As more and more monthly data are released, Θ^{vj}_n 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:

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

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:

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

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.

[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.

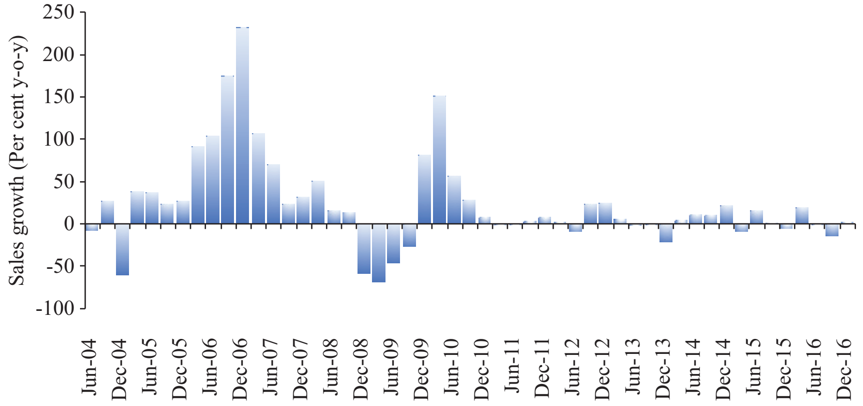
Section IV
Data

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

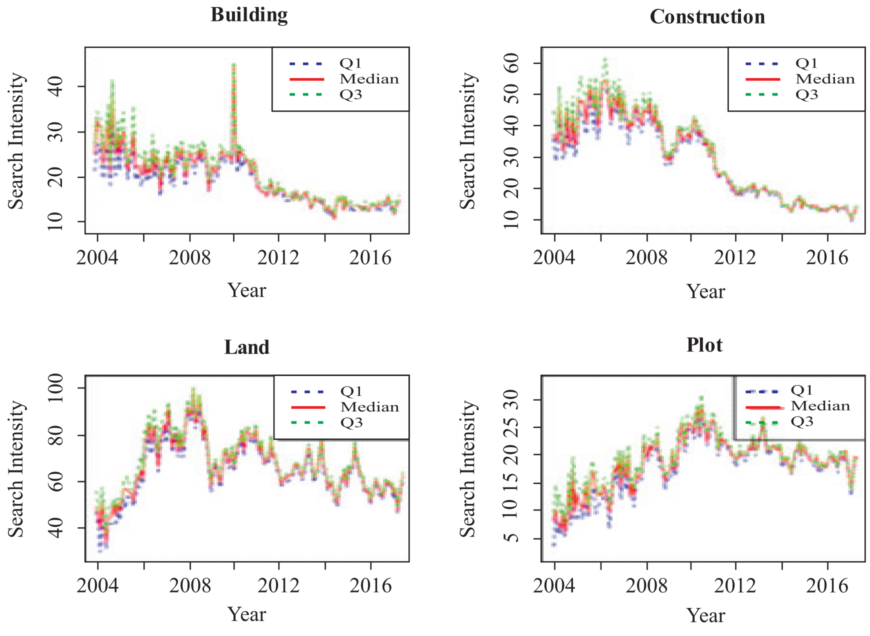
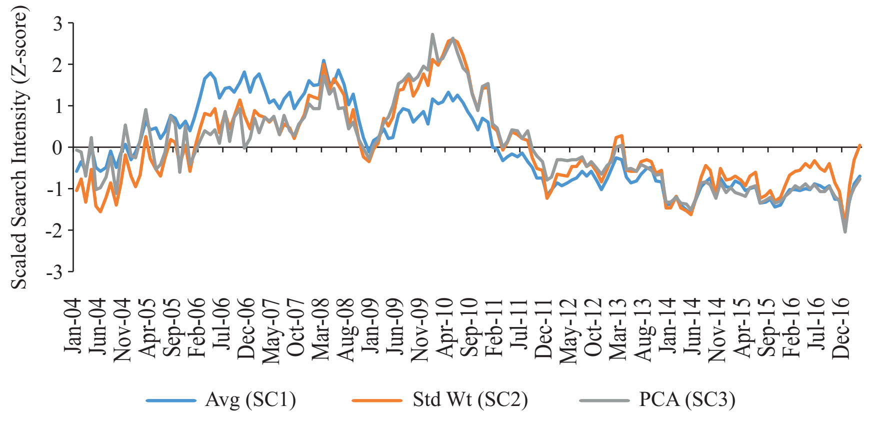


Chart 5: Search Intensity over Time



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).

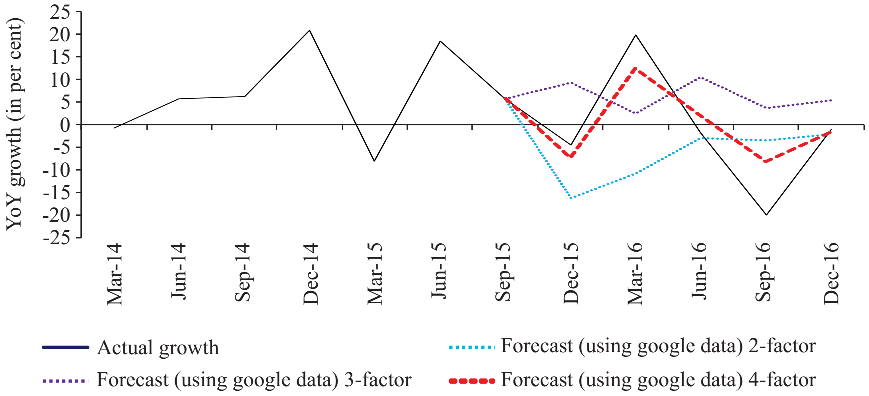
Improvement in Forecast Performance due to Google Search

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

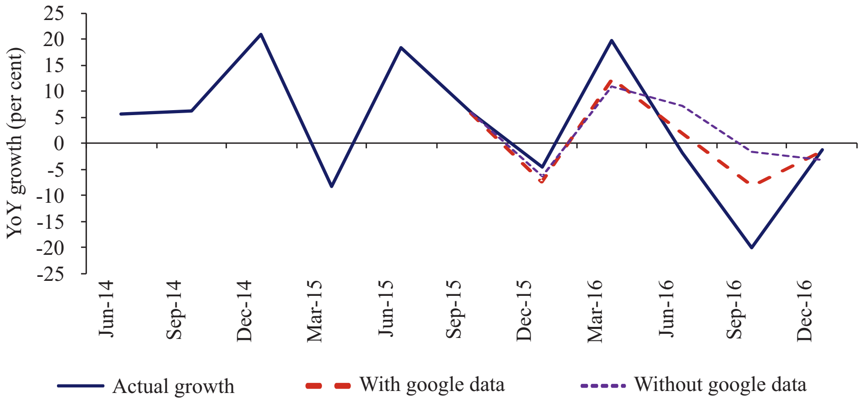


Table 1. Rolling Forecast Performance of Different Models

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.

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Annex : 1
Queries used in Google Trends

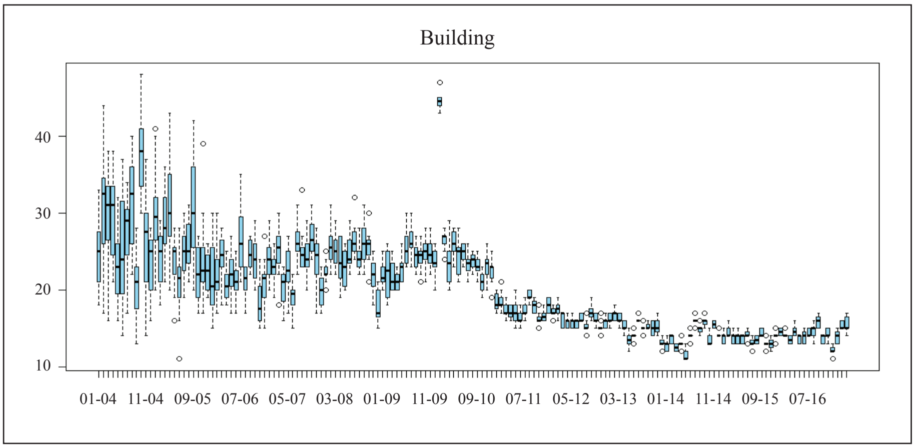
independent house	www.magicbricks.com	BHK flat
Building	www.sulekha.com	1 BHK
construction	www.99acres.com	2 BHK
Flat	estate agents	3 BHK
apartment	property dealers	1 RK
land	independent house in Mumbai	housing society
land for sale	independent house in Bangalore	brokerage
real estate	independent house 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

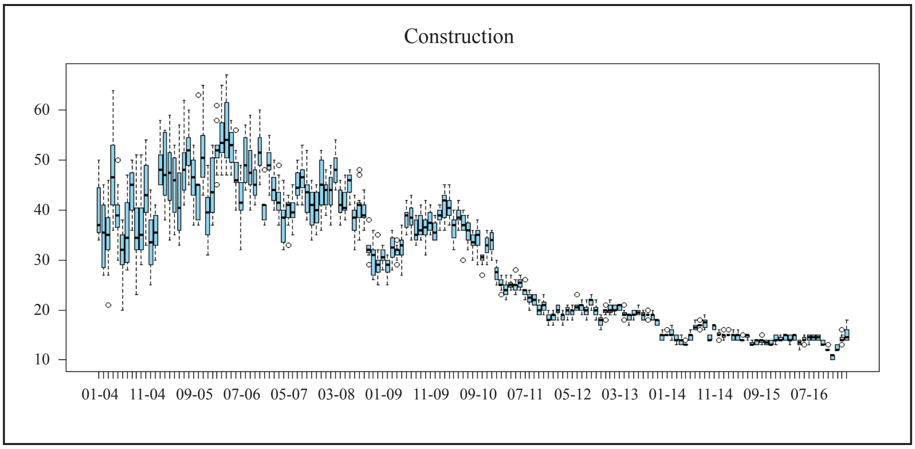
Annex : 2
Economic Indicators used for Nowcasting

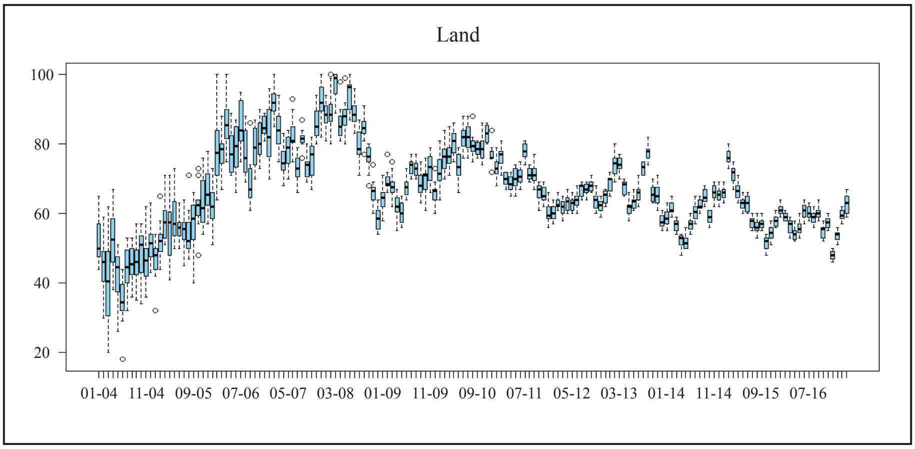
Index of Industrial Production (IIP)	IIP Manufacturing
IIP Basic Goods	IIP Electricity
IIP Capital Goods	IIP Consumer Durables
IIP Intermediate Goods	IIP Consumer non-durables
IIP Manufacturing NIC-2 digit level	Cement Production
Steel Production	Eight Core Industries
Baltic Dry Index	Cargo handled at 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)

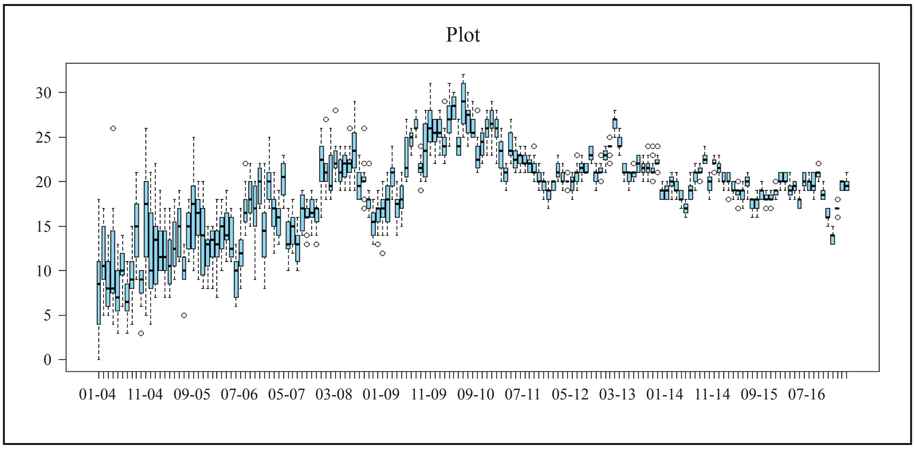
Annex : 3

Inter-sample Variation of Keyword Search Intensity





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