Does Google Search Index Help Track and Predict Inflation Rate?
An Exploratory Analysis for India

By

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Abstract: The forward looking outlook or market expectations on inflation constitute valuable input to monetary policy, particularly in the ‘inflation targeting' regime. However, prediction or quantification of market expectations is a challenging task. The time lag in the publication of official statistics further aggravates the complexity of the issue. One way of dealing with non-availability of relevant data in real-time basis involves assessing the current or nowcasting the inflation based on a suitable model using past or present data on related variables. The forecast may be generated by extrapolating the model. Any error in the assessment of the current inflationary pressure thus may lead to erroneous forecasts if the latter is conditional upon the former. Market expectations may also be quantified by conducting suitable surveys. However, surveys are associated with substantial cost and resource implications, in addition to facing certain conceptual and operational challenges in terms of representativeness of the sample, estimation techniques, and so on. As a potential alternative to address this issue, recent literature is examining if the information content of the vast Google trend data generated through the volume of searches people make on the keyword ‘inflation' or a suitable combination of keywords. The empirical literature on the issue is mostly exploratory in nature and has reported a few promising results. Inspired by this line of works, we have examined if the search volume on the keywords ‘inflation’ or ‘price’in the Google search engine is useful to track and predict inflation rate in India. Empirical results are very encouraging. Future research may focus on fine-tuning of the present work further and to check the robustness of the results over time and across countries.

Keywords: Inflation Expectations, Surveys, Internet Search, Google Trend, Google search Index

1. Introduction

Inflation expectations constitute an important ingredient to monetary policy formulation, particularly under the Inflation Targeting approach. However, the forward-looking assessment or forecasting inflation has been an extremely challenging task. The time lag in the release of official statistics on inflation often aggravates the problem further. To address the issue, the conventional literature suggests two broad approaches, viz., developing forecasting models and conducting surveys for measuring inflation expectations. The modelling exercise usually attempts to exploit inter-relationship between inflation and relevant economic variable and indicators, either under some economic theories or extracting data-driven patterns. The empirical estimation of such models uses data released by official statistics, which are traditionally compiled offline at a fixed interval, and usually released by compiling agencies with a substantial lag. At times, it may also employ the survey-based results as additional information.

Surveys have been an alternative tool to quantify market expectation on an economic variable/parameter and also to fill-in potential data gap or providing nowcasting indicator for a target variable, mainly data on which are released with lag. As regards surveys for inflation sentiments, international best practices have devoted to assessing future inflation based on either qualitative or quantitative responses from well-designed and representative target group. While qualitative responses help in assessing the direction of change or movement of the future inflation rate, quantitative results directly reflect the respondents' perception about the level of future inflation numerically. Answering qualitative questions on a variable, mostly asking an opinion on ‘no change' or direction of change of the variable, are easier than providing a quantitative response, and may improve the response rate in a survey. There has been a quite rich literature on converting the qualitative responses on a variable to the corresponding numeric value of the variable. However, conducting surveys may be costly in terms of monetary expenditure, time requirement and human resources. Further, for the time requirement, survey-based results may fail to capture information real-time basis. To address these issues, many researchers have explored if vast metadata and documents available freely in online resources could be useful in tracking and predicting economic variables. With the advent of the internet and digital platform fast growing habits of people on the internet searching,

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expressing opinions and sentiments in social media and digital platform, a few researchers have examined if the internet resources available at more timely and more frequent manner than traditional data can be useful to assess expectations of economic agents. There have been wide varieties of online resources such as websites of business houses, online retailers, social media like Twitter, search queries in internet search engine like Google, digital or printed documents uploaded by various statistical and Government agencies, academic institutes, policy makers and regulators, etc. Each of these alternative resources has been experimentally assessed by the researchers for different purposes. For example, Choi and Varian (2009a, 2009b, 2012), Ettredge, et al. (2005), Guzmán, 2011, and Seabold and Coppola (2015) explored the usefulness of Google search data on tracking/nowcasting various economic activities and macroeconomic variables; Agarwal et al. (2011) attempted sentiment analyses based on Twitter messages; Cavallo (2013, 2015, 2016 & 2017), and Cavallo and Rigobon (2011, 2016) constructed price indices based on online prices and analysed various aspects of prices; and Cavallo et al. (2015) have studied the price impact of joining a currency union.

India has a long tradition of model building for analysing and predicting the inflation rate. In addition to building macro models and simultaneous-equation based system, researchers usually exploited multiple alternative techniques with varying degree of success. First, univariate time series models – both linear and non-linear – and both conditional homoscedastic and heteroscedastic models. This approach models interrelationship between current and past observations of time series data on a target variable. Second, single equation models by regressing inflation on own past as well as present and past observations of influential variables or determinants of inflation. Third, multivariate time series models exploiting the interrelationships of inflation and one or more related variables. These models could be either pure data-driven, such as Vector Auto Regression (VAR) or model developed following certain economic principles as could be done in structural-VAR or Vector Error Correction Models (VECM) under the co-integration framework. Fourth, the construction of composite leading indicators for tracking Inflation. Fifth, estimating economic-theory based models, such as P-Star model, different variants of Phillips-Curve or output-gap models. For past several years, the Reserve Bank of India (RBI), India's Central Bank, has been conducting many monetary policy surveys to gauge market expectations on inflation, growth and other economic parameters. While some of these surveys capture qualitative responses from the respondents, a few are capturing quantitative forecasts. As regards inflation, two of these surveys, viz., 'Inflation Expectation Survey of Household' (IESH), and 'Survey of Professional Forecasters' (SPF) capture quantitative forecasts of inflation. While the target group of respondents to IESH covers households, the SPF, as the name suggests, captures responses from a select list of professional forecasters[2].

Though inflation in India has modelled by various approaches in the past, hardly any attempt is made to assess the information content of online resources to track inflation behaviour. Accordingly, this paper examines empirically if the data on internet search queries using Google engine can be gainfully employed to predict inflation for India. The plan of the paper is as follows. Section 2 provides a literature review on predicting inflation based on Google search index and the consumer-theory based approach adopted by Guzmán (2011). Section 3 presents data and empirical results, and Section 4 concludes.

2. Methodology

As this paper focuses on assessing the information content of Google search index for inflation rate, the dataset consists of two main components: First, the official statistics on price index which forms the basis of estimating inflation. Second, the Google search index for suitable keywords. Monthly data on these series are collected for a period of seven years from April 2012 to March 2019.

2.1 Data on Price Index

In India, inflation is now measured by annual percentage changes in Consumer Price Index (CPI) compiled by National Statistics Office (NSO), Ministry of Statistics and Programme Implementation (MoSPI), Government of India. Monthly data are released under three broad heads, viz., CPI-Urban (CPI-U), CPI-Rural (CPI-R) and CPI-Combined (CPI-C). While CPI-R and CPI-U represent price index for rural and urban India, respectively, the CPI-C is overall price index arrived at by combining CPI-R and CPI-U.

[2] *The SPF captures forecasts for inflation along with many other macroeconomic variables, such as growth, export, import, the exchange rate from professional forecasters.*

2.2 Google Search Indicators/Indices

Each Google trend series is characterised by two important features (Guzmán, 2011; Seabold and Coppola 2015): First, the numbers at various time points over the data period do not provide the absolute search volumes on the given keywords. Instead, they represent relative estimates in a sense that the time point with maximum search interest over the entire enquiry period is assigned a value 100 and the actual search volumes in other time points are rescaled accordingly. Second, the time series replica of search index on given key words for a specified period depends on the date when the search enquiry was made. Thus, time series data may change with search date even when the reference period for search index remain unchanged. These typical issues with Google search index have been handled by a two-step process. We first gather replicas of time series data on Google search Index on the keyword 'inflation' (with location: India) for the period April 2012 to March 2019 on three different dates of May 2019. As expected, the replica of relative measures on three different dates appears numerically different. We constructed an overall replica of time series by taking geometric-mean of the replicas obtained in three different dates and denote these geometric-mean based overall indices for the keywords 'inflation' and 'price' as GMInfl and GMPrice, respectively.

2.3 Change in Indices/Variables, Inflation Rates and Codes/Symbols Used for Different Variables

The k-period inflation rates for t-th month, based on CPIs are the log-return or continuously compounding, are computed as

$$\pi_t^m = 100 * [\ \log_e X_t - \log_e X_{t-m}\ ] \qquad \text{..... (3)}$$

Where π_t^m is the m-period change or inflation rate at t-th month; m=1 for monthly change/inflation and m=12 for annual inflation/change; X=CPI-C, CPI-U, CPI-R or Google trend indices GMPrice, GMInfl.

For convenience in referencing any transformation or derived variable for a time series, say X, we used codes/symbols as follows; gX = annual percentage changes as in Eqn. (3); lnX = $\log_e(X)$; ΔX and Δ2X represent 1st and 2nd difference of X, respectively; eX and e2X are residual obtained by fitting linear and quadratic time trends on X respectively; where X = CPI-C, CPI-U, GMPrice, GMInfl or corresponding log-transformations.

3. Results

The assessment of the information content of a given Google search Index is carried out in a multi-step process. First, we examine basic time series properties, such as stationarity or non-stationarity, of offline price indices, Google trend index, change in indices and inflation rates.

3.1 Tests for Unit-Root – Difference-Stationary and Trend-Stationary Processes

We applied Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests for examining if (a) log-transformed indices are stationary, and (b) if any detected non-stationary series belongs to trend-stationary (TS) or difference-stationary (DS) class. The equation considered for implementing ADF tests for a time series X_t is of the following general form.

$$\Delta X_t = \alpha + \beta t + \rho X_{t-1} + \sum_{i=1}^{l} \delta_i \Delta X_{t-i} + \varepsilon_t \qquad \text{..... (4)}$$

Where Δ is the difference operator; α,β,ρ and δ_I's are unknown constants, and ε_t is the usual error series.

In Eqn. (4), parameters of interest are β and ρ. If β=0 and ρ < 1 then X_t is a stationary, i.e. I(0) series, and if (β,ρ) =(0,1) then X_t has unit-root and belongs to difference-stationary process, i.e. X_t is non-stationary I(1) and ΔX_t is I(0) process. However, if β ≠ 0 and ρ < 1, then also X_t is non-stationary and belongs to trend-stationary (TS) series. Removal of deterministic time trend from a TS series would yield a stationary or I(0) series. The unit-root tests were first carried out for for log(CPI-C), log(CPI-U), log(GMPrice) and log(GMInfl) directly, and found some mixed results (Table 1). It appears that while lnCPI-C and lnCPI-U are I(2) processes, lnGPPrice and lnGMInfl are I(1) processes. Further, we examined the stationarity or unit-root properties of annual inflation rates based on CPI-C and CPI-U, and the annual percentage change in GMPrice and GMInfl computed in line with Eqn. (3). The test results (Panel A of Table 2), identified all these annual inflation/change series to be I(1). As a reconfirmation to these findings, the unit-root tests identified the first-difference of each of the four annual change series to be stationary, i.e. I(0) processes (Panel B, Table 2).

Table 2: Unit-Root Tests – Different transformed-variables

Variable	Augmented Dickey-Fuller					Phillips-Perron				
	Optimal Lag	Unit-Root Test		Test for Trend		Band-width	Unit-Root Test		Test for Trend	
		Test Statistics	p-value	Test Statistics	p-value		Test Statistics	p-value	Test Statistics	p-value
(A) Annual Inflation Rate/Annual Percentage Change										
lnCPI-C	7	-2.8429	0.1869	1.7515	0.0843	3	-2.2117	0.4769	1.3288	0.1876
lnCPI-U	7	-3.7490	0.0247	2.8582	0.0056	3	-2.6516	0.2592	1.9785	0.0512
lnGMPrice	6	- 3.9981	0.0125	3.0147	0.0036	1	-3.4091	0.0569	1.8850	0.0629
lnGMInfl	0	-5.8940	0.0000	-5.2213	0.0000	2	-5.8860	0.0000	-5.2213	0.0000
(B) First-Difference of Variables at (A) above										
ΔlnCPI-C	6	-7.0514	0.0000	-4.3018	0.0001	0	-5.6672	0.0000	-2.0093	0.0478
ΔlnCPI-U	6	-6.4774	0.0000	-3.4508	0.0010	2	-6.0054	0.0000	-1.7980	0.0759
ΔlnGMPrice	3	-5.9215	0.0000	-0.9223	0.3593	8	-8.1457	0.0000	-0.6333	0.5283
ΔlnGMInfl	1	-9.4089	0.0000	-0.0126	0.9900	13	-20.5903	0.0000	0.1838	0.8546
(C) Second-Difference of Variables at (A) above										
Δ^2lnCPI-C	7	-7.8157	0.0000	0.3484	0.7287	8	-15.7029	0.0000	0.1071	0.9150
Δ^2lnCPI-U	7	-7.7350	0.0000	0.5843	0.5610	4	-11.9371	0.0000	0.2176	0.8283
Δ^2lnGMPrice	4	-8.7383	0.0000	-0.0139	0.9889	6	-51.1038	0.0001	0.0135	0.9892
Δ^2lnGMInfl	4	-7.7786	0.0000	-0.0493	0.9913	6	-51.2341	0.0001	0.0234	0.9852
(D) De-Trending Linear-Time-Trend of Variables at (A) above										
elnCPI-C	7	-2.8428	0.1869	-5.1194	0.0000	1	-5.3040	0.0002	0.0916	0.9273
elnCPI-U	7	-3.7490	0.0247	-4.8328	0.0000	3	-2.6516	0.2592	-2.9244	0.0044
elnGMPrice	6	-3.9981	0.0125	-0.5160	0.6075	1	-3.4091	0.0569	-0.6357	0.5267
elnGMInfl	0	-5.8940	0.0000	0.1911	0.8489	2	-5.8860	0.0000	0.1911	0.8489
(E) De-Trending Quadratic-Time-Trend of Variables at (A) above										
e2lnCPI-C	1	-4.4954	0.0027	-0.5439	0.5880	3	-3.2540	0.0811	-0.4989	0.6191
e2lnCPI-U	1	-3.6238	0.0336	-0.4053	0.6864	3	-2.8794	0.1743	-0.3621	0.7182
e2lnGMPrice	3	-3.6125	0.0348	-0.4351	0.6647	1	-3.5711	0.0384	-0.3378	0.7364
e2lnGMInfl	0	-6.0223	0.0000	0.0601	0.9522	1	-6.0519	0.0601	0.0601	0.9522

Table 2: Unit-Root Tests – Annual Inflation Rate/Change in Google Index

Variable	Augmented Dickey-Fuller					Phillips-Perron				
	Optimal Lag	Unit-Root Test		Test for Trend		Band-width	Unit-Root Test		Test for Trend	
		Test Statistics	p-value	Test Statistics	p-value		Test Statistics	p-value	Test Statistics	p-value
(A) Annual Inflation Rate/Annual Percentage Change										
gCPI-C	1	-3.1547	0.1018	-2.1941	0.0316	3	-2.3619	0.3961	-1.4354	0.1556
gCPI-U	4	-1.8559	0.6669	-0.7415	0.4610	5	-1.8075	0.6912	-0.5764	0.5662
gGMPrice	0	-5.3040	0.0002	0.0916	0.9273	1	-5.3040	0.0002	0.0916	0.9273
gGMInfl	0	-2.2835	0.4373	-0.8676	0.3885	4	-2.5811	0.2900	-0.8676	0.3885
(B) First-Difference Series of the Variables at (A) above										
ΔgCPI-C	11	-4.3419	0.0052	1.5623	0.1248	13	-6.2063	0.0000	0.7070	0.4819
ΔgCPI-U	1	-6.6947	0.0000	1.0733	0.2869	13	-5.9064	0.0000	1.0946	0.2774
ΔgGMPrice	1	-9.1522	0.0000	0.1058	0.9161	26	-20.2929	0.0001	-0.1534	0.8785
ΔgGMInfl	0	-7.8708	0.0000	-0.2613	0.7946	2	-7.8397	0.0000	-0.2613	0.7946

3.2 Predictive Ability - Granger Causality Tests

The predictive or forecasting ability of Google trend data is assessed under the Granger Causality framework (Guzmán (2011). This technique is also useful to test if past price situation or realised inflations have any bearing on volume of internet search. The Granger causality tests for a pair of variables, say X_t and Y_t are carried out based on following general equations.

$$X_t = \alpha_0 + \sum_{i=1}^{l} \alpha_i X_{t-i} + \sum_{j=1}^{l} \beta_j Y_{t-j} + \varepsilon_t \qquad \text{..... (5)}$$

$$Y_t = \alpha_0 + \sum_{i=1}^{l} \alpha_i X_{t-i} + \sum_{j=1}^{l} \beta_j Y_{t-j} + \varepsilon_t \qquad \text{..... (6)}$$

Where, α_i's, i=0,1, ….. and β_j's, j=1,2,…. are unknown constants; l is suitable chosen positive integer; and ε_t is usual residual/error series.

We examine causal relationship between some form of inflation or transformed price indices and Google search indices for relevant search words. In particular, we considered two price indices, viz., CPI-C and CPI-U, and two Google search indicators, viz., GMPrice and GMInfl.

Table 5: Predictive Power – Granger Causality

Google Search Data	Null Hypothesis	Obs	Lag	F-Statistics	P-Value
gGMPrice	gGMPrice does not Granger Cause gCPI-C	66	9	1.9125	0.0732
	gCPI-C does not Granger cause gGMPrice	66	9	2.0230	0.0575
	gGMPrice does not Granger Cause gCPI-U	72	3	0.6434	0.5899
	gCPI-U does not Granger cause gGMPrice	72	3	3.3392	0.0246
ΔgGMPrice	ΔgGMPrice does not Granger Cause ΔgCPI-C	72	2	0.9296	0.3937
	ΔgCPI-C does not Granger cause ΔgGMPrice	72	2	3.4142	0.0387
	ΔgGMPrice does not Granger Cause ΔgCPI-U	72	2	1.7898	0.1749
	ΔgCPI-U does not Granger cause ΔgGMPrice	72	2	3.3384	0.0415
ΔgGMInfl	ΔgGMInfl does not Granger Cause ΔgCPI-C	62	12	1.6213	0.1279
	ΔgCPI-C does not Granger cause ΔgGMInfl	62	12	2.0394	0.0483
	ΔgGMInfl does not Granger Cause ΔgCPI-U	62	12	1.6005	0.1341
	ΔgCPI-U does not Granger cause ΔgGMInfl	62	12	2.8420	0.0073
Δ2lnGMInfl	Δ2lnGMInfl does not Granger Cause Δ2lnCPI-C	66	7	2.0053	0.0721
	Δ2lnCPI-C does not Granger cause Δ2lnGMInfl	66	7	2.2713	0.0431
	Δ2lnGMInfl does not Granger Cause Δ2lnCPI-U	63	10	1.4382	0.1974
	Δ2lnCPI-U does not Granger cause Δ2lnGMInfl	63	10	2.0800	0.0483
e2lnGMPrice	e2lnGMPrice does not Granger Cause e2lnCPI-C	78	9	2.7336	0.0098
	e2lnCPI-C does not Granger cause e2lnGMPrice	78	9	2.6099	0.0131
	e2lnGMPrice does not Granger Cause e2lnCPI-U	78	9	2.8349	0.0077
	e2lnCPI-U does not Granger cause e2lnGMPrice	78	9	3.4623	0.0017
e2lnGMInfl	e2lnGMInfl does not Granger Cause e2lnCPI-C	78	9	1.1596	0.3334
	e2lnCPI-C does not Granger cause e2lnGMInfl	78	9	2.0825	0.0456
	e2lnGMInfl does not Granger Cause e2lnCPI-U	78	9	0.6332	0.7640
	e2lnCPI-U does not Granger cause e2lnGMInfl	78	9	2.2178	0.0332

3.3 Correlation

The tracking ability of GMPrice or GMInfl is examined simply by correlation coefficient between GMPrice/GMInfl and price index either in their original or stationary-transformed forms. Significance of these correlation coefficients would establish the tracking or nowcasting ability of Google search index. Table 4 presents correlation coefficients for (a) different pairs of annual rate of inflation or change in CPI-C, CPI-U, GMPrice and GMInfl; (b) monthly change (i.e. first difference) of the annual inflation or growth rates; and (c) similar results for stationary-transformed series for lnCPI-C, lnCPI-U, lnGMPrice, and lnGMInfl. As seen, the annual percentage change in GMInfl is strongly correlated with annual inflation rates based on both CPI-C and CPI-U, indicating that Google search index GMInfl is useful in tracking annual inflation rates. Further, positive sign of correlation coefficients indicates the pairs of variables usually movement in same direction.

Table 4: Correlation Coefficient between Different Pairs of Variables

Variable Pair	Correlation Coefficient	Variable Pair	Correlation Coefficient
gGMPrice & gCPI-C	0.1805 (0.1212)	gGMInfl & gCPI-C	0.3591 (0.0016)
gGMPrice & gCPI-U	0.1641 (0.1595)	gGMInfl & gCPI-U	0.3509 (0.0020)
ΔgGMPrice & ΔgCPI-C	0.0150 (0.8985)	ΔgGMInfl & ΔgCPI-C	*0.1608 (0.1704)*
ΔgGMPrice & ΔgCPI-U	-0.0082 (0.9447)	ΔgGMInfl & ΔgCPI-U	*0.1710 (0.1450)*
ΔlnGMPrice & ΔlnCPI-C	0.1695 (0.1186)	ΔlnGMInfl & ΔlnCPI-C	0.0373 (0.7333)
ΔlnGMPrice & ΔlnCPI-U	0.1401 (0.1981)	ΔlnGMInfl & ΔlnCPI-U	-0.0280 (0.7977)
e2lnGMPrice & e2lnCPI-C	0.3977 (0.0001)	e2lnGMInfl & e2lnCPI-C	0.2557 (0.0168)
e2lnGMPrice & e2lnCPI-U	0.3701 (0.0013)	e2lnGMInfl & e2lnCPI-U	0.2913 (0.0062)

Figures within ( ) are p-values.

4. Discussion and Conclusions

Prediction of inflation or quantification of market expectations on inflation is always very challenging. Other than model-based forecast, a conventional way of measuring market expectations involves conducting suitable surveys to capture current assessment and forward-looking outlook of the appropriate target group. However, surveys are associated with substantial cost and resource implications, in addition to facing specific conceptual and operational challenges. As a potential alternative to address the issue, many researchers argue that interest on Google search on a relevant keyword, such as 'inflation' reflects the 'revealed expectations' of people and examine if the Google search volume track or predict inflation rate. Though the short empirical literature on the subject is mainly exploratory in nature, some of those studies have reported quite encouraging results.

In this paper, we assess the information content of Google search volume on two relevant keywords, viz., 'price' and 'inflation' in tracking or predicting the inflation rate in India. Empirical results show that such an index for the keyword 'inflation' is useful to track inflation rates India based on both CPI-Combined and CPI-Urban. Granger's causality tests also detect the strong predictive ability of the search index. Future research in this emerging area can be generalised in various ways, such as examining the information content of Google search data about related keywords, checking the robustness of the findings at different sub-national regions of India.

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