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Forecasting Food Inflation using News-based Sentiment Indicators

Bhanu Pratap*, Abhishek Ranjan*, Vimal Kishore* and Binod B. Bhoi*

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Combining high frequency information on prices with market intelligence on high-impact food items helps nowcast food inflation and generate near-term inflation forecasts. Three key vegetables *viz.,* tomatoes, onions and potatoes (TOP), with a combined weight of 2.2 per cent in the consumer price index (CPI) basket in India, however, contribute heavily to volatility in both food inflation and headline inflation, impacting the performance of nowcasts. Using big data techniques and information on these three items reported in nine leading English news dailies published during 2011-2021, this paper constructs commodity sentiment indices to capture price dynamics of TOP commodities. Empirical findings suggest an inverse relationship between the constructed news sentiment indices of TOP and changes in TOP prices. Exploiting this feature in a formal forecasting framework to predict inflation in vegetables and food prices, it is found that adding news-based information in the form of net sentiments improves forecasting accuracy.

JEL: C22, C32, C45, C55, E31, E37

Keywords: Inflation, big data, news sentiment, time-series, forecasting

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Introduction

Under the flexible inflation targeting (FIT) framework introduced in India in 2016, inflation target is defined as 4 per cent CPI headline inflation with a tolerance band of ± 2 per cent around the target[1]. While the monetary policy committee (MPC) is entrusted with the task of maintaining headline inflation around this target, the high share of food and beverages in the CPI basket along with its high price volatility driven by recurrent supply shocks often complicates this task besides exposing inflation forecasts to greater uncertainty.

Tomatoes, onions and potatoes (TOP), the three main vegetables that are produced and consumed widely in the country form an integral part of the Indian diet, so much so that they are hard to substitute. India also happens to be the second largest producer of these vegetables after China besides being amongst the major consumers in the world[2]. However, the indispensable nature of these items gives rise to a major problem for households as well as for generating reliable inflation forecasts, which serve as the intermediate target for monetary policy under inflation targeting. High volatility in TOP prices, often caused by crop damages on account of the vagaries of nature (excess or deficient rainfall and other extreme weather events) lead to production shortfalls, pushing up food inflation as well as headline inflation. Extreme weather events driven by climate change also made the task of forecasting inflation quite challenging in the last few years (Ghosh *et al.*, 2021) such that augmenting models with information on extreme weather events can improve forecasting performance (Kishore and Shekhar, 2022 forthcoming). The Reserve Bank of India (RBI) also noted that "*in a rapidly changing scenario where volatility in prices of key vegetables has substantial fallout on headline inflation, there is a need for real time monitoring of price situation, especially in case of perishables*" (RBI, 2021). This underscores the need for exploring

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1 Headline inflation is measured by year-on-year changes in the all-India CPI-Combined (Rural + Urban) with base year: 2012=100 released by the National Statistical Office (NSO), Ministry of Statistics and Programme Implementation, Government of India.

2 PIB link - https://static.pib.gov.in/WriteReadData/specificdocs/documents/2021/oct/doc2021102961.pdf

alternative sources of information that can be useful for forecasting food inflation in India.

In this context, newspaper articles about crop damages, extreme weather events, pest attacks, trade restrictions, transporters' strikes or other adverse events - which can have a significant impact on future prices - can provide useful additional information. The sentiment associated with each article and the coverage frequency of these events can provide helpful information regarding such price shocks. This forward-looking information can be extracted and analysed using text mining analysis. Current developments in natural language processing (NLP) help in quantifying such information, which can then be used in forecasting models to make more accurate predictions about the variables of interest (Shapiro *et al.,* 2020; Kalamara *et al.,* 2020; Barbaglia *et al.,* 2022). Keeping this in mind, in this paper, we leverage the information content of news articles to forecast food price inflation in India. In doing so, we construct a large unstructured dataset consisting of daily news items related to TOP commodities and quantify the sentiment or tone expressed in these articles as a measure of expected price pressures in the TOP commodities[3]. We then introduce these news-based sentiment indicators into a time-series forecasting framework to assess whether news-based data can help in improving inflation projections.

While there are several studies on inflation forecasting in India, such as Thakur *et al.,* (2016), Maji and Das (2017), Pratap and Sengupta (2019), John *et al.,* (2020) and Jose *et al.,* (2021), none of the studies have explored the predictive ability of news data for forecasting inflation in India. Our study aims to add to this literature through a detailed analysis of news data for predicting food price inflation. Adopting a suite of time-series forecasting models premised on monthly and daily high-frequency data, we show that addition of news-based sentiment indicators to inflation forecasting models can be beneficial. The gains from the information content of news items

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[3] According to Munezero *et al.* (2014), *sentiment* is one of the so-called human subjectivity terms that may reflect a person's desires, beliefs, and feelings that are features of a person's private state of mind which can only be observed through textual, audio, or visual communication. Algaba *et al.* (2020) define s*entiment* as "the disposition of an entity toward an entity, expressed via a certain medium".

depends upon the forecast horizon of interest and the frequency of input data. Importantly, our sentiment indicators also prove useful as an input for inflation forecasting when compared to an alternative secondary dataset consisting of daily prices of food items. Accuracy gains from incorporating daily news data in a mixed frequency setup are especially observed in case of near-term projections or 'nowcast' of inflation.

Primarily, our paper relates to two strands of the literature. The first strand of literature concerns itself with natural language processing (NLP) tasks and text mining. This literature is concerned with the optimal processing of information embedded in various forms of communication – audio, video and written – between humans and machines (Munezero *et al.,* 2014; Liu, 2015; Ravi and Ravi, 2015; and Taboada, 2016). The second stream of literature is housed within the larger time-series forecasting literature. Within this space, coinciding with the advent of big data and internet, there has been an evolving literature aimed at efficiently incorporating alternate data sources (internet searches, news text, *etc.*) as well as large volumes of data in standard time-series forecasting frameworks, especially those seeking to forecast macroeconomic variables like GDP, investment, consumption, employment and inflation. For instance, Lei *et al.,* (2015), Gandomi and Haider (2015), Larsen and Thorsrud (2019), Shapiro *et al.,* (2020), Goshima *et al.,* (2021), Rambacussing and Kwiatkowski (2021), Tilly *et al.,* (2021) are examples of such work in the context of advanced countries like the US, the UK and Japan as well as developing countries like China. A thorough introduction to the use of text as an input for economic research is provided by Gentzkow *et al.,* (2019), while application of text mining analysis to central banking has been dwelled upon by Bholat *et al.,* (2015). More recently, Aprigliano *et al.,* (2022), Barbaglia *et al.,* (2022) and Ellingsen *et al.,* (2022) also show that news-based text data, especially in the form of sentiment indicators, can improve macroeconomic forecasts over and above hard economic indicators. Priyaranjan and Pratap (2020), Kumari and Giddi (2020), Sahu and Chattopadhyay (2020) and Bannerjee *et al.,* (2021) are examples of related recent work in the Indian context.

The rest of the paper is structured into five sections. Section II presents the stylised facts related to the price dynamics of TOP, vegetables sub-group and food group in the CPI. Section III discusses the coverage of our news dataset and construction of sentiment indicators/indices using text-mining techniques. This is followed by a preliminary data analysis to determine the relationship between constructed news-based sentiment indices of TOP and TOP prices in section in section IV. The forecasting performance of sentiment indices is formally analysed in Section V, which is followed by concluding observations and scope for future research as a way forward in Section VI.

Section II
Stylised Facts

Forecasting food inflation has been a challenging task in India due to its high volatility and susceptibility to recurrent domestic supply shocks as well as sporadic global food price shocks (Kapur, 2013; Sahoo *et al.,* 2020). The high volatility in food inflation coupled with the high weight of the food group in the CPI basket has resulted in significant contributions of food inflation to overall inflation during episodes of food price spikes (Chart 1a)[4].

For instance, contribution of food inflation to headline inflation was almost 67 per cent in November 2013, 62 per cent in July 2016 and 75 per cent in December 2019 (just before the pandemic), while the average contribution during the full period January 2012 to March 2022 was around 47 per cent. Within food, the contributions of vegetables inflation ranged from (-) 374 per cent in January 2012 to 64 per cent in January 2019, although its average contribution during January 2012 – March 2022 was 14.4 per cent against its weight of 13.2 per cent in the CPI-Food (Chart 1b).

Vegetables prices, which display high seasonality - with prices easing during winters and hardening during summers - due to the crop production and harvesting patterns in the country impart seasonality to food inflation. Vegetables price inflation is, in turn, driven by prices of TOP, which have

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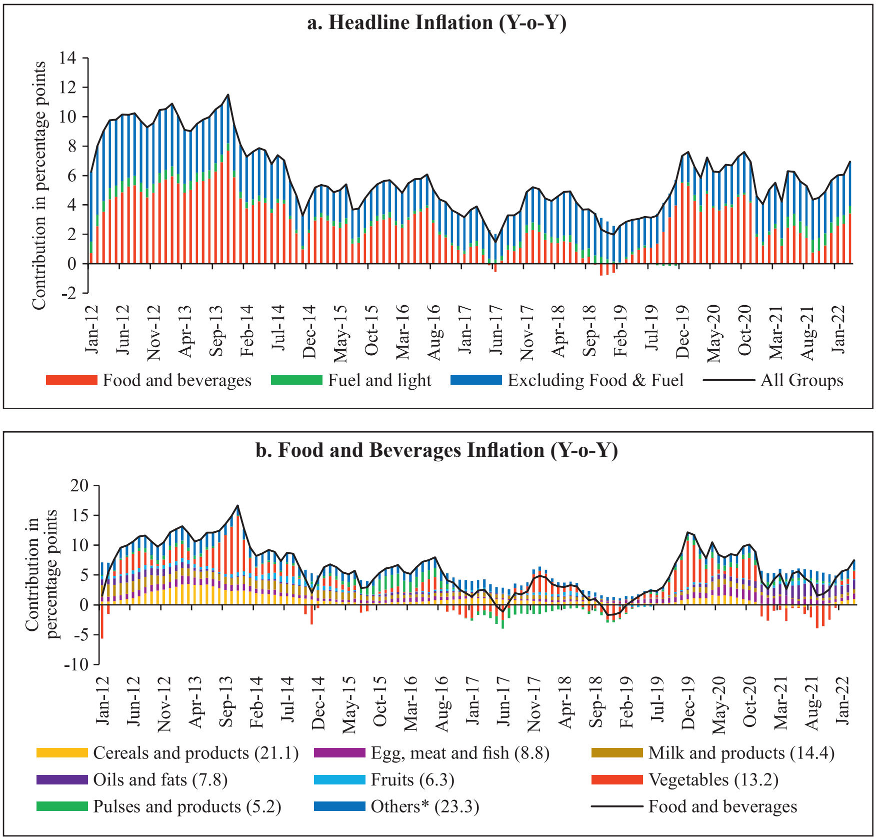
[4] The share of food and beverages in overall consumer price index - combined basket is 45.86 per cent (Base: 2012=100).

Chart 1: Drivers of Inflation

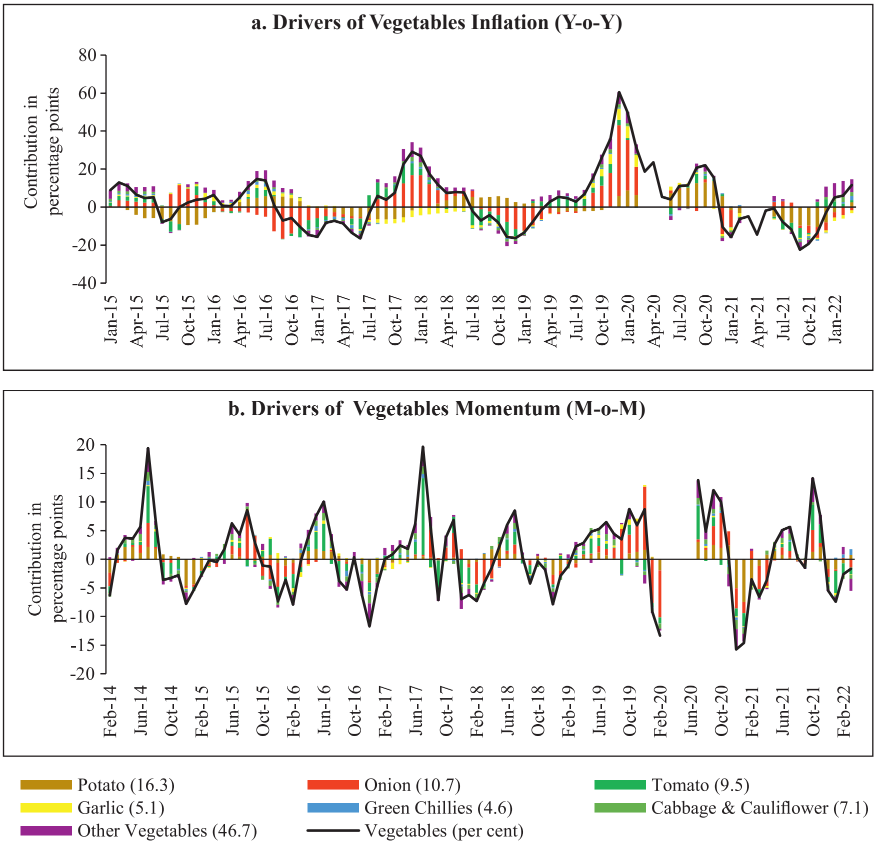


Note: * Others include Sugar and confectionery; Spices, Non-alcoholic beverages and Prepared meals, snacks, sweets, etc. Figures in parentheses indicate weights in the CPI-Food and beverages group (Base: 2012=100).
Source: NSO and authors' calculations.

a combined weight of 36.5 per cent in the CPI-Vegetables basket (4.8 per cent in the CPI-Food basket and 2.2 per cent in the CPI-Combined basket) (Chart 2).

Being seasonal items and subjected to various weather shocks, prices of TOP exhibit large intra-year volatility which, in turn, contributes significantly to the variance of vegetables, food and headline CPI inflation (Chart 3). In fact, the contribution of TOP to the variance of inflation in vegetables rose sharply in 2017-18 and remained elevated thereafter (Chart 3a) explaining a

Chart 2: Drivers of Vegetables Price Inflation and Momentum

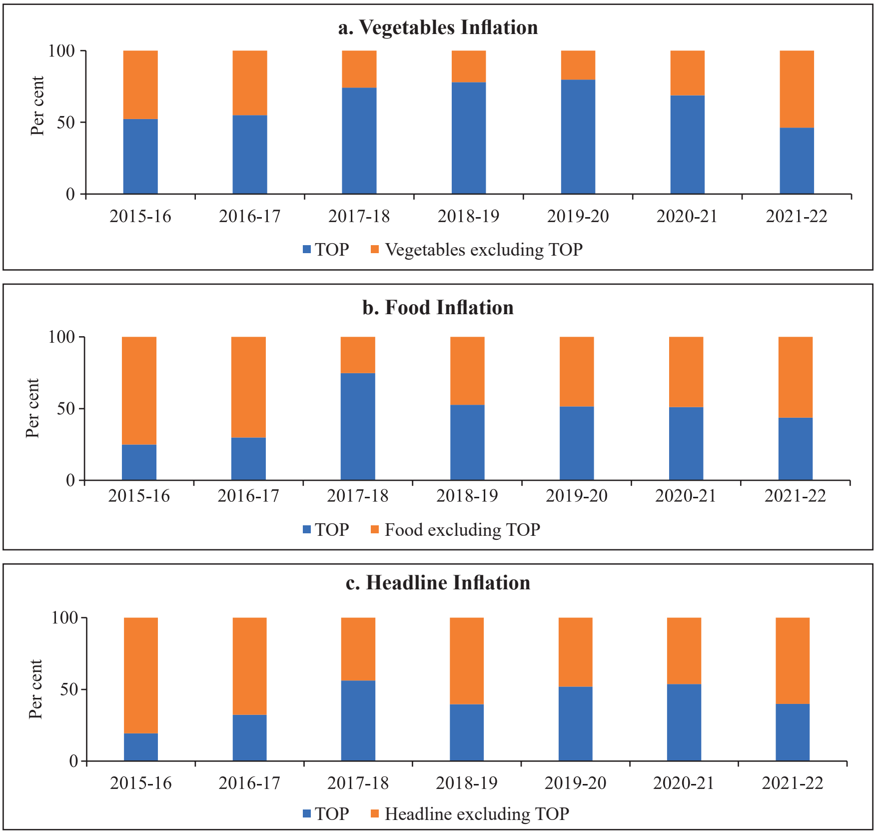


Note: Item level CPI data at 2012 base are available from January 2014. These data could not be collected during the first wave of COVID-19 and hence were not released by the NSO during March-May 2020. Figures in parentheses indicate weights in CPI-Vegetables.
Source: NSO and authors' calculations.

large part of the variance in food inflation in the range of 50-70 per cent and headline inflation in the range of 40-56 per cent (Charts 3b and c).

With such high contribution to variance of headline inflation, these three items warrant a closer scrutiny to assess likely build-up of price pressures in the near-term, as a sharp spike in their prices can derail the headline inflation from a stable trajectory. As already stated, India is the second largest producer of these vegetables in the world. However, while consumption of these items is ubiquitous, their production is concentrated in specific parts of the country under different agro-climatic conditions.

Chart 3: Contributions of TOP to Total Variance in Inflation[5]



Note: Data for 2019-20 is for the period April 2019-February 2020, for 2020-21 it is for June 2020-February 2021 and for 2021-22 it is for June 2021-March 2022, as item level CPI data could not be collected during the first wave of COVID-19 and hence were not released by the NSO during March-May 2020.
Source: NSO and authors' calculations.

For instance, Maharashtra has the highest share in production of onions, while Madhya Pradesh and Uttar Pradesh are the leading producers of tomatoes and potatoes, respectively (Table 1). The top 5 states had a share of around 76 per cent, 50 per cent and 84 per cent in total production of onions, tomatoes and potatoes, respectively, during the period of 2017-18 to 2021-22. Such a skewed distribution of production indicates probable concentration of

[5] Contribution of subgroup (say, A) to variance in total (A+B) is calculated using the following formula: Contribution (A) = W(A)W(A) Cov(A, A) + W(A)W(B) Cov(A, B), where W is the weight of the sub-group and Cov is covariance.

Table 1: Top Five States by Production and Average Share in Production (2017-18 to 2021-22)

S. No.	Onion		Tomato		Potato	
	State	% Share	State	% Share	State	% Share
1	Maharashtra	39.3	Madhya Pradesh	13.4	Uttar Pradesh	29.1
2	Madhya Pradesh	16.1	Andhra Pradesh	12.6	West Bengal	24.6
3	Karnataka	10.3	Karnataka	10.8	Bihar	16.1
4	Gujarat	5.4	Gujarat	7.0	Gujarat	7.2
5	Bihar	5.1	Odisha	6.6	Madhya Pradesh	6.6

Source: Department of Agriculture and Farmers Welfare, Ministry of Agriculture and Farmers Welfare.

risk, emanating from adverse weather events or other supply shocks in these states, which could transmit to all over the country.

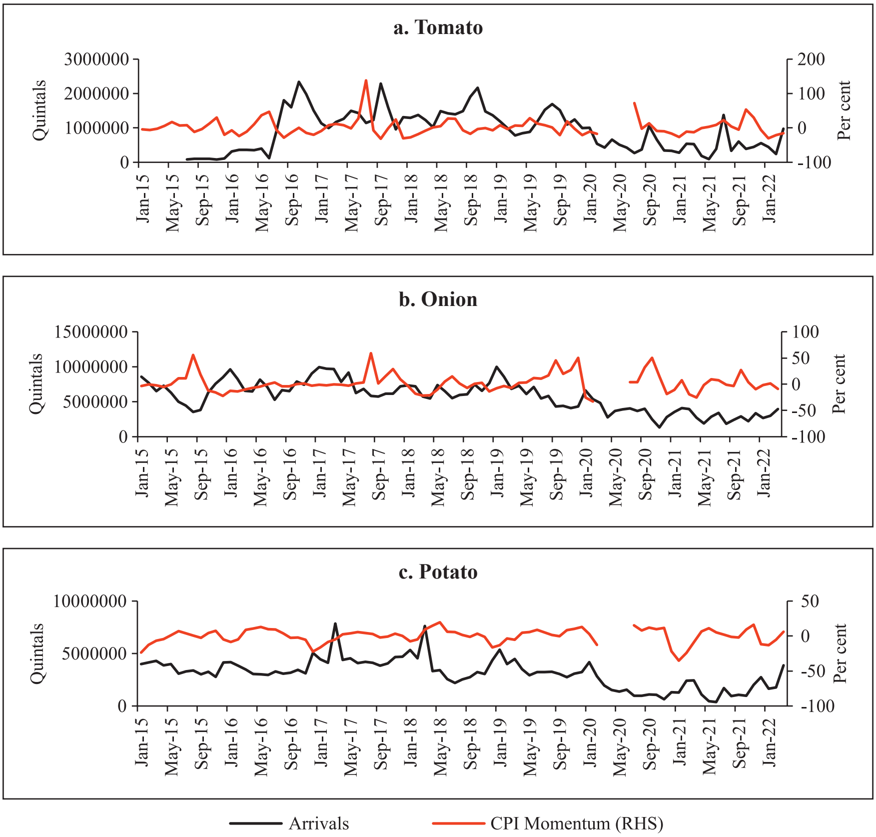
Market arrivals of the TOP crops in the regional wholesale markets or *"mandis"* are therefore tracked to form a view about expected price movements in the near-term, such that lower/higher arrivals indicate higher/lower prices (Chart 4 and Annex Table A8). Such information is available through various government sources like the Agmarknet portal, National Horticulture Board (NHB), National Horticultural Research and Development Foundation (NHRDF) and a few private agencies which track these items. Yet, with fruits and vegetables being delisted from the Agriculture Produce Market Committee (APMC) Act in many states, arrivals data from APMC *mandis*, may not indicate the true picture with respect to prices[6].

At the same time, another important source of price information for these items is the Department of Consumer Affairs (DCA) under the Ministry of Consumer Affairs, which collects daily data on prices of essential food items from 167 centres across the country[7]. In case of tomato, onion and potato, these prices have a high correlation of around 99 per cent with corresponding CPI indices (Annex Table A7). Thus, DCA data provide a good indication of price movement of these items for the current month as the data is released on a daily basis and can be used for nowcasting food inflation.

6 For instance, Assam and Meghalaya delisted fruits and vegetables in January 2014, Delhi in September 2014, Odisha in February 2015, Gujarat in April 2015, Maharashtra in July 2016, *etc*.

7 Coverage of centres keep changing, earlier it was around 120.

Chart 4: Market Arrivals and Price Momentum



Note: Item level CPI data could not be collected during the first wave of COVID-19 and hence were not released by the NSO during March-May 2020. Arrival data refers to the total arrival across all the mandis for which data is available in NHRDF for that month.
Source: NHRDF and NSO.

But this data cannot be used for understanding the nature of price pressures, for which researchers often rely on news articles, announcements by ministry officials, information from traders and retailers and private agencies that track ground-level information for these commodities. This additional information on factors behind sudden price changes can be utilised to estimate the possible direction and duration of price shock and the magnitude of expected price changes.

Since TOP items have a high contribution to food inflation volatility and their prices are subject to supply shocks often induced by localised extreme weather events, farmers' protests, transporters' strikes, storage losses and sometimes speculative stocking by traders – all of which are covered by local newspapers – news articles related to TOP can provide additional information at an early stage of accumulating price pressures. Such information, which is usually in the form of unstructured data, can be used to create sentiment scores. If these commodity sentiments have lead information about future prices, they can be helpful in nowcasting and forecasting food inflation.

Section III
Data and Methodology

For the construction of a news-based sentiment indicator, we develop a novel dataset of daily news items related to TOP commodities from nine leading English news dailies published during January 2011 - August 2021. The newspapers are selected based on their national coverage and reporting on events and issues related to agri-commodities. In the first step, we use generic search terms, such as the name of a given commodity, to extract news articles related to a given commodity at scale[8]. Such text-mining applications are prone to 'noise' wherein articles unrelated to the topic of interest might also creep in, thereby lowering the signal-to-noise ratio of the data. Therefore, to avoid noise in the data, we create a set of keywords – 'supply', 'demand' and 'prices' – that capture the market dynamics of TOP commodities. We then filter and retain only those news items which contain at least one keyword each from the set of commodity, supply-demand and price-related keywords.[9]

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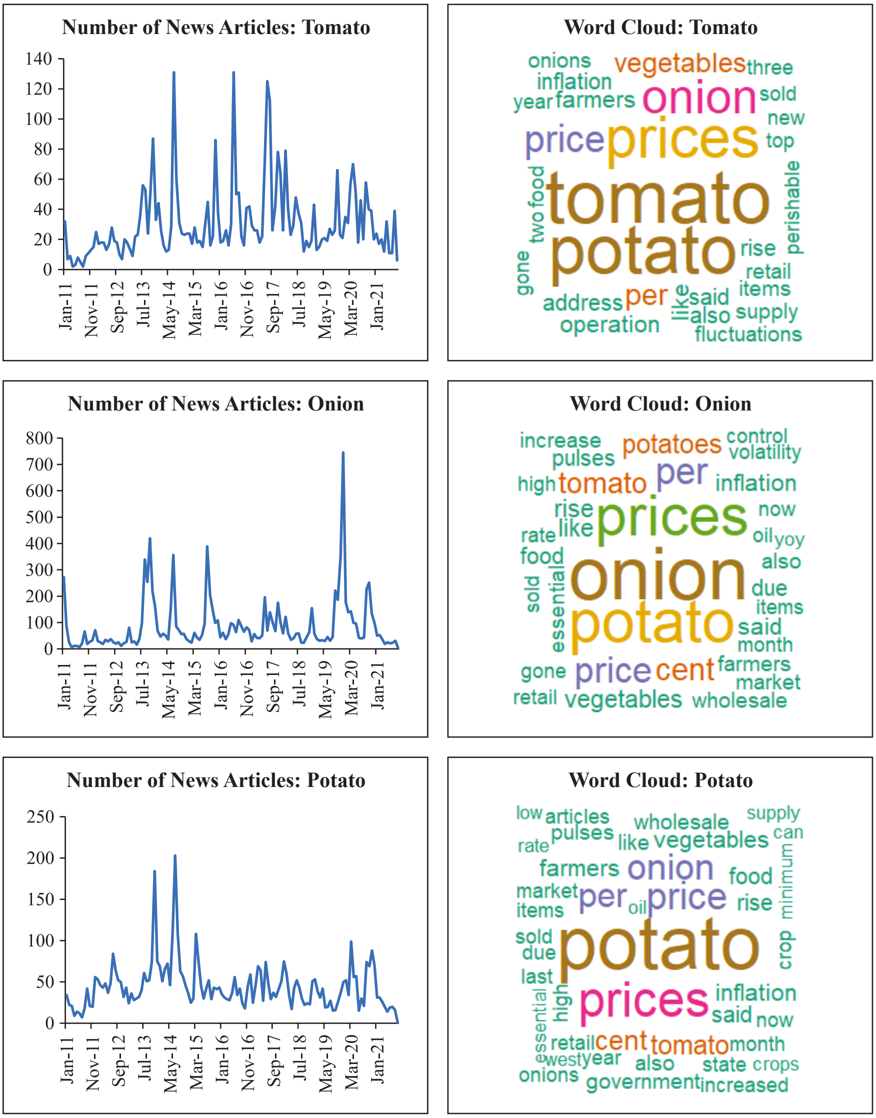
8 The news dataset has been constructed using application developed by Meltwater Inc., https://www.meltwater.com/en.

9 The keyword sets are as follows: **commodity** = (onion/tomato/potato, onions/tomatoes/potatoes); **prices** = (price, prices, inflation); **supply-demand keywords** = (increase, increases, increased, hike, hikes, rise, rose, rising, surge, surges, surged, soar, soaring, climbed, climbing, skyrocketed, skyrocketing, shoot, push, peak, peaked, fall, fell, decrease, decreases, decreased, crash, crashed, plunge, plunged, drop, dropped, decline, declined, down, cool, cooling, tumbled, slipped, harvest, rain, rainfall, flood, floods, flooding, rain damage, destroy, destroyed, stock, stocking, market arrival, market arrivals, arrivals, arrival, production, supply, bottleneck, supply chain, shortage, shortages, export, sowing, sowing delay, spoiled crop, rotten, hoarding, cold storage, transport strike, truckers strike, pest attack, drought, demand, increased demand, high demand, festival demand, bumper crop, supply, supply glut, higher production, supply boost, import, export ban, fresh crop arrivals, increased market arrivals, stock limit, stock limits, hoarding, buffer stock, low demand, sluggish demand, weak demand, lack of demand, hailstorm, unseasonal, protest, farmer protest, protests).

This filtering step ensures that the dataset contains only the most contextual and meaningful information for our analysis , to the best extent possible (Chart 5). Finally, the text data are subjected to routine data cleaning procedure, such as removal of stopwords, numbers, white spaces and word stemming, *etc.*, to organise the final dataset containing day-wise news items.

Chart 5: Article Frequency and Commodity-wise Word Clouds



Source: Authors' own calculations.

Next, we use the framework laid down by Ardia *et al.,* (2021) for the computation of sentiment indices using newspaper text data[10]. While there are several approaches for sentiment computation, we adopt a lexicon-based approach, in particular a *valence-shifting bigrams* approach for the computation of commodity-wise sentiment indices. The lexicon-based approach is generally considered flexible, transparent, and computationally convenient as compared to other alternatives (Algaba *et al.,* 2020). Briefly put, this approach matches words (or group of words) occurring in a document with a pre-defined wordlist of polarized (positive and negative) words and assigns quantitative scores to each matching word depending on whether its tonality is 'positive' or 'negative'. For our purpose, the Loughran-McDonald lexicon – designed specifically for analysing economic and financial texts – was used (Loughran and McDonald, 2011)[11]. More specifically:

1. For each commodity-specific news item, the Loughran-McDonald lexicon was used to assign a sentiment score $\{v_i S_{i,n,t}\}$ to each polarized word i occurring in a news article d_n published at time t. The term v_i captures the impact of *valence shifters* or keywords that may negate, amplify or de-amplify polarized words in the given document.

2. Thus, 'positive' and 'negative' words were assigned a sentiment score of (+1) and (-1), respectively. The scores were then adjusted for valence shifting words depending on whether such words appear before polarized words in the document. It may be noted that this computation occurs at the sentence-level to better account for such valence-shifting keywords[12].

3. The sentence-level score obtained above is then aggregated at the document-level by taking a sum of the adjusted sentiment scores

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10 We use the R *sentometrics* package for end-to-end computational purpose.

11 The dictionary can be accessed here - https://sraf.nd.edu/loughranmcdonald-master-dictionary/.

12 Valence-shifting keywords tend to negate, amplify or de-amplify the meaning of other words thereby changing the tone of the sentence. For instance, "this is not good" would be assigned a score of (+1) under the normal sentiment scoring approach. However, it would be assigned a score of (-1) due to the presence of a negating word 'not' under the approach adopted by in our case.

$\{v_i S_{i,n,t}\}$. Therefore, $\{S_{n,t}\}$ is equal to the document-level sentiment score, such that $S_{n,t} = \frac{1}{w_d}\sum_{i=1}^{Q_d} v_i S_{i,n,t}$ where Q_d represents the total number of polarized words and w_d is the total number of words in each news article.

4. In the last step, the document-wise sentiment score was aggregated on a daily basis, such that $NSS_t = \sum_{n=1}^{N_t} S_{n,t}$ represents the time-series for the final net sentiment score (NSS), where N_t is total number of news articles for the given commodity on day 't'.

We assume that a positive (negative) sentiment score is indicative of an expected fall (increase) in the prices of the given commodity. This interpretation is corroborated by the analysis presented in the next section that sheds light on the historical relationship between our constructed sentiments and actual price movements of TOP commodities.

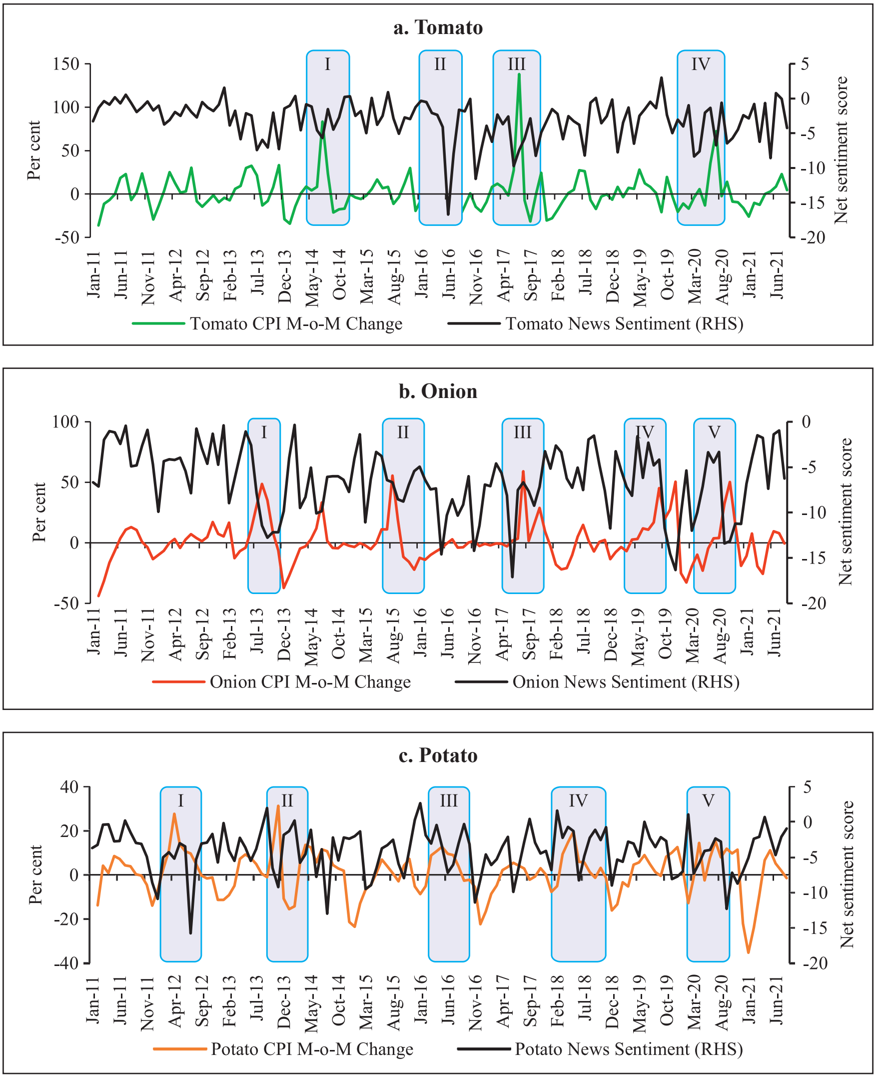
Section IV
TOP Sentiment Indices - Preliminary Data Analysis

TOP prices exhibit a seasonal pattern which is based on crop sowing and market arrivals across the country. However, they occasionally undergo major spikes due to localised factors, inducing high volatility to overall food inflation. The three vegetables were thus made part of essential commodities and were covered under the Essential Commodities Act, 1955 and hence their prices are monitored regularly by the government. Onion and potato, however, were removed from the list of essential commodities in September 2020 through an amendment to the Act with a rider that these items can be included in the list again only under extraordinary circumstances like wars, famines, or other natural calamities.

As expected, the derived monthly net sentiment score of TOP and changes in their prices as reflected in CPI showcase an inverse relationship between them[13] (Chart 6). Large increases in TOP prices seen after major

[13] As mentioned earlier, CPI item level data were not released by NSO during March-May 2020. To create a continuous series of CPI indices for tomato, onion and potato – for comparison with sentiment indices and for charts – momentums of DCA for tomato, onion and potato were used to impute corresponding CPI indices for the missing months, given the high correlation between the two.

Chart 6: Relationship Between Major Price Shocks to TOP and News Sentiments



Note: The shaded areas in graphs represent the following episodes:
Tomato: (I) Low production - low rainfall, (II) Heatwave affected production, (III) Farmers' protests, (IV) Excess rains; **Onion:** (I) Speculative behaviour by market participants, (II) Unseasonal rains and stocking, (III) Excess rains, (IV) Late withdrawal of monsoon , (V) Excess rains; **Potato:** (I) Low production – blight in Uttar Pradesh, (II) Low production due to unseasonal rains, (III) Low production – blight in West Bengal, (IV) Low production, (V) Low storage.
Sources: NSO; and Authors' own calculations.

supply shocks coincide with large fall in sentiment related to each of the three commodities. Major price spikes observed in TOP in the recent past were often associated with supply shocks. During the period of our study *i.e.,* from January 2011 to August 2021 (more than 10 years), tomato prices have undergone four major price spikes while both onion and potato have undergone five major price spikes.

The major causes of these sharp spikes include farmers' protests, blight disease in potato, speculative stock holding by traders, heatwave, excess rains, *etc.*, but the major and recurring source is related to weather related shocks. Unseasonal, excess or deficit rains affect the production of these perishable vegetables. The extent of price spikes, as measured by the month-on-month (m-o-m) change in CPI indices of these vegetables, *i.e.*, momentum, indicate that the maximum spike was observed in tomato prices in July 2017 (138 per cent), which was the result of farmers' protests in response to low prices of tomatoes being received by them. The extent of spikes in potato prices, however, is much lower compared to tomatoes and onions (maximum momentum of 31.4 per cent in November 2013). It can also be observed that the sharp spikes in prices usually last for one to two months in case of tomatoes and around three months in case of onions and potatoes. Given the importance of TOP, the government often resorts to supply management measures – like restricting exports, imposing condition of minimum export price (MEP), increasing imports, placing stockholding limits on traders, wholesalers and retailers – to ensure availability in the domestic market and stabilise prices.

The inverse relationship between TOP prices as well as their sentiments is also corroborated by the pair-wise statistical correlations for the most recent five-year daily data sample from 2016-2021 (Table 2). For instance, while onion and potato prices have a correlation of 0.45, the correlation between their sentiments is 0.67. Similarly, correlation between prices of tomato with prices of potato and onion is 0.40 and 0.28, respectively, whereas related sentiments exhibit a much stronger correlation of 0.56 and 0.39, respectively. Correlation between the price-sentiment pair of tomato, onion and potato is (-)0.20, (-)0.42 and (-)0.33, respectively. Overall, the correlation between TOP sentiments and prices is negative signifying that a decrease in TOP sentiments is associated with an increase in related prices.

Table 2: Price-Sentiment Correlation Matrix

Correlation	Tomato Price	Onion Price	Potato Price	Tomato Sentiment	Onion Sentiment	Potato Sentiment
Tomato Price	1.00					
Onion Price	0.28^{***}	1.00				
Potato Price	0.40^{***}	0.45^{***}	1.00			
Tomato Sentiment	**-0.20*****	**0.02**	**-0.11**	1.00		
Onion Sentiment	**-0.09**	**-0.42*****	**-0.36*****	0.39^{***}	1.00	
Potato Sentiment	**-0.06**	**-0.21*****	**-0.33*****	0.56^{***}	0.67^{***}	1.00

Note: 1. * p < 0.1, ** p < 0.05, *** p < 0.01 denotes the level of significance.
2. The above analysis uses 30-day daily moving average of prices/sentiments.
Source: Authors' own calculations.

As a next step, we subject the daily TOP prices and sentiment indices to a Granger Causality test to ascertain whether news-based sentiments are helpful in capturing the change in prices. Our results show that sentiment *Granger causes* prices for all the three commodities supporting the argument that the constructed sentiment indices are indeed helpful in capturing the future change in prices (Table 3).

Table 3: Price-Sentiment Granger Causality Test

Variable	H01: Price does not *Granger cause* sentiment	H02: Sentiment does not *Granger cause* price
Potato	0.108	0.003^{***}
Onion	0.401	0.000^{***}
Tomato	0.678	0.000^{***}

Note: * p < 0.10, ** p < 0.05, *** p < 0.01 denotes the level of significance.
Source: Author's own calculations.

Section V
Empirical Analysis

The preliminary statistical analysis in the previous sections is indicative of useful forward-looking information contained in the commodity sentiment indices. To formally analyse this, we undertake a time-series forecasting analysis. This section lays down the details of our forecasting analysis conducted using monthly and daily high-frequency data. In the first part of our forecasting analysis, we augment various univariate and multivariate time-series models with our sentiment indices and test their forecasting performance against a benchmark model. Like the news-based sentiment data, DCA provides an alternative set of high-frequency information on prices of food commodities across different centres in India. This data can be regarded as 'hard' information which can also be used in inflation projections. Therefore, the second part of our analysis focuses on comparing the forecasting performance of models augmented with sentiment data *vis-à-vis* DCA price data for TOP commodities. In the final part of our analysis, we showcase how daily high-frequency sentiment indices can be used to forecast CPI-Food inflation in a mixed-frequency sample framework.

V.1. Forecasting using Monthly Data

For the formal forecasting analysis, we consider monthly changes in CPI-Vegetables and CPI-Food & beverages, both in month-on-month (m-o-m) and year-on-year (y-o-y) per cent change terms, as our target variables. Thus, we have four different target variables. In line with standard practice, we divide the full sample of data into a training and a testing sample. The train sample, from January 2011 to August 2019, was used for estimation of the models. The test sample, from September 2019 to August 2021, was used for comparing model forecast performance in terms of the root mean-squared error (RMSE) of forecasts generated by different models.

We consider different specifications of autoregressive integrated moving average (ARIMA) models[14]. Taking the approach of parsimony, we combine all TOP-related news articles and use the sentiment scoring method described in section III to construct a composite TOP sentiment index. We introduce this index into our suite of ARIMA models to assess whether inclusion of such news-based information leads to gains in forecasting accuracy. Following Jose *et al.,* (2021), other drivers of domestic food prices, such as global food prices, rainfall and minimum support prices (MSP), were also included as control

[14] ARIMA and SARIMA are popular time-series models due to faster computation, interpretation and better predictive ability for short-term forecasting. ARIMA and seasonal ARIMA methods are frequently used for inflation forecasting in the Indian context (Jose *et al.,* 2021). Model selection in case ARIMA(p,d,q) and SARIMA(p,d,q)(P,D,Q) was done using the Akaike Information Criterion (AIC). Model estimation was done using maximum likelihood estimation (MLE) technique.

variables in the forecasting model for robustness (additional results provided in the Appendix).

The out-of-sample forecast performance of various models is provided in Tables 4-7. To capture the performance of models augmented with sentiment data over time, we combine the standard out-of-sample forecasting approach with a rolling window to ensure a dynamic and robust evaluation of model forecast performance across horizons. For ease of comparison, we present the results in terms of relative performance *vis-à-vis* a benchmark AR(1) model, where relative performance is defined as RMSE of model *m* at horizon *h* scaled by the RMSE of the benchmark model for the same horizon. Any value less than one suggests gains in forecasting accuracy as it indicates that the actual RMSE value for a given model is lower than that of the benchmark model.

Beginning with Table 4, which presents results for the m-o-m changes in CPI-Vegetables series, almost all models from M2-M6, are able to outperform the benchmark AR model (M1) across different horizons, particularly less than 6-months. However, addition of sentiment data is seen to improve forecasting performance across all horizons. For instance, augmenting a simple AR(1) model with NSS (M2) results in forecasting gains of about 2-6 per cent across horizons. Similarly, adding NSS to seasonal ARIMA model (M6 *vs.* M5) leads to better forecast performance, such that M6 is able to generate accuracy gains to the tune of 7-10 per cent over the benchmark across horizons.

Table 4: Rolling-window Out-of-Sample Forecasting Performance CPI-Vegetables (m-o-m, per cent)

Model/ Description	*Forecast Horizon (in months)*											
	1	2	3	4	5	6	7	8	9	10	11	12
M1 AR(1)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
M2 AR(1) + NSS	0.95	0.94	0.95	0.96	0.96	0.97	0.98	0.98	0.98	0.98	0.98	0.97
M3 ARIMA	0.99	0.96	0.99	1.00	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00
M4 ARIMA + NSS	0.96	0.93	0.97	0.98	0.97	0.98	0.99	0.99	0.99	0.98	0.98	0.98
M5 SARIMA	0.95	0.92	0.95	0.96	0.95	0.96	0.95	0.96	0.96	0.96	0.95	0.95
M6 SARIMA + NSS	0.93	0.90	0.93	0.94	0.94	0.95	0.95	0.95	0.95	0.94	0.93	0.94

Note: The table shows the relative RMSE of each model *m* for horizon *h* measured over the test sample. The AR(1) model is taken as the benchmark model. *NSS* refers to the TOP Net Sentiment Score Index.
Source: Authors' own calculations.

Table 5: Rolling-window Out-of-Sample Forecasting Performance CPI-Vegetables (y-o-y, per cent)

Model/ Description	Forecast Horizon (in months)											
	1	2	3	4	5	6	7	8	9	10	11	12
M1 AR(1)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
M2 AR(1) + NSS	0.99	0.99	0.99	0.99	0.99	0.99	0.98	0.98	0.98	0.99	0.99	0.99
M3 ARIMA	0.99	1.04	0.99	0.96	0.97	0.93	0.95	0.96	1.04	1.05	0.89	0.73
M4 ARIMA + NSS	0.99	1.04	0.99	0.96	0.97	0.93	0.94	0.95	1.03	1.03	0.88	0.72
M5 SARIMA	0.77	0.92	0.95	0.93	0.95	0.98	1.09	1.07	0.89	0.74	0.56	0.53
M6 SARIMA + NSS	0.79	0.91	0.97	0.97	0.98	1.03	1.08	1.01	0.90	0.72	0.58	0.55

Note: The table shows the relative RMSE of each model m for horizon h measured over the test sample, where an AR(1) model is taken as the benchmark model. A relative RMSE value of less than 1 indicates improvement in forecasting accuracy. NSS refers to the composite TOP Sentiment Index.
Source: Authors' own calculations.

Forecasting performance in case of y-o-y measure of CPI-Vegetables showcases the benefits of incorporating news-based information even further, especially at the near-term horizon (Table 5). While not much improvement is seen in case of ARIMA models (M2-M4), SARIMA models deliver better forecast performance.

The forecasting performance of models for the m-o-m changes in CPI-Food and beverages, however, are mixed (Table 6). The AR(1) model augmented with NSS delivers better forecast performance compared to the benchmark model, although these gains are comparatively modest (2-5 per

Table 6: Rolling-window Out-of-Sample Forecasting Performance CPI-Food & beverages (m-o-m, per cent)

Model/ Description	Forecast Horizon (in months)											
	1	2	3	4	5	6	7	8	9	10	11	12
M1 AR(1)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
M2 AR(1) + NSS	0.96	0.95	0.96	0.97	0.97	0.97	0.98	0.98	0.98	0.98	0.97	0.96
M3 ARIMA	1.08	1.12	1.17	1.09	1.11	1.08	1.13	1.05	1.07	1.05	1.08	1.10
M4 ARIMA + NSS	1.06	0.98	1.02	0.99	1.01	1.02	1.04	1.05	1.01	1.01	1.00	1.02
M5 SARIMA	1.05	1.00	1.08	1.00	1.05	1.03	1.01	1.04	0.99	1.01	1.07	1.16
M6 SARIMA + NSS	1.06	0.98	1.02	0.99	1.01	1.02	1.04	1.05	1.01	1.01	1.00	1.02

Note: The table shows the relative RMSE of each model *m* for horizon *h* measured over the test sample, where an AR(1) model is taken as the benchmark model. A relative RMSE value of less than 1 indicates improvement in forecasting accuracy. *NSS* refers to the composite TOP Sentiment Index.
Source: Authors' own calculations.

cent) relative to CPI-Vegetables. Rest of the models fails to outperform the benchmark.

Lastly, in case of CPI-Food and beverages y-o-y series, SARIMA model (M5) and SARIMA model with sentiment information (M6) provides the best forecasts (Table 7). As seen in the earlier cases, adding sentiment information to forecasting models leads to a general improvement in forecasting accuracy.

V.2. Forecast Comparison between Sentiment data and DCA Data

To compare the extent of forward-looking information embedded in news-based 'soft' data and 'hard' DCA data, we estimate separate bivariate vector autoregression (VAR) models containing each set of indicators and compare their out-of-sample forecasting performance. A bivariate VAR model can be generally expressed as follows:

$$y_{1,t} = c_1 + \emptyset_{11}y_{1,t-1} + \emptyset_{12}y_{2,t-1} + \varepsilon_{1,t}$$

$$y_{2,t} = c_2 + \emptyset_{21}y_{1,t-1} + \emptyset_{22}y_{2,t-1} + \varepsilon_{2,t}$$

where $y_{i,t}$ represents a set of endogenous variables whereas $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ are white noise processes that may be contemporaneously correlated. Our basic framework, including the target indicators, forecast horizon and train-test

Table 7: Rolling-window Out-of-Sample Forecasting Performance CPI-Food & beverages (y-o-y, per cent)

Model/ Description	*Forecast Horizon (in months)*											
	1	2	3	4	5	6	7	8	9	10	11	12
M1 AR(1)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
M2 AR(1) + NSS	0.98	0.99	0.99	0.98	0.98	0.99	0.99	0.99	0.99	0.99	0.99	0.98
M3 ARIMA	1.02	1.01	1.00	0.95	0.96	0.95	0.93	0.93	0.92	0.89	0.84	0.88
M4 ARIMA + NSS	0.99	1.00	1.00	0.96	0.95	0.96	0.94	0.93	0.92	0.90	0.84	0.86
M5 SARIMA	0.76	0.74	0.74	0.72	0.72	0.70	0.73	0.74	0.66	0.57	0.55	0.58
M6 SARIMA + NSS	0.76	0.74	0.74	0.72	0.72	0.71	0.73	0.74	0.66	0.57	0.55	0.58

Note: The table shows the relative RMSE of each model *m* for horizon *h* measured over the test sample, where an AR(1) model is taken as the benchmark model. A relative RMSE value of less than 1 indicates improvement in forecasting accuracy. *NSS* refers to the composite TOP Sentiment Index.
Source: Authors' own calculations.

sample, remains the same as in the last subsection[15]. We estimate the VAR model using ordinary least squares (OLS) method while choosing optimal lag structure *via* the AIC criterion. The forecasting performance based on rolling out-of-sample forecasts, in the form of relative RMSE with respect to a benchmark AR(1) model, is provided in Table 8.

In case of CPI-Vegetables inflation, both set of indicators showcase a similar forecasting ability across time horizons. In some cases, such as m-o-m CPI-Vegetables model augmented with sentiment or DCA data fail to outperform the benchmark. However, in case of CPI-Food & beverages inflation, bivariate VAR model with sentiment data outperforms both the

Table 8: Forecasting Performance – Sentiment *vs.* DCA data

Model/ Description	*Forecast Horizon (in months)*											
	1	2	3	4	5	6	7	8	9	10	11	12
CPI-Vegetables (m-o-m, per cent)												
M1 AR(1)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
M2 VAR with DCA	1.02	0.98	0.99	0.99	1.01	1.00	1.02	1.02	1.01	1.01	1.02	1.01
M3 VAR with NSS	0.99	0.97	0.99	1.00	1.00	1.00	1.02	1.02	1.01	1.01	1.02	1.01
CPI-Vegetables (y-o-y, per cent)												
M1 AR(1)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
M2 VAR with DCA	0.98	1.00	0.92	0.88	0.86	0.87	0.89	0.93	0.98	0.97	0.85	0.77
M3 VAR with NSS	0.97	0.99	0.92	0.89	0.89	0.88	0.93	0.96	1.01	0.99	0.87	0.77
CPI-Food & beverages (m-o-m, per cent)												
M1 AR(1)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
M2 VAR with DCA	1.04	0.98	0.99	0.99	1.00	1.00	1.01	1.01	1.00	1.00	1.02	1.01
M3 VAR with NSS	0.68	0.66	0.69	0.70	0.70	0.70	0.80	0.80	0.84	0.87	1.07	1.14
CPI-Food & beverages (y-o-y, per cent)												
M1 AR(1)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
M2 VAR with DCA	1.00	1.01	0.97	0.92	0.94	0.96	0.95	0.97	0.99	0.97	0.89	0.91
M3 VAR with NSS	0.44	0.29	0.27	0.25	0.26	0.28	0.29	0.28	0.31	0.30	0.28	0.26

Note: The table shows the relative RMSE of each model *m* for horizon *h* measured over the test sample, where an AR(1) model is taken as the benchmark model. A relative RMSE value of less than 1 indicates improvement in forecasting accuracy. *NSS* refers to the composite TOP Sentiment Index.
Source: Authors' calculations.

[15] To ensure the stationarity condition, CPI-Vegetables, CPI-Food & beverages and DCA price data are taken in y-o-y (per cent) or m-o-m (per cent), as applicable for a given model and target indicator. The composite TOP sentiment index is taken in level form since it was found to follow an I(0) process.

benchmark and DCA data-based model across horizons. In case of m-o-m measure, the gains in forecasting accuracy range from 13 to 32 per cent, whereas even higher gains ranging from 56 to 75 per cent accrue when sentiment data is used to forecast the CPI-Food & beverages y-o-y measure of inflation. This highlights the efficacy of sentiment data for forecasting inflation over and above the only other existing high-frequency prices data provided by DCA.

V.3. Forecasting using Mixed-frequency Data: A MIDAS Approach

Having access to high-frequency news data, we exploit the information embedded in daily news sentiments to forecast monthly inflation series. A mixed data sampling (MIDAS) regression approach comes in handy by allowing the use of data sampled at different frequencies in the same regression. In particular, the MIDAS methodology proposed by Ghysels *et al.* (2002; 2006; 2007) and Andreou *et al.* (2010) allows the estimation of regression models where the dependent variable is sampled at a lower frequency compared to one or more of the independent variables. Thus, MIDAS helps in incorporating the information in higher-frequency data into the lower frequency regression model in a flexible and parsimonious way. A MIDAS regression model can be generally specified as follows:

$$y_t = \beta \cdot X_t + f\left(\{X^H_{t/S}\}, \theta, \tau\right) + \varepsilon_t$$

where y_t and X_t are the dependent and independent variables, respectively, sampled at a low frequency at time *t*, $X^H_{t/S}$ is the high-frequency independent variable with *S* number of values each, $f\{\cdot\}$ is the functional mapping of the high-frequency data to the low-frequency dependent variable and β, θ and τ are estimated parameters.

Traditional approaches to mixed-frequency regression either introduce a sum/average of the high-frequency data with a single coefficient (implicitly equal weights) or include individual components of the high-frequency variable in the model allowing for separate coefficients. On the other hand, by allowing for several different weighting functions to decide optimal weights and reducing the number of estimated parameters by placing adequate constraints, the MIDAS approach offers a flexible framework to incorporate high-frequency information into a regression model.

Various weighting schemes available under this approach are (a) step-weighting; (b) polynomial distributed lag (PDL) weighting; (c) exponential PDL weighting; (d) normalised beta function weighting; and (e) individual coefficients weighting technique (U-MIDAS). Adopting a similar train-test approach as in the previous sub-section, we use a simple AR(1) model estimated using the MIDAS framework with PDL and U-MIDAS weighting techniques for predicting our target variable. We incorporate the high-frequency information by introducing up to 30 lags of combined TOP net sentiment score computed at a daily frequency. The out-of-sample forecasts on test data are generated using the dynamic rolling window approach from one- to 12-months ahead horizon. The forecast performance, in the form of relative RMSE of forecasts generated by best-performing MIDAS model compared to the AR(1) benchmark, is presented in Table 9.

Table 9: Mixed-frequency Forecasting Target: CPI-Vegetables/ CPI-Food & Beverages

Model	*Forecast Horizon (in months)*											
	1	2	3	4	5	6	7	8	9	10	11	12
CPI-Vegetables (m-o-m, per cent)												
M1 AR(1)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
M2 MIDAS: AR(1) + Daily NSS	0.95	0.96	0.98	0.97	0.98	0.98	1.00	1.00	1.00	0.99	1.02	1.05
CPI-Vegetables (y-o-y, per cent)												
M1 AR(1)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
M2 MIDAS: AR(1) + Daily NSS	1.00	0.99	1.00	1.00	1.00	1.04	1.11	1.14	1.20	1.21	1.15	1.09
CPI-Food & beverages (m-o-m, per cent)												
M1 AR(1)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
M2 MIDAS: AR(1) + Daily NSS	0.96	0.96	0.97	0.97	0.98	0.98	0.99	0.98	0.99	0.98	1.02	1.05
CPI-Food & beverages (y-o-y, per cent)												
M1 AR(1)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
M2 MIDAS: AR(1) + Daily NSS	1.01	1.08	1.19	1.26	1.28	1.31	1.28	1.19	1.20	1.22	1.18	1.18

Note: The table shows the relative RMSE of each model *m* for horizon *h* measured over the test sample, where an AR(1) model is taken as the benchmark model. A relative RMSE value of less than 1 indicates improvement in forecasting accuracy. *NSS* refers to the composite TOP Sentiment Index.

Source: Authors' own calculations.

As is evident from Table 9, leveraging daily news-based sentiment data has clear benefits in terms of gains in forecasting accuracy in m-o-m space. In case of m-o-m changes in CPI-Vegetables and CPI-Food and beverages, the MIDAS model with daily data outperforms the benchmark model at the one-month ahead horizon. In addition to these one-month ahead predictions or nowcasts, the MIDAS model outperforms the benchmark for two- to six-months ahead horizon, where the gains range from 2-5 per cent for m-o-m changes in CPI-Vegetables and CPI-Food and beverages series. On the other hand, sentiment augmented model fails to outperform the benchmark model in case of inflation measures taken in y-o-y terms across different horizons. Thus, overall, it can be said that daily news-based sentiment indicators for TOP commodities can help near-term month-on-month projections of price index for CPI Vegetables and CPI Food and beverages over different forecast horizons.

Section VI
Conclusion and the Way Forward

Recurrent supply disruptions driven by unseasonal rainfall, floods, droughts, pest attacks, protests by farmers/transport operators, *etc.,* makes the task of inflation forecasting an arduous challenge in India. In this study, therefore, we develop a novel dataset consisting of news articles related to three main agricultural commodities *viz.,* tomato, onion and potato or TOP to forecast CPI-based inflation in vegetables and food & beverages. We quantify the information content of news articles using natural language processing (NLP) techniques to assess whether news-based alternate data can help in achieving better forecasts. Through various forecasting methods premised on monthly and daily data, we provide empirical evidence to conclude that news-based data in the form of sentiment indices provides gains in forecasting accuracy. The forward-looking information content embedded in news data, therefore, suggests the use of news-based sentiment indicators as an additional source of information for inflation forecasting. This is crucial from a policy perspective in an environment of highly uncertain food price dynamics that are increasingly becoming climate dependent.

While this study is a first step in the direction of using news-based big data for food inflation forecasting, the analysis can be extended in several ways. From the perspective of forecasting headline inflation and its components, a larger number of commodities and other items corresponding with the official CPI basket can be included in the forecasting framework. More nuanced NLP techniques, such as those based on *supervised* machine-learning methods for sentiment quantification, or *unsupervised* topic modelling approach can be used to derive more granular information on topics such as supply and demand for various items. The suite of time-series methods can also be expanded to experiment with other advanced techniques, such as dynamic factor models, penalized regressions and deep learning models which might help achieve better forecasting accuracy. Moreover, given the forward-looking content of news-based data, it can also be used for turning point analysis of inflationary shocks to the economy. Finally, while we have focused on point forecasts in this paper, it remains to be seen whether news-based information can also help in reducing the uncertainty around forecasts. We leave these issues for future research.

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Appendix

Table A1: Rolling-window Out-of-Sample Forecasting Performance - CPI-Vegetables (m-o-m, per cent)

Model/ Description	*Forecast Horizon (in months)*											
	1	2	3	4	5	6	7	8	9	10	11	12
M1 AR(1)	6.49	6.77	6.65	6.72	6.84	6.85	5.79	5.91	5.64	5.70	5.62	5.02
M2 AR(1) + NSS	6.15	6.34	6.34	6.46	6.55	6.64	5.69	5.79	5.54	5.56	5.49	4.87
M3 ARIMA	6.44	6.47	6.59	6.72	6.78	6.84	5.80	5.92	5.65	5.72	5.63	5.02
M4 ARIMA + NSS	6.25	6.33	6.44	6.57	6.65	6.74	5.75	5.85	5.58	5.61	5.53	4.94
M5 SARIMA	6.16	6.20	6.32	6.44	6.53	6.58	5.51	5.67	5.40	5.47	5.32	4.79
M6 SARIMA + NSS	6.01	6.08	6.20	6.31	6.42	6.50	5.48	5.62	5.34	5.38	5.23	4.73
M7 SARIMA + Exo	6.19	6.38	6.45	6.55	6.69	6.70	5.81	5.93	5.47	5.52	5.63	5.28
M8 SARIMA +Exo + NSS	6.14	6.30	6.38	6.46	6.58	6.59	5.68	5.78	5.35	5.41	5.49	5.20

Note: The table shows the RMSE of each model *m* for horizon *h* measured over the test sample. The AR(1) model is taken as the benchmark model. *Exo* refers to exogenous variables such as global food prices, rainfall and minimum support prices (MSP) while *NSS* refers to the composite TOP Sentiment Index.
Source: Authors' own calculations.

Table A2: Rolling-window Out-of-Sample Forecasting Performance - CPI-Vegetables (y-o-y, per cent)

Model/ Description	*Forecast Horizon (in months)*											
	1	2	3	4	5	6	7	8	9	10	11	12
M1 AR(1)	11.14	16.80	19.47	21.06	19.81	17.09	15.29	15.17	14.03	14.67	17.36	20.41
M2 AR(1) + NSS	11.08	16.69	19.26	20.81	19.60	16.88	14.98	14.93	13.80	14.47	17.25	20.28
M3 ARIMA	11.06	17.40	19.29	20.28	19.13	15.95	14.49	14.59	14.64	15.34	15.45	14.84
M4 ARIMA + NSS	11.05	17.44	19.37	20.31	19.13	15.89	14.37	14.46	14.49	15.17	15.30	14.68
M5 SARIMA	8.63	15.40	18.55	19.64	18.88	16.67	16.69	16.18	12.55	10.79	9.77	10.74
M6 SARIMA + NSS	8.76	15.23	18.79	20.34	19.49	17.59	16.56	15.31	12.61	10.56	10.11	11.19
M7 SARIMA + Exo.	4.99	6.05	9.00	9.57	10.98	12.44	13.69	13.57	14.21	14.73	15.08	14.95
M8 SARIMA+ Exo +NSS	2.94	5.33	8.80	9.71	11.20	12.90	14.60	15.11	15.07	15.51	16.18	16.46

Note: The table shows the RMSE of each model *m* for horizon *h* measured over the test sample. The AR(1) model is taken as the benchmark model. *Exo* refers to exogenous variables such as global food prices, rainfall and minimum support prices (MSP) while *NSS* refers to the composite TOP Sentiment Index.
Source: Authors' own calculations.

Table A3: Rolling-window Out-of-Sample Forecasting Performance - CPI-Food & Beverages (m-o-m, per cent)

Model/ Description	*Forecast Horizon (in months)*											
	1	2	3	4	5	6	7	8	9	10	11	12
M1 AR(1)	1.27	1.27	1.26	1.26	1.29	1.29	1.14	1.18	1.14	1.14	0.95	0.87
M2 AR(1) + NSS	1.21	1.21	1.21	1.22	1.24	1.26	1.12	1.15	1.12	1.12	0.92	0.84
M3 ARIMA	1.37	1.42	1.48	1.37	1.43	1.39	1.29	1.24	1.22	1.20	1.02	0.96
M4 ARIMA + NSS	1.34	1.25	1.29	1.24	1.29	1.32	1.18	1.23	1.15	1.14	0.95	0.89
M5 SARIMA	1.33	1.28	1.36	1.27	1.35	1.33	1.15	1.22	1.13	1.14	1.01	1.01
M6 SARIMA + NSS	1.34	1.25	1.29	1.24	1.29	1.32	1.18	1.23	1.15	1.14	0.95	0.89
M7 SARIMA + Exo.	1.33	1.28	1.36	1.27	1.35	1.33	1.15	1.22	1.13	1.14	1.01	1.01
M8 SARIMA+Exo+NSS	1.34	1.22	1.32	1.26	1.35	1.34	1.11	1.22	1.13	1.17	0.96	0.98

Note: The table shows the relative RMSE of each model *m* for horizon *h* measured over the test sample. The AR(1) model is taken as the benchmark model. *Exo* refers to exogenous variables such as global food prices, rainfall and minimum support prices (MSP) while *NSS* refers to the composite TOP Sentiment Index.
Source: Authors' own calculations.

Table A4: Rolling-window Out-of-Sample Forecasting Performance CPI-Food & beverages (y-o-y, per cent)

Model/ Description	*Forecast Horizon (in months)*											
	1	2	3	4	5	6	7	8	9	10	11	12
M1 AR(1)	1.94	2.86	3.27	3.52	3.50	3.26	3.21	3.44	3.18	3.19	3.58	4.05
M2 AR(1) + NSS	1.91	2.82	3.24	3.46	3.45	3.23	3.19	3.39	3.14	3.17	3.54	3.98
M3 ARIMA	1.98	2.90	3.26	3.35	3.35	3.10	2.98	3.19	2.92	2.85	3.02	3.55
M4 ARIMA + NSS	1.93	2.86	3.27	3.37	3.34	3.12	3.03	3.19	2.91	2.87	3.00	3.50
M5 SARIMA	1.47	2.12	2.41	2.55	2.51	2.28	2.34	2.56	2.11	1.83	1.98	2.36
M6 SARIMA + NSS	1.48	2.11	2.41	2.55	2.51	2.30	2.33	2.55	2.10	1.81	1.98	2.35
M7 SARIMA + Exo.	0.52	1.11	1.60	2.14	2.67	3.18	3.61	3.94	4.15	4.46	4.85	5.25
M8 SARIMA+Exo+NSS	0.51	1.10	1.60	2.12	2.65	3.17	3.60	3.93	4.15	4.46	4.86	5.27

Note: The table shows the relative RMSE of each model *m* for horizon *h* measured over the test sample. The AR(1) model is taken as the benchmark model. *Exo* refers to exogenous variables such as global food prices, rainfall and minimum support prices (MSP) while *NSS* refers to the composite TOP Sentiment Index.
Source: Authors' own calculations.

Table A5: Forecasting Performance – Sentiment *vs.* DCA data

Model	*Forecast Horizon (in months)*											
	1	2	3	4	5	6	7	8	9	10	11	12
CPI-Vegetables (m-o-m, per cent)												
M1 AR(1)	6.49	6.77	6.65	6.72	6.84	6.85	5.79	5.91	5.64	5.70	5.62	5.02
M2 VAR with DCA	6.62	6.64	6.58	6.66	6.88	6.86	5.91	6.01	5.71	5.76	5.73	5.05
M3 VAR with NSS	6.43	6.58	6.60	6.72	6.81	6.87	5.89	6.01	5.71	5.75	5.71	5.06
CPI-Vegetables (y-o-y, per cent)												
M1 AR(1)	11.14	16.80	19.47	21.06	19.81	17.09	15.29	15.17	14.03	14.67	17.36	20.41
M2 VAR with DCA	10.97	16.73	17.98	18.56	17.01	14.82	13.60	14.13	13.80	14.16	14.74	15.65
M3 VAR with NSS	10.84	16.57	17.90	18.82	17.55	15.03	14.19	14.50	14.16	14.58	15.11	15.74
CPI-Food & beverages (m-o-m, per cent)												
M1 AR(1)	1.27	1.27	1.26	1.26	1.29	1.29	1.14	1.18	1.14	1.14	0.95	0.87
M2 VAR with DCA	1.31	1.25	1.25	1.25	1.28	1.29	1.16	1.18	1.14	1.14	0.97	0.88
M3 VAR with NSS	0.86	0.84	0.87	0.88	0.90	0.90	0.92	0.94	0.96	0.99	1.02	0.99
CPI-Food & beverages (y-o-y, per cent)												
M1 AR(1)	1.94	2.86	3.27	3.52	3.50	3.26	3.21	3.44	3.18	3.19	3.58	4.05
M2 VAR with DCA	1.94	2.89	3.17	3.25	3.29	3.11	3.07	3.33	3.14	3.09	3.18	3.68
M3 VAR with NSS	0.85	0.84	0.88	0.89	0.90	0.93	0.94	0.97	0.99	0.96	1.01	1.04

Note: The table shows the RMSE of each model *m* for horizon *h* measured over the test sample. The AR(1) model is taken as the benchmark model. NSS refers to the composite TOP Sentiment Index

Source: Authors' calculations.

Table A6: Mixed-frequency Forecasting Target: CPI-Vegetables

Model	Forecast Horizon (in months)											
	1	2	3	4	5	6	7	8	9	10	11	12
CPI-Vegetables (m-o-m, per cent)												
M1 AR(1)	6.49	6.77	6.65	6.72	6.84	6.85	5.79	5.91	5.64	5.70	5.62	5.02
M2 MIDAS: AR(1) + Daily NSS	6.18	6.50	6.51	6.54	6.72	6.74	5.78	5.89	5.65	5.67	5.72	5.26
CPI-Vegetables (y-o-y, per cent)												
M1 AR(1)	11.14	16.80	19.47	21.06	19.81	17.09	15.29	15.17	14.03	14.67	17.36	20.41
M2 MIDAS: AR(1) + Daily NSS	11.12	16.65	19.53	20.97	19.78	17.84	16.91	17.26	16.78	17.74	19.88	22.25
CPI-Food & beverages (m-o-m, per cent)												
M1 AR(1)	1.27	1.27	1.26	1.26	1.29	1.29	1.14	1.18	1.14	1.14	0.95	0.87
M2 MIDAS: AR(1) + Daily NSS	1.22	1.23	1.22	1.22	1.26	1.27	1.13	1.16	1.13	1.11	0.97	0.92
CPI-Food & beverages (y-o-y, per cent)												
M1 AR(1)	1.94	2.86	3.27	3.52	3.50	3.26	3.21	3.44	3.18	3.19	3.58	4.05
M2 MIDAS: AR(1) + Daily NSS	1.96	3.09	3.89	4.44	4.48	4.27	4.10	4.10	3.82	3.89	4.24	4.77

Note: The table shows the RMSE of each model *m* for horizon *h* measured over the test sample. The AR(1) model is taken as the benchmark model. NSS refers to the composite TOP Sentiment Index.
Source: Authors' own calculations.

Table A7: Contemporaneous Correlation Coefficient Between CPI Indices and DCA Prices (Period: January 2014 to February 2020)

	CPI-Potato	CPI-Onion	CPI-Tomato	DCA-Potato	DCA-Onion	DCA-Tomato
CPI-Potato	1					
CPI-Onion	0.22*	1				
CPI-Tomato	0.15	0.2*	1			
DCA-Potato	0.99***	0.25**	0.17	1		
DCA-Onion	0.22*	1***	0.2*	0.26**	1	
DCA-Tomato	0.2*	0.25**	0.99***	0.23**	0.25**	1

Note: ***, ** and * indicate significance at 1 per cent, 5 per cent and 10 per cent levels of significance, respectively. Period begins from January 2014 as CPI item level indices in the current base are available from then and period ends in February 2020 as item level CPI data were not released by NSO during March-May 2020.

Table A8: Contemporaneous Correlation Coefficient Between CPI Momentum and Arrivals (Period: July 2015 to February 2020)

	Arrivals-Potato	Arrivals-Onion	Arrivals-Tomato	Momentum-Potato	Momentum-Onion	Momentum-Tomato
Arrivals-Potato	1					
Arrivals-Onion	0.46***	1				
Arrivals-Tomato	0.06	0.07	1			
Momentum-Potato	-0.34**	-0.47***	-0.12	1		
Momentum-Onion	-0.19	-0.5***	0.09	0.2	1	
Momentum-Tomato	-0.09	0.03	-0.19	0.32**	0.02	1

Note: ***, ** and * indicate significance at 1 per cent, 5 per cent and 10 per cent levels of significance, respectively. Period begins from July 2015 as continuous arrivals data are available from then and period ends in February 2020 as item level CPI data were not released by NSO during March-May 2020.

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Behavioural Equilibrium Exchange Rates in Emerging Market Economies

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Higher productivity growth in emerging market economies (EMEs) *vis-à-vis* advanced economies (AEs) during 2000s has been a key factor shaping the diverging views on currency misalignments (overvaluation/undervaluation) in EMEs. Against this backdrop, this paper provides an estimate of equilibrium exchange rate based on Behavioural Equilibrium Exchange Rate (BEER) model. Using annual data from 1994-2020 for 10 EMEs and employing panel cointegration methods, it finds that the real effective exchange rate (REER) in EMEs is driven by its fundamental determinants such as the Balassa-Samuelson effect. Among other determinants, an improvement in terms of trade, net foreign assets position and an increase in interest rate differentials *vis-à-vis* the US are found to appreciate the REER, while an increase in government debt depreciates it. The findings indicate that the equilibrium exchange rate of a country experiencing higher economic growth could move upward due to high productivity growth, which should not be treated as loss of external competitiveness.

JEL: C23, F31, F32

Keywords: Real Effective Exchange Rate, Balassa-Samuelson Effect, BEER Model, Panel Cointegration, DOLS, FMOLS

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Introduction

In the past two decades, several emerging market economies (EMEs) have recorded either a secular increase (*e.g.*, China, India, Indonesia, Philippines and Thailand) or decrease (*e.g.*, Brazil and South Africa) in their REER, even though volatile capital flows and changes in risk aversion have triggered two-way fluctuations intermittently in the short-run. An increase in real exchange rate is usually considered as a loss of export competitiveness, while a persistent undervaluation may be viewed as currency manipulation. The explanation of non-stationary real exchange rates in the long-run is, however, provided by the Balassa-Samuelson hypothesis (Balassa, 1964; Samuelson, 1964). It postulates that a rise in labour productivity in tradable sector of a country leads to an increase in wages and relative prices in that sector, which eventually leads to higher inflation in the country. Thus, it suggests that the secular trend in real exchange rate could be a reflection of productivity differences. For example, a country experiencing higher productivity growth *vis-à-vis* its trading partners may experience an appreciation of REER, which could be indicating an increase in the level of its equilibrium REER. On the other hand, there is a strand of literature which argues for rethinking of the significance of the Balassa-Samuelson effect, given the sensitivity of findings to empirical methods chosen, sample of countries considered and the type of data used (Tica and Družić, 2006; Gubler and Sax, 2019).

In practice, the real exchange rate is driven by structural and cyclical factors. While the productivity differential determines the long-run trend in real exchange rate, domestic output gap, global spillovers, and central bank interventions dictate the short-run movements. From another perspective, studies have pointed at exchange rate being determined in slowly adjusting output markets in the long run and in volatile asset markets in the short run (Patnaik and Pauly, 2001). EMEs may tend to stabilise their currencies in the short-run through various policy tools, however, it may be difficult to pursue the same in the long-run as deviations from the equilibrium level have macroeconomic costs such as high inflation and reduction in foreign capital inflows. Appreciation of REER during a phase of subdued domestic demand and export growth may trigger economic slowdown and currency crisis (Pattanaik, 1999). Undervalued exchange rate promotes export growth as envisaged in the mercantilist view, however, currency misalignments (undervaluation) could be harmful to economic growth due to its impact channelised through valuation effects of foreign-currency denominated debt (Grekou, 2018).

Economic history has well documented the significant role of external sector in the catching up process of EMEs with the advanced countries. Since REER is considered as a measure of export competitiveness which directly captures movements in monetary variables such as nominal exchange rates and prices, and it is indirectly influenced by interest rate (Pattanaik, 1999), it assumes importance as a monetary indicator. Therefore, along with price stability, exchange rate stability is also considered critical for economic growth (Mohanty, 2013). This underscores the importance of equilibrium exchange rate, *i*.e., an exchange rate consistent with internal balance in the form of full employment and low inflation, and external balance in the form of sustainable balance of payments position (Williamson, 1994). Thus, empirical estimation of equilibrium exchange rate is gaining momentum, mainly based on the behavioural equilibrium exchange rate (BEER) model as it captures the short-run determinants based on uncovered interest rate parity along with long-run fundamentals such as the Balassa-Samuelson effect (MacDonald, 1997; Clark and MacDonald 1998).

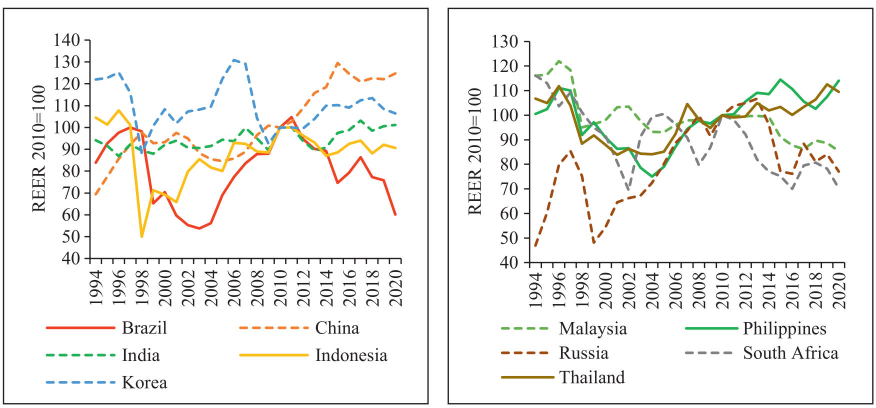
Against this backdrop, this paper using data on a panel of 10 EMEs examines the equilibrium exchange rate by applying BEER model. The contribution of the paper is mainly in the form of determinants used: (i) proxy of productivity, *i.e.,* relative real per capita GDP *vis-à-vis* 59 trading partners; (ii) different benchmarks of interest rate differentials such as short and long-term interest rate differentials *vis-à-vis* the US; and (iii) public debt to GDP ratio, which are relevant for the EMEs. Rest of the paper is divided into six sections. The following section provides stylised facts relevant to REER in EMEs. A review of literature is presented in Section III. The details of computation of variables and the methodology used are explained in Section IV. Empirical results are discussed in Section V and a comparison of actual and equilibrium REER is provided in Section VI. Concluding observations are set out in Section VII.

Section II
Stylised Facts

The real effective exchange rate provides a composite value in the form of exchange rate of a country's currency *vis-a-vis* its trading partners which is adjusted for relative price movements. The movement in REER over a period of time shows changes in a country's trade competitiveness *vis-à-vis* its trading partners. An increasing REER of a country indicates a rise in the value of its currency *vis-à-vis* trading partners (trading partners will pay more for buying domestic goods) and thus, a loss of competitiveness. As it is computed against a basket of currencies and adjusted for price differences, REER is usually less volatile than the bilateral nominal exchange rate and shows a steady pattern over medium to long-term. Nevertheless, macroeconomic and financial shocks influence short-term trend in REER (Chart 1). For example, most of the EMEs, barring India and China, witnessed sharp depreciation in their REER in 1998 following the East Asian crisis. Korea and South Africa recorded sharp depreciation in their REER during global financial crisis while Brazil, India, Indonesia and South Africa witnessed a sharp fall in their REER during the taper tantrum period in 2013.

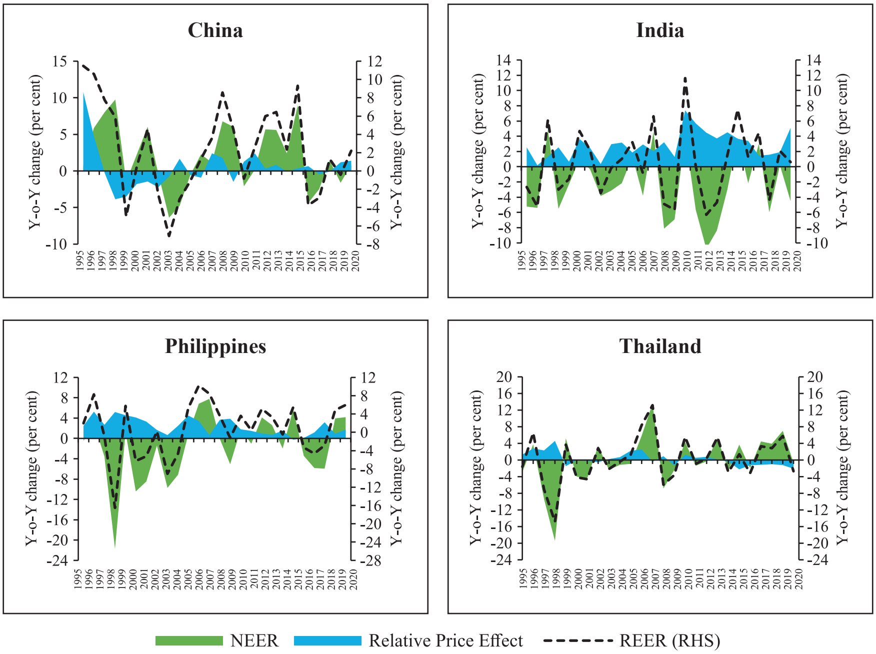
Apart from macroeconomic shocks, movement in a country's real exchange rate is driven by price differentials *vis-à-vis* its trading partners. Thus, changes in REER can be decomposed into nominal effective exchange

Chart 1: Real Effective Exchange Rate



Source: BIS.

Chart 2: Drivers of REER: Nominal Effective Exchange Rate and Relative Prices

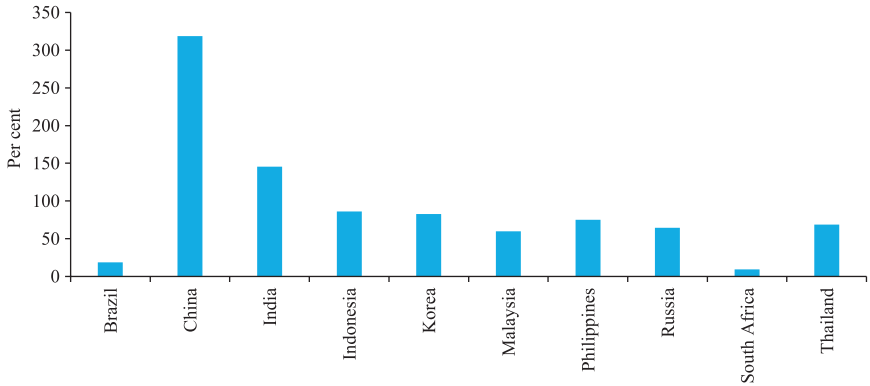


Note: Relative price effect is taken as residual of percentage change in REER and percentage change in NEER.

rate (NEER) and relative price effect (Chart 2). As depicted in Chart 2, movements in REER in China, Philippines and Thailand in post-2010 period are driven mainly by nominal effective exchange rates. In contrast, trend in variations of India's REER was contributed largely by relative price effect.

While the impact of macro-financial shocks and cyclical factors is usually short-lived, long-term trend in REER could be reflective of structural changes taking place in the economy. One of the important factors driving long-term trend of REER is the changes in productivity level of the economy's tradable sector. For example, an increase in labour productivity of a country causes output per worker to increase at a faster pace *vis-à-vis* its trading partner which leads to an increase in REER of its currency. China, India, Indonesia, Philippines and Thailand recorded increase in their REERs, whereas Brazil, Russia and South Africa witnessed decrease in their REER during the post-2010 period (Chart 1). The increase in REER of these countries (China, India and Indonesia) coincided with higher growth in their relative per capita GDP (Chart 3). Further, higher

Chart 3: Growth of Relative Per Capita GDP (2000-20)

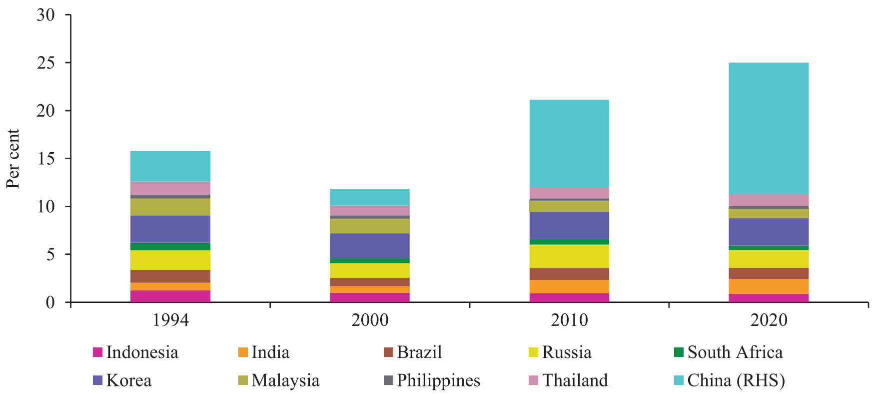


Source: IMF and the World Bank database, and Author's Calculations.

productivity growth of China and India is also reflected in their rising share in world exports (Chart 4).

According to the World Bank (2020), the sharp increase in the share of emerging market and developing economies (EMDEs) in world GDP post-2000[1] coincided with their higher productivity growth during 2003-08 at

Chart 4: Share of EMEs in World Exports



Source: IMF and the World Bank database, and Author's Calculations.

[1] The share of emerging market and developing economies (EMDEs) in world GDP at current prices (in US$) was 24 per cent in 1980 which decreased to 21 per cent in 2000 but increased to 41 per cent in 2020 (IMF World Economic Outlook, October 2020). In terms of GDP at current prices in US$ PPP, the share of EMDEs increased from 37 per cent in 1980 to 41 per cent in 2000 and further to 58 per cent in 2020.

around 5 per cent as compared to that of 2 per cent in advanced economies. Further, the World Bank (2020) observed that *"In some large EMDEs, such as China and India, productivity is growing substantially faster than in advanced economies….."*. Both China and India witnessed higher growth of labour productivity as well as the total factor productivity (TFP). However, China witnessed relatively higher productivity growth (both labour productivity and TFP). Further, the improvement in productivity began much earlier in China (mid-1980s) than in India (mid-1990s). In 2000s, a few other EMEs such as Malaysia, Philippines, Russia and Thailand intermittently posted higher TFP and labour productivity growth than the advanced economies. IMF (2011) pointed out that a large part of the increase in global trade over long-term horizon was driven by rapidly growing EMEs. It is also observed that trade expansion took place in high-technology products like computers, and the subsequent shift of technology content towards EMEs had implications for relative price changes; and countries with higher level of income embodied in exports witnessed higher growth of per capita GDP. Consequently, EMEs witnessed higher inflation than the advanced economies even though the gap is converging since mid-1990s due to growing emphasis on price stability as evident from the adoption of inflation targeting by EME central banks.

Section III
Review of Literature

The purchasing power parity (PPP) theory postulates that the equilibrium exchange rate between two countries is determined by their respective purchasing powers, *i.e.*, inflation. The PPP theory is based on the "law of one price" which argues that in frictionless markets (no tariffs or other trade barriers), where there are no transaction/transportation costs, the price of an identical tradeable commodity is same across countries. In other words, consumer in every country will have the same purchasing power measured in common currency, implying that the relative price levels determine the real exchange rate (Equation 1).

$$E = e^{*}P / P^{f} \qquad ...(1)$$

where, 'E' denotes real exchange rate, 'e' is nominal exchange rate, 'P^f' represents foreign price level and 'P' is domestic price level.

Monetary approach to the exchange rate stresses that excess money supply, output and interest rate relative to foreign economy drive nominal exchange rate. Real interest parity implies that differences in nominal interest rates equal the difference in expected inflation plus expected percentage change in real exchange rate. Another theory which provides an explanation of exchange rate movements is the Balassa-Samuelson effect (Balassa, 1964; Samuelson, 1964). It argues that productivity gains in the tradable sector lead to higher wages which gets generalised in the non-tradable sector, thereby causing an increase in inflation and therefore, an appreciation of the real exchange rate of domestic currency.

In practice, however, several other factors – both domestic and external – have their influence on the behaviour of real exchange rate. Such factors include the demand side of the economy, country risk premium and capital flows. For example, the concept of Fundamental Equilibrium Exchange Rate (FEER) postulated by Williamson (1994) states that the equilibrium exchange rate will be determined by internal balance characterised by full employment level of output and low and stable inflation, and external balance, *i.e.,* sustainability of balance of payments in the medium term. Internal balance is achieved by changes in REER driven by productivity differences, while external balance is achieved through the impact of the REER on current account. Therefore, if the current account balance is unsustainable, the REER will depreciate, and it will improve the current account balance to a sustainable level. Extending the FEER approach, MacDonald (1997) and Clark and MacDonald (1998) proposed BEER model based on theoretical underpinning of uncovered interest rate parity (UIP). Clark and MacDonald (1998) include relative price of non-traded to traded goods *(tnt)*, net foreign assets *(nfa)*, terms of trade *(tot)*, short-term interest rate differentials (*r-r*)* and the risk premium component represented by public debt (*gdebt/gdebt*)*, as determinants of the real exchange rate (Equation 2).

$$BEER = f\,(r\text{-}r^*,\ gdebt/gdebt^*,\ tot,\ tnt,\ nfa) \qquad ...(2)$$

where 'r' stands for domestic real interest rate and 'r*' is world real interest rate, 'gdebt' is government debt as a ratio to GDP and 'gdebt*' is foreign government debt as a ratio to foreign GDP. '*tot*' represents terms of trade, 'tnt' stands for relative price of non-traded to traded goods and '*nfa*' denotes net foreign assets of a country (external assets – external liabilities).

In view of the policy implications for global trade and development, real exchange rates are monitored and analysed by policymakers, multilateral organisations as well as by the research institutions. For example, the IMF provides an assessment of equilibrium REER of major AEs and EMEs in its External Sector Report by using External Balance Assessment (EBA) methodology, which consists of three approaches. These include the current account (CA) approach, real effective exchange rate (REER) regression and the external sustainability approach.[2] However, some studies criticise that the sustainable current account argued in models such as FEER or the IMF's EBA put extra layer of judgement of calculating current account elasticity (MacDonald, 2000; Grekou 2018). The Centre d'Etudes Prospectives et d'Informations Internationales **(**CEPII) France estimates the equilibrium REER and misalignment *(Actual REER – Equilibrium REER)* for all countries based on determinants such as proxy of Balassa-Samuelson (BS) effect, net foreign assets, terms of trade and trade openness (Couharde *et al.,* 2017) and provides country-wise data on proxies of BS effect, *viz.,* per capita GDP, GDP per worker, and consumer price index (CPI) to producer price index (PPI) ratio. The Institute of International Finance (IIF) provides an update of its exchange rate assessment based on FEER model.

Empirical literature suggests that studies consider per capita GDP or labour productivity or CPI to PPI ratio as determinants of real exchange rate along with other variables such as terms of trade, and net foreign assets or net capital flows (Lane and Milesi-Ferretti, 2004; Coudert *et al,* 2013). Some studies have also considered other determinants such as trade openness or trade

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2 In current account (CA) approach, first the predicted current account balance is obtained using CA regression and the difference between actual and predicted current account is taken as a residual. Then the policy gap (gaps in fiscal policy, public expenditure on health, changes in reserves, private credit and capital controls) as the difference between domestic policy gap and world policy gap is calculated. CA norm is calculated as the difference between predicted CA and policy gap. Finally, actual CA and CA norms are compared, and elasticity of CA to REER to bring CA at norm level is used to obtain REER gap. In the REER regression approach, residual is obtained from predicted and actual value of REER. Then, the residual and policy gap (like CA approach) are used to determine the REER gap. In the external sustainability approach, first the benchmark net foreign assets are obtained as the threshold of external sustainability. In the next step, current account norm consistent with threshold NFA is calculated. In the third step, CA gap is calculated as CA norm and actual CA. Finally, as in the case of CA regression approach, elasticity of CA to REER is applied to obtain CA at norm level and accordingly, the REER gap is calculated.

balance (Maeso-Fernandez *et al.,* 2004; Hossfeld, 2010; and Hajek, 2016), and government expenditure or public debt (Clark and MacDonald, 1998; Maeso-Fernandez *et al.,* 2004; Ricci *et al.,* 2008; Hossfeld, 2010; Bussière *et al.,* 2010; Mancini-Griffolo *et al.,* 2014; and Adler and Grisse, 2014) to assess the role of demand side factors. Long-term or short-term interest rate differentials have been a relatively new addition to the set of determinants of real exchange rate (Clark and MacDonald, 1998; Maeso-Fernandez *et al.,* 2001; Bénassy-Queré *et al.,* 2009; and Fidora *et al.,* 2017). While most of the studies use short-term interest rate as indicated in BEER model, Maeso-Fernandez *et al.,* 2001 argued for long-term interest rate citing empirical evidence on the absence of equalisation in interest rate differential across countries in the long-run. A few studies have also explored relative trade openness (Griffoli *et al*. 2015; Fidora *et al.* 2017), relative terms of trade and relative government expenditure (Fidora *et al.* 2017) as determinants of real exchange rate. Volatile capital flows and changes in risk aversion in global financial markets also influence exchange rate movements. Therefore, some studies take into account different types of capital flows such as foreign direct investment (FDI), foreign portfolio investment (FPI), and other flows (Joyace and Kamas 2003).

In the Indian context, a few studies have analysed the determinants of exchange rate. Patel and Srivastava (1997) considered terms of trade and a few other determinants and found real exchange rate of the Indian rupee appreciating with an increase in capital flows and tariffs protection, and depreciating with an increase in investment/GDP ratio and seigniorage-GDP ratio. Pattanaik (1999) found India's REER aligned to PPP in the long-run as observed by its mean reversion. The author found that misalignments, *i.e.,* deviations from PPP, are corrected through nominal exchange rate and price movements. While analysing REER of India, Joshi (2006) found the real demand effect (money supply and fiscal deficit together named as real demand effect) to be a fundamental determinant besides relative supply variable (index of industrial production of India relative to industrial countries) and relative nominal shocks (price indices in India relative to industrial countries). Kumar (2010) observed that India's real exchange rate in the long-run was driven by productivity differentials, external sector openness, terms of trade and net foreign assets. Randive and Burange (2013) found government expenditure, openness, inflation differential, foreign institutional investment and long-term interest rate differential as the drivers of real exchange rate. Recent studies based on panel of EMEs including India (Giannellis and Koukouritakis, 2018) found that real exchange rate was broadly aligned to its equilibrium value determined by net foreign assets, productivity and interest rate differentials. Banerjee and Goyal (2020) analysed REER using determinants such as terms of trade, openness, productivity, and fiscal deficit, and found that China, India and Mexico had higher equilibrium exchange rate in the pre-GFC period, than the post-GFC period. The rate of misalignment of REER remained within the range of +/-5 per cent. Guria and Sokal (2021) found bi-directional causality between productivity differential and REER in India. They pointed out that causality from productivity differentials to REER confirms the Balassa-Samuelson hypothesis, while causality from REER to productivity differentials indicates the impact of appreciation in real exchange rate on the productivity growth[3].

Section IV
Data and Methodology

Among various explanations of movements in REER in the long-run, the BS effect is the most widely accepted determinant. However, we use other possible determinants as suggested in the literature on BEER model. The BEER model considers both structural and temporary factors which influence the real exchange rate. Further, the BEER model does not involve any normative content or judgement while estimating equilibrium exchange rate which is the case with other methodologies such as the IMF's EBA. Therefore, the recent literature on equilibrium real exchange rate has largely preferred the BEER model (Macdonald and Dias, 2007; Melecký and Komárek, 2007; Fidora *et al.,* 2017; Michele *et al.,* 2020). The advantage of this approach lies in obtaining the equilibrium value directly from empirically estimated model.[4]

3 For example, the real exchange rate appreciation will reduce the cost of imported capital goods and enhance the capital-labour ratio, thereby boosting technical progress and productivity; or, the appreciation may boost foreign competition which can induce a rise in technical efficiency and productivity of firms.

4 First, real effective exchange rate is regressed up on plausible determinants. Then in the second step, predicted value obtained from estimated model is taken as the equilibrium REER.

In this paper, the BS effect is proxied by per capita GDP relative to trading partners, while other determinants considered are net foreign assets, terms of trade index, interest rate differentials and debt-GDP ratio. Due to the non-availability of productivity data for traded and non-traded sectors separately, studies mostly use per capita GDP as a proxy of the BS effect.[5] As alluded earlier, rise in productivity growth *vis-à-vis* trading partners is expected to result in an appreciation of the real exchange rate. With regard to the impact of fiscal policy on real exchange rate, studies have considered public expenditure-GDP ratio or the debt-GDP ratio. The increase in public expenditure boosts aggregate demand, which may lead to more imports than exports and therefore, more demand for foreign currency, and eventually the depreciation of real exchange rate. However, if higher expenditure is associated with increased taxes, its impact would be neutralised. The debt position of the current period captures debt financed public expenditure or the excess of expenditure over revenues $(debt_t = debt_{t-1} + deficit_t)$. Apart from the impact channelised through demand, an increase in public expenditure results in higher deficit and public debt, which can influence the exchange rates due to higher country risk premium (RBI, 2019). The increase in public debt may cause higher interest rate which may lead to a surge in capital flows and the appreciation of exchange rate. The implications of public debt for country risk premium and interest rate are important for EMEs, particularly for countries like India where debt-GDP ratio is higher than the recommended levels (RBI, 2022). Therefore, we use debt-GDP ratio to assess the impact of fiscal policy on exchange rate.

As mentioned earlier, the size of net foreign assets (*nfa*) is an important determinant considered in empirical literature and is found to be positively associated with REER. Intuitively, higher foreign liabilities increase interest and non-interest payments from the country, necessitating surplus in the current account through currency depreciation to finance additional payments. Improvements in net terms of trade are generally found to be positively associated with real exchange rate due to the income effect being stronger than the substitution effect. Favourable export prices *vis-à-vis* trading partners increase domestic income to be spent on tradables and non-tradables, which

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5 However, some studies have also considered relative price indices.

may lead to inflationary pressures. While the prices of tradables are generally externally determined and thus remain largely unaffected, domestic prices of non-tradables generally respond positively to changes in export prices. By contrast, higher export prices may gradually reduce foreign demand for tradable goods and, therefore, resource diversion to non-tradable sectors reduces inflation in the economy which, in turn, causes depreciation in real exchange rate of local currency. Finally, as alluded earlier, short-term interest rate is also argued to be an important determinant of the exchange rate (MacDonald 1997; and Clark and MacDonald 1998). The uncovered interest rate parity theory suggests that high domestic interest rate relative to foreign interest rate would lead to depreciation of domestic currency against foreign currency. In view of the above discussion and following literature on equilibrium exchange rate (Couharde *et al.,* 2017, Fidora *et al.,* 2017, and Giannellis and Koukouritakis, 2018), we consider the following form of BEER model.

$$LREER_{it} = \alpha_i + \beta_1(y_{it}/y_{it}*) + \beta_2 nfa_{it} + \beta_3 tot_{it} + \beta_4(r_{it} - r_{it}*) + \beta_5 debt_{it} + \varepsilon_{it} \quad ...(3)$$

where, *LREER* is the log of CPI based REER index with base year 2010 obtained from the Bank for International Settlements (BIS). These are weighted indices based on time varying trade weights with 59 trading partners. $y_{it}/y_{it}*$, *i.e.,* relative per capita GDP, is calculated as:

$$y_{it}/y_{it}* = \frac{y_{it}}{\sum_{j=1}^{n}(y_{jt})W_{ij,t}}$$

where, y_{it} is the real per capita GDP of country 'i' at time 't', and $W_{ij,t}$ is country i's trade weight for its trading partner 'j'. y_{jt} is per capita GDP of 'j'th trading partner at time 't'. Thus, foreign per capita GDP ($y_{it}*$) is represented by weighted average of per capita GDP of 59 trading partners. We have used BIS trade weights matrix of 60 countries to make weights of per capita GDP consistent with those of REER. The data on real per capita GDP (*i.e.*, PPP-adjusted per capita GDP in US dollar) are obtained from the World Bank database.

In equation 3, 'r' represents domestic real interest rate and r* is foreign real interest rate, and r_{it}-r_{it}* is the interest rate differential between domestic and foreign interest rate. Foreign interest rate is proxied by interest rates in the US. Further, we use two types of interest rates to calculate the interest rate differential – short-term interest rate differential and long-term interest rate differential. For calculating the long-term real interest rate differential, interest rate (lending rates of banks) data are sourced from the World Bank, and the GDP deflators are used to convert them into real interest rate. For calculating the short-term real interest rate differential, money market rate and CPI based inflation data obtained from the IMF are used.

Variable '*nfa*' in equation 3 is net foreign assets as a ratio to GDP. Net foreign assets data are sourced from 'External Wealth of Nations' database of Lane and Milesi-Ferretti (2017). Nominal GDP available in World Bank database is used for computing net foreign assets to GDP ratio. '*tot*' stands for natural logarithm of terms of trade index (June 2012=100) which is obtained from the IMF database (Gruss and Kebhaj 2019). It is the commodity net export price index (weighted by net exports to GDP). '*debt*' stands for public debt to GDP ratio which is obtained from IMF's 'Global Debt Database', historical debt database and Fiscal Monitor (October 2021). Sample used for empirical estimation in this paper consists of annual data from 1994 to 2020 for ten countries, *viz.,* Brazil, China, India, Indonesia, Korea, Malasiya, Philippines, Russia, South Africa and Thailand. Thus, our sample includes all BRICS countries which account for 24 per cent of world GDP and 16 per cent of world trade, and other major emerging market economies in Asia.

Section V
Empirical Results

As the choice of econometric method depends largely on time series properties of the data, we checked stationary property of variables by using panel unit root tests, *viz.,* Levin-Lin-Chu (LLC), Im-Pesaran-Shin (IPS) and cross-sectionally augmented IPS (CIPS) test proposed by Pesaran (2007). While the null hypothesis in LLC test assumes common unit root process, in IPS test, the null hypothesis assumes individual unit root process, *i.e.,* all panels contain unit roots. LLC and IPS test are widely used and are first-generation panel unit root test, however, CIPS test which accounts for cross-sectional dependence is considered as second generation panel unit root test. The size of estimated panel unit root test can be affected by the cross-sectional dependence in data (Annex 1) and thus the CIPS test is recommended (Banerjee *et. al,* 2005). The results of LLC, IPS and CIPS tests are provided in Table 1 which reveal that the null hypothesis of unit root cannot be rejected for log of REER *(LREER),* relative per capita GDP, terms of trade, debt and net foreign assets, when the variables are used in level form. However, upon first differencing, all these variables are found to be stationary. On the other hand, short-term and long-term interest rate differentials are found to be stationary at levels as well as in the first difference form. Overall, the results indicate that most of the variables are non-stationary at levels in at least one test but all the variables used in the first difference form are found to be stationary in all three tests. Further, the results of cross-sectionally augmented CIPS test are consistent with LLC and IPS tests. In the context of REER, unit root testing assumes special significance as stationary REER can be considered as an evidence of equilibrium exchange rate, if the productivity growth in a country *vis-à-vis* its trading partners is stable.

To ascertain an evidence on the cause-and-effect relationship between *LREER* and its potential determinants, causality test developed by Dumitrescu and Hurlin (2012) is undertaken. The null hypothesis (H_0) in Dumitrescu and Hurlin test is 'no causal relationship'. The results of causality test shown in Annex 2 indicates unidirectional causality running from relative per capita GDP (y_{it}/y_{it}*), terms of trade *(tot)*, public debt *(debt)* and interest rate differential *(ST_USA)* to log of REER *(LREER)*. However, there is an evidence of bi-directional causality between net foreign assets (*nfa*) and *LREER* which is possibly reflecting J-curve effect as the stock of net foreign assets is largely a reflection of accumulation of current account balance[6].

In view of the above results of panel unit root tests, we examine the long-run relationship of REER with its macroeconomic fundamentals. Accordingly, we use panel cointegration tests developed by Kao (1999), Pedroni (1999 and 2004) and Westerlund (2007). Westerlund (2007) test differs from the other two tests in terms of the alternative hypothesis *i.e.,* 'some panels are cointegrated', as against the alternative hypothesis 'all panels are cointegrated'

[6] J-curve effect shows depreciation causing deterioration in trade balance/current account balance in the short-run and improvement in the long-run as the demand becomes more price elastic.

Table 1: Results of Panel Unit Root Tests
(Sample period: 1994-2020)

Variable	Level			First difference		
	LLC t statistic	**IPS W statistics**	**CIPS T statistic**	**LLC t statistic**	**IPS W statistic**	**CIPS T statistic**
LREER	-0.39	-1.27	-1.93	-4.74***	-5.57***	-3.06***
y_{it}/y_{it}*	3.52	0.63	-1.21	-1.75**	-3.05***	-3.04**
	(1.00)	(0.74)		(0.04)	(0.00)	
tot	0.07	0.29	-1.37	-1.86**	-3.53***	-4.37***
	(0.53)	(0.61)		(0.03)	(0.00)	
nfa	0.06	1.22	-1.67	-2.94***	-5.40***	-3.27***
	(0.52)	(0.89)		(0.00)	(0.00)	
debt	1.81	-0.77	-0.93	-5.87***	-2.88***	-3.09***
	(0.97)	(0.22)		(0.00)	(0.00)	
ST_USA	-6.16***	-3.74***	-2.88***	-16.59***	-10.93***	-9.08***
	(0.00)	(0.00)		(0.00)	(0.00)	
LT_USA	-4.57***	-4.61***	-3.87***	-12.64***	-8.04***	-5.36***
	(0.00)	(0.00)		(0.00)	(0.00)	

LLC: Levin-Lin-Chu (2002); IPS: Im-Pesaran-Shin (2003); CIPS: Cross-sectionally augmented IPS
***, **, * indicate statistical significance at 1 per cent, 5 per cent and 10 per cent levels, respectively.

Note: 1. For the LLC test, the null hypothesis is 'panels contain unit roots'; for the IPS and CIPS it is 'all panels contain unit roots'.
2. Lag length selection based on AIC.
3. ST_USA: Short-term real interest rate differential with USA; and LT_USA: Long-term real interest rate differential with USA.

in Kao (1999) and Pedroni (1999 and 2004) tests. Further, the Westerlund test is error-correction based and accounts for possible cross-sectional dependence (Cheik and Cheik, 2013). In our baseline model, all the three tests confirm cointegration, suggesting the presence of a long-run equilibrium relationship between REER and relative per capita GDP in EMEs (Table 2). In the next step, we augment our model sequentially by incorporating additional variables in alternative specifications. The presence of cointegrating relationship between REER and its determinants is observed across all the augmented specifications. In the most augmented model, the cointegration between *LREER* and other variables such as net foreign assets, terms of trade, interest rate differential and debt-GDP ratio has been confirmed.

Table 2: Panel Cointegration Test Results

Variables	Kao test ADF	Pedroni test							Westerlund Test
		Within-dimension (Panel)				Between-dimension (Group)			
	t-statistic	Panel v-Statistic	Panel rho-statistic	Panel PP t statistic	Panel ADF t tatistics	Group rho-statistic	Group PP t statistic	Group ADF t tatistics	Variance Ratio statistic
LREER, y_{it}/y_{it}^*	-3.33***	4.16***	-2.82***	-3.38***	-3.97***	-1.05	-2.88***	-4.26***	-2.02**
LREER, y_{it}/y_{it}^*, *nfa*	-3.31***	3.88***	-2.34***	-4.14***	-4.50***	-0.35	-3.03***	-3.89***	-1.88**
LREER, y_{it}/y_{it}^*, *nfa*, *tot*	-3.54***	2.91***	-1.05	-2.84***	-3.51***	0.77	-2.15**	-3.61***	-2.24***
LREER, y_{it}/y_{it}^*, *nfa*, *tot*, *debt*	-3.93***	2.11**	-0.33	-4.12***	-5.39***	1.43	-5.90***	-6.16***	-2.18***
LREER, y_{it}/y_{it}^*, *nfa*, *tot*, *debt*, *ST_USA*	-4.04***	0.90	0.81	-3.48***	-3.21***	2.31	-4.44***	-4.81***	-1.76**
LREER, y_{it}/y_{it}^*, *nfa*, *tot*, *debt*, *LT_USA*	-4.08***	0.59	0.99	-3.10**	-4.37***	2.43	-3.39***	-4.53***	-1.53*

Note: ***, **,* indicate statistical significance at 1 per cent, 5 per cent and 10 per cent levels, respectively.

After confirming cointegration, panel Dynamic Ordinary Least Square (DOLS) model is estimated to obtain the coefficient of each determinant (Table 3). Fully Modified Ordinary Least Square (FMOLS) method proposed by Phillips and Hansen (1990) or DOLS proposed by Stock and Watson (1993) are consistent in the event of endogeneity and serial correlation as against potentially inconsistent OLS. Kao and Chiang (2000), Mark and Sul (1999, 2003), and Pedroni (2001) proposed extensions of DOLS estimator to panel data settings. While FMOLS follows a non-parametric approach, panel DOLS uses cross-section specific leads and lags of first difference of independent variables to take care of asymptotic serial correlation and endogeneity. While estimating DOLS, pooled (weighted) estimator is chosen which also accounts for heterogeneity across cross-sections. It uses cross-section specific estimates of the conditional long-run residual variances to reweight the moments for each cross-section. As a robustness check of the empirical results, FMOLS estimator

Table 3: Determinants of REER - Results of DOLS/FMOLS estimation

Model	DOLS	FMOLS	DOLS	FMOLS	DOLS	FMOLS	DOLS	FMOLS	DOLS	FMOLS
	1	2	3	4	5	6	7	8	9	10
y_{it}/y_{it}^*	1.99*** (7.44)	1.72*** (4.02)	2.24*** (5.76)	1.92*** (6.31)	2.36*** (6.33)	1.85*** (7.61)	1.09*** (3.27)	1.43*** (5.37)	1.43*** (5.94)	1.44*** (10.06)
nfa			0.39*** (4.16)	0.42*** (4.07)	0.41*** (3.54)	0.41*** (4.98)	0.40*** (3.26)	0.33*** (4.11)	0.59*** (7.87)	0.33*** (8.31)
tot					0.90** (2.08)	1.23*** (4.11)	0.81** (2.18)	0.87*** (2.91)	0.99*** (3.70)	0.89*** (5.61)
debt							-0.003** (-2.85)	-0.003*** (-3.57)	-0.003** (-3.99)	-0.002** (-5.12)
ST_USA									0.02*** (7.70)	0.003*** (4.15)
R^2	**0.71**	**0.65**	**0.81**	**0.68**	**0.87**	**0.71**	**0.94**	**0.73**	**0.95**	**0.77**
Adjusted R^2	**0.61**	**0.61**	**0.70**	**0.64**	**0.74**	**0.67**	**0.82**	**0.69**	**0.80**	**0.74**

Note: 1. Figures in brackets are t-statistics.
2. ***,** and * indicates statistical significance at 1 per cent, 5 per cent and 10 per cent levels, respectively.

is also used (Table 3). Further, due to a mix of stationary and non-stationary variables (interest rate differential is found to be stationary both at levels and in first differenced form), panel ARDL model is applied as an additional 'safety net' (Table 4).

In Table 3, columns 1 and 2 provide results of the baseline model where relative per capita GDP *(y_{it}/y_{it}^*)* is the only explanatory variable of REER. Per capita GDP is found to be a significant determinant of REER, both statistically and numerically. This finding is consistent with higher productivity growth of EMEs than that of AEs as explained in section II and thus it indicates the presence of the BS effect. In the next step, the model is augmented to include net foreign assets (columns 3 and 4). The coefficient of net foreign assets *(nfa)* is having an expected sign and it is statistically significant. Further, the coefficient of terms of trade *(tot)* added with per capita GDP and *nfa* (columns 5 and 6) is found to be statistically significant. This was followed by adding debt to GDP ratio as an additional determinant. An increase in debt to GDP ratio, as *a priori* expected, is found to have a depreciating effect on REER (columns 7 and 8), substantiating the inverse relationship between the two, possibly reflecting the adverse effects on exchange rate channelised through (i) expansionary fiscal policy, and (ii) country risk premium. Finally, to examine the impact of interest rate differentials, we use two proxies of real interest rate

Table 4: Results of ARDL Model

Variables	1	2	3	4	5
y_{it}/y_{it}*	2.22*** (6.51)	3.26*** (9.77)	3.46*** (11.71)	1.89*** (7.44)	1.30*** (5.19)
nfa		0.64*** (9.37)	0.60*** (10.82)	0.27*** (4.33)	0.32*** (5.11)
tot			0.68* (1.89)	0.19 (0.77)	0.53** (2.21)
debt				-0.004*** (-6.78)	-0.005*** (-7.91)
ST_USA					0.004** (2.03)
Error correction term	***-0.43*** (-7.91)***	***-0.48*** (-4.07)***	***-0.50*** (-3.96)***	***-0.57*** (-4.94)***	***-0.51*** (-5.68)***

Note: 1. ***, ** and * indicate statistical significance at 1 per cent, 5 per cent and 10 per cent levels, respectively.
2. Figures in brackets are t-statistics.

differentials, *viz.,* short-term interest rate differential with USA *(ST_USA)*, and long-term interest rate differential with USA *(LT_USA)*. However, only short-term real interest rate differential with USA is found to be statistically significant. The results of FMOLS and DOLS with respect to the sign and magnitude of independent variables in explaining REER are broadly similar. Further, due to stationarity properties of interest rate differentials, empirical estimation using the panel ARDL model as proposed by Pesaran *et al*. (1999) for the same set of dependent and explanatory variables is undertaken. The coefficients of most of the variables are broadly similar in terms of the sign, their magrnitude and the statistical significance (Table 4). The error correction term of panel ARDL model is found to be negative and statistically significant.

Section VI
Trend in Equilibrium REER and the Extent of Misalignments

As alluded earlier, overvaluation or undervaluation of the real exchange rate of EME currencies has always attracted attention of policymakers. Persistent undervaluation of exchange rate is considered as a mercantilist policy where a country by intervening in the foreign exchange market devalues exchange rate for export promotion. On the other hand, overvaluation of exchange rate such as during surges in capital inflows adversely affects exports and domestic employment. Therefore, an assessment of exchange rate compared to its equilibrium value assumes importance. Predicted value obtained from estimated model as given in column 9 in Table 3 is considered as equilibrium REER level which is compared with actual REER to assess the extent of misalignment of each currency.[7] Accordingly, the difference between the actual REER and the equilibrium REER is called as misalignments *i.e.,* overvaluation or undervaluation.

Misalignment = Actual REER – Equilibrium REER

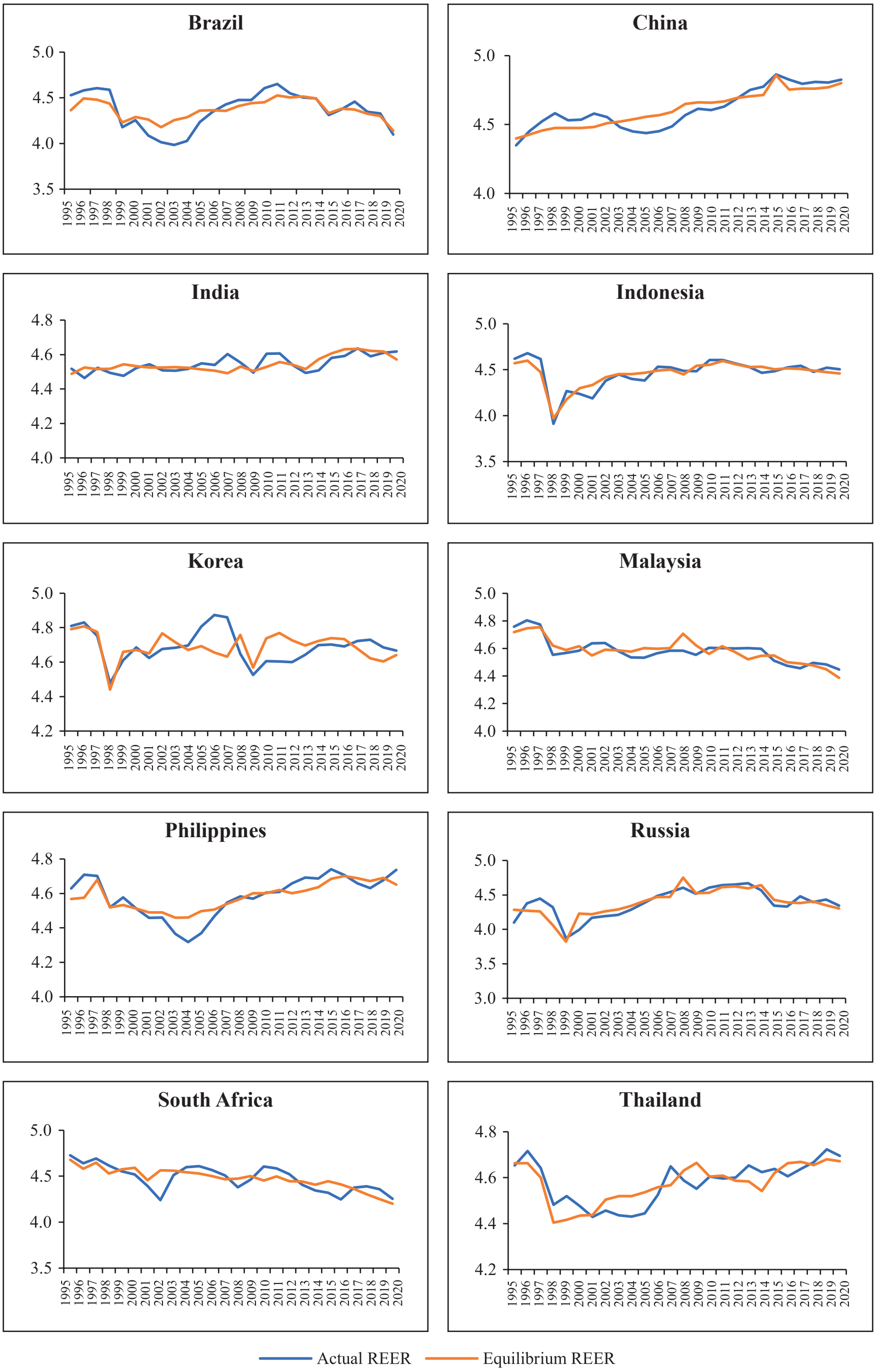
Overvaluation = Actual REER > Equilibrium REER

Undervaluation = Actual REER < Equilibrium REER

The comparison of actual and equilibrium values as shown in Chart 5 provides several attributes of REER behaviour in EMEs. *First,* the trend in actual REER in most of the sample countries is in sync with their respective paths of equilibrium values implying exchange rate being driven by macroeconomic fundamentals (Chart 5). *Second,* the diverging trend in equilibrium REER across the EMEs (*i.e.,* equilibrium REER increased in some countries and decreased in other countries) over the sample period is largely showing an impact of structural changes, *viz.,* productivity growth, confirming presence of the BS effect among EMEs. For example, uptrend in both actual and equilibrium REER in China, India, Philippines and Thailand is in line with their higher relative per capita GDP growth. On the other hand, South Africa and Brazil which witnessed lower growth in their relative per capita GDP also recorded decline in their actual and equilibrium REER. *Third,* misalignment of REER *i.e.,* deviation from equilibrium value, is lower and remained range-bound at around 2-3 per cent. *Fourth,* the misalignment is asymmetric across EMEs. For example, actual REER of China, Philippines and Thailand during 2000s generally remained lower than the equilibrium values, while in India and South Africa, it remained above the equilibrium level. The countries experiencing overvaluation in post-GFC years, *viz.,* Brazil, India and Philippines recorded relatively higher inflation, while those having undervaluation, *viz*., China and Korea, recorded relatively lower inflation. In view of this, the REER misalignment [defined

[7] Equilibrium value obtained as per this method is sensitive to the choice of model and variables used and thus, is subject to the assumptions of model specification and limitations (Clark and Macdonald 1998; Fidora *et al*., 2017; Giannellis and Koukouritakis, 2018).

Chart 5: Actual and Equilibrium Values of REER (in logarithm)



as, log (REER) – log (equilibrium REER)] was regressed upon changes in log of NEER and change in relative prices. Results based on panel ordinary least square estimation shown in Annex 3 indicate that the REER misalignment in EMEs is driven by changes in NEER. However, country-specific regressions indicate that the change in relative prices (*vis-à-vis* trading partners) is the major factor leading to misalignment in Brazil and India. On the other hand, the NEER is found to influence REER's misalignment in Philippines and South Africa. *Fifth,* EMEs witnessed sharp movements in both actual and equilibrium REER during macro-financial shocks such as the East Asian Crisis and the Global Financial Crisis. These results with respect to equilibrium REER and the rate of misalignment are broadly similar to Giannellis and Koukouritakis (2018) and Banerjee and Goyal (2020).

Section VII
Conclusion

Against the backdrop of inconclusive empirical evidence in the literature with regard to the equilibrium exchange rate, this paper provides an estimate of equilibrium REER for select EMEs. Using annual data from 1994 to 2020 for ten EMEs, the paper finds that persistent appreciation/depreciation in REER in the long-run is consistent with the equilibrium level as determined by macroeconomic fundamentals. For example, an increase in the level of the equilibrium REER in some countries reflects the presence of the Balassa-Samuelson effect. Improvements in net terms of trade and net foreign assets are found to cause REER appreciation. However, expansionary fiscal policies may be associated with higher country-risk premium, as evident from an inverse relationship between debt-GDP ratio and REER. The impact of interest rate differential is found to be positive.

The comparison of actual and equilibrium REER levels suggests that the REER is being determined by macroeconomic fundamentals and the misalignment (overvaluation/undervaluation) is usually within a narrow range of +/- 3 per cent. Like most EMEs, India's REER also showed two-way movements around its equilibrium value, implying no evidence of currency manipulation or mercantilist undervaluation. Thus, the observed upward co-movements of actual and equilibrium REER in some EMEs like India and China shows the productivity driven increase in REER, which is not a sign of loss of external competitiveness.

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Annex 1: Cross-Sectional Dependence Test

Variable	Breusch-Pagan LM Test	Pesaran Scaled LM Test	Bias-Corrected Scaled LM Test	Pesaran CD
LREER	191.79***	15.47***	15.28***	6.06***
$y_{it}/y_{it}*$	946.61***	95.04***	94.85***	30.52***
tot	762.24***	75.60***	75.41***	-1.10
nfa	355.55***	32.73***	32.54***	9.51***
debt	282.78***	25.06***	24.87***	4.00***
ST_USA	131.52***	9.12***	8.93***	2.81***
LT_USA	144.93***	10.53***	10.34***	4.55***

*** indicate statistical significance at 1 per cent level.

Note: ST_USA: Short-term real interest rate differential with USA; and LT_USA: Long-term real interest rate differential with USA.

Annex 2: Panel Causality Test Results

Null Hypothesis	Pair-wise Dumitrescu and Hurlin Panel Causality Tests		
	W-statistic	Z-bar statistic	P-Value
Relative per capita GDP ($y_{it}/y_{it}*$) does not homogeneously cause *LREER*	6.09	4.93	0.00
LEER does not homogeneously cause Relative per capita GDP ($y_{it}/y_{it}*$)	1.66	-0.72	0.47
nfa does not homogeneously cause *LREER*	7.68	6.94	0.00
LREER does not homogeneously cause *nfa*	5.50	4.17	0.00
tot does not homogeneously cause *LREER*	3.75	1.95	0.05
LREER does not homogeneously cause *tot*	2.28	0.08	0.94
debt does not homogeneously cause *LREER*	8.86	8.44	0.00
LREER does not homogeneously cause *debt*	1.71	-0.65	0.51
ST_USA does not cause homogeneously *LREER*	9.30	9.01	0.00
LREER does not homogeneously cause *ST_USA*	2.73	0.65	0.52

Notes: lag length (2 lags) is selected based on AIC.

Annex 3: Results of drivers of misalignment

[Dependent variable misalignment = log (REER) – log (equilibrium REER)]

Panel of 10 countries			
	Change in log(NEER)	***Change in relative prices***	***Constant***
	0.11** (2.40)	0.07 (1.06)	0.003 (0.58)
Cross-Section specific coefficients			
Country	***Change in log(NEER)***	***Change in relative prices***	***Constant***
Brazil	0.22 (1.34)	0.35** (2.45)	-0.001*** (0.04)
China	0.32 (1.31)	-0.43 (-0.62)	-0.007 (-0.43)
India	0.07 (0.44)	0.67*** (2.87)	-0.005 (-0.51)
Indonesia	0.09 (1.19)	0.04 (0.25)	0.007 (0.59)
Korea	0.10 (0.40)	-0.18 (-0.11)	0.002 (0.01)
Malaysia	0.23 (1.24)	-1.52 (-1.59)	0.004 (0.38)
Philippines	0.37* (1.89)	0.47 (0.55)	-0.001 (-0.05)
Russia	-0.11 (-0.73)	-0.23 (-1.32)	0.02 (0.78)
South Africa	-0.26** (-2.26)	-0.40 (-0.62)	0.001 (0.03)
Thailand	0.19 (0.84)	0.90 (1.09)	-0.001 (-0.16)

Note: 1. ***, ** and * indicate statistical significance at 1 per cent, 5 per cent and 10 per cent levels, respectively.
2. Figures in brackets are t-statistics.

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India's Innovation Ecosystem for Productivity-led Growth: Opportunities and Challenges

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Research and Development (R&D) has been considered as a major driver of productivity to achieve higher economic growth. The low participation of the private corporate sector in R&D activities continues to pose a major challenge, despite significant government initiatives undertaken to strengthen India's innovation ecosystem. A panel data analysis covering ten emerging market economies and eleven advanced economies shows that a country's quality of institutions (intellectual property rights, addressing inefficiencies in the legal framework for settling disputes and challenging regulations, and easing of doing business conditions), physical and financial infrastructure, extent of downstream commercialisation (proxied by high-tech exports) and the degree of openness can influence R&D expenditure. Going ahead, further improvements on business regulations, investment in human capital and addressing a range of bottlenecks affecting stalled projects could help to strengthen the innovation ecosystem in India.

JEL Classification: O31, O38, O47

Keywords: Innovation, Research & Development, Productivity

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Introduction

The Indian economy witnessed a slowdown in economic growth during 2017-18 to 2019-20 as India's average annual growth of GDP fell to 5.7 per cent during this period after growing at an average rate of 7.9 per cent during 2014-15 to 2016-17. Evidence based on India's KLEMS (Capital, Labour, Energy, Materials, and Services) data suggests that this slowdown was mostly driven by the slowdown in total factor productivity (TFP) growth, which broadly measures the growth rates in technology and productivities in an economy. The contribution of TFP to India's aggregate GDP growth has come down from over 30 per cent to 13 per cent between 2014 and 2017. The neo-classical branch of economics pioneered by Solow (1956), and subsequent literature in endogenous growth theories established that TFP growth is the key driver of economic growth in the long run. More recent empirical studies (*e.g.*, OECD, 2015; ADB, 2017) found empirical support for these hypotheses. Therefore, the slowdown in India's TFP growth and its shrinking contribution to aggregate GDP growth raises some doubts about the sustainability of India's growth over the long-term.

The endogenous growth theories popularised since the mid-1980s have brought in the concept of productivity of an economy as an endogenous process where investments in human capital, knowledge-based capital, and innovation capacities assume precedence. The endogenous growth models linking innovation to growth were developed in three distinct phases. In the first phase, the AK model of growth hypothesised that higher growth rates of an economy depend on thrift, some of which would finance higher productivity and lead to growth (Romar, 1987; Rebelo, 1991). In the second phase, the endogenous growth model developed by Romar (1990) hypothesised that innovation drives the development of new varieties of intermediate goods, and the greater supply and variety of innovative intermediate goods leads to higher growth. In the third phase, endogenous growth models followed the Schumpeterian approach, where vertical innovations would drive technological knowledge, increase productivity and generate economic growth. Innovation in these Schumpeterian approach-based models is a result of investment in research and development activities.

As innovation forms an important pillar for raising productivity, emerging economies have rapidly increased their policy attention to innovation in recent years. India has shown significant advancement in transforming its economy into a knowledge-based economy and turned into one of the prominent global hubs of offshore Information Technology related activities. India has also performed remarkably well in exports of Information and Communication Technology (ICT) based services. Several momentous reforms directed at enhancing the production capacity and raising the trend growth trajectory of the economy are also introduced from time to time. India, however, lags in terms of its expenditure on Research and Development (R&D) relative to other major economies in both public and private sectors (OECD, 2015).

Against this backdrop, the paper reviews the progress of innovation activities in India compared to other emerging and developed countries in the recent decade. The main objective of the study is to motivate policy discussions on the state of innovation activities in India. We, therefore, document the more recent patterns of R&D expenditures across countries, and how they compare with the institutions, human, and physical capital across countries. To the best of our knowledge, the latest coverage on India's aggregate R&D expenditure along similar lines was done by Herstatt *et al*. (2008). In this paper, we aim to provide an updated comparison of India's aggregate R&D expenditure *vis-à-vis* the global leaders and peer countries focusing on the recent decade. An attempt has been made to assess whether the R&D expenditures in aggregate and by the businesses align with several macroeconomic factors like quality of institutions, physical and financial infrastructure, stages of external openness, *etc*. using data on 21 major emerging and advanced nations between 2007 and 2016. Although our empirical framework broadly follows Furman *et al.* (2002), to the best of our knowledge, our paper is the first attempt to look at a mixed sample of both emerging and developed nations on this topic[1]. Even with a mixed sample of developing and developed countries, we find evidence that the variation in R&D expenditure arises due to the quality of institutions, degree of external openness, and level of downstream commercialisation in respect of exports and absorptive capacity.

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1 Furman *et al.* (2002) looked at only the OECD countries.

The study is divided into seven sections. Section II provides a brief review of the literature. Section III presents some stylised facts on the status of innovation activities in India and related challenges at an aggregate level. In Section IV, macroeconomic factors explaining the stylised facts have been analysed. Section V describes the data and method of the emperical model. Section VI presents the results. In Section VII, the government measures taken so far in India to boost innovations are discussed. Section VIII concludes the paper with policy suggestions.

Section II
Review of Literature – Innovation for Productivity led Growth

Innovation is the primary driver of long-term productivity growth and development (Schumpeter, 1934; Freeman and Louçã, 2001). Despite being risky, and prone to failure, innovation is still essential for boosting a firm's survival, competitiveness, and market power (Porter, 1990; Dodsgon, 2017). Many empirical studies have tried to find the relationship between indicators of innovation (namely R&D expenditure and patenting) and productivity growth. For instance, Westmore (2013) for a set of 19 OECD countries, found a positive link between innovation intensity, and multifactor productivity. Donselaar and Koopmans (2016) established that a 10 per cent increase in R&D investment leads to productivity gains in the range of 1.1 – 1.4 per cent. Coe *et al.* (2009) found for a sample of 22 developed countries that productivity gains through R&D activities depend on the domestic stock of knowledge as well as R&D spillovers from foreign countries.

Some cross-country studies find a virtuous circle where innovation, productivity, and growth reinforce each other. Galindo and Mėndez (2014) using panel data for 13 developed countries for the period 2002 to 2007, examined the relationship between three variables- entrepreneurship, innovation, and economic growth. The analysis of the study shows that innovation and entrepreneurship have a positive effect on economic growth and also there exists a circular relationship whereby all variables exert a positive effect on each other. Economic activity encourages entrepreneurship and innovation, which in turn, again enhances economic activity. Using firm-level micro data and innovation surveys, Crespi and Zuniga (2012) find a positive association between technological innovation and labour productivity for six Latin American countries- Argentina, Chile, Columbia, Costa Rica, Panama, and Uruguay. For developing countries, a positive association between innovation and productivity has also been found for Malaysia (Hegde and Shapira, 2007); Taiwan (Yan Aw, Roberts, and Yi Xu, 2008); China (Jefferson, Huamao, Xiaojing, and Xiaoyun, 2006); Argentina (Arza and Lo´pez, 2010); and Brazil (Raffo, Lhuillery, and Miotti, 2008).

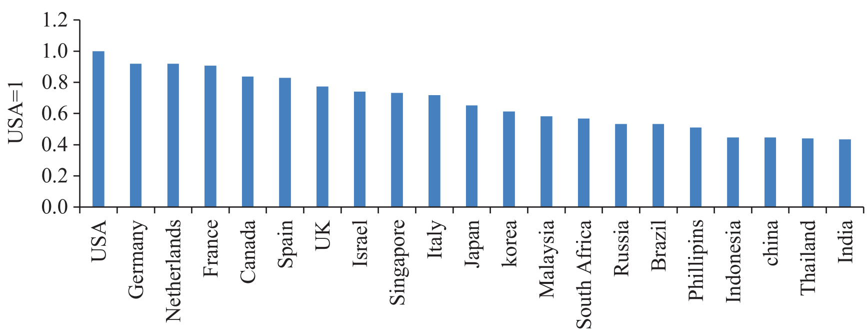
Contrary to the above findings, many recent studies have contested that there exists an 'innovation-productivity paradox', which shows that despite rapid progress in existing new technologies like artificial intelligence, digitalisation, and robotics, the trend of global productivity slowdown continues with no signs of reversal in the near short term (Bitard, Edquist, and Hommen, 2008; Lengyel and Leydesdorff, 2011; Fragkandreas, 2013; Fragkandreas, 2021). Studies find that an ageing population, increase in capital deepening, reduced dependence on global value chains, rising income inequalities, and declining business dynamism have led to productivity slowdown worldwide (Syverson, 2017; Crafts, 2018; Goldin *et al*., 2020).

Various studies have tried to identify the factors that drive innovation. The literature shows that firm-level innovation is affected by the development of financial markets (Amore, Schneider, and Zaldokas, 2013; Cornaggia, Mao, Tian, and Wolfe, 2015), institutional ownership (Aghion *et al*., 2013), bankruptcy laws (Acharya and Subramaniam, 2009) and labour laws (Acharya *et al.,* 2014). Although the literature on factors influencing innovation is quite vast, it is very limited for India. One pioneering study made for India is Herstatt *et al.* (2008) which examined the elements and inherent strengths and weaknesses of India's innovation system, particularly in knowledge-intensive sectors. Kale and Rath (2018) is another macro-level study that constructs an innovation index at an aggregate level and finds a cointegrating relationship between innovation and total factor productivity for India. There are some other studies available for India but those are at the firm level. For instance, studies by Parameswaran (2009), Goldberg *et al.* (2010), and Topalova and Khandelwal (2011) for manufacturing firms have found that the import of foreign technology has a positive impact on a firm's productivity. Studies have shown that R&D investment leads to a higher market value of a firm's stocks than investment in tangible assets (Chadha and Oriani, 2009). Most of these studies are sector-specific covering pharmaceutical and electronic industry sectors (Sarkar and Sarkar, 2005; Chatterjee, 2007) and do not cover the macro scenario that affects innovation capacity across all sectors of the economy. To fill this gap in the literature, this paper analyses the macroeconomic determinants of innovation with a special focus on India. It is important to note here that this paper does not look into innovation -productivity linkage but tries to identify the macroeconomic characteristics that affect the innovation capacity of a country. The empirical analysis in the paper takes R&D expenditure for a set of countries as a proxy for innovation and tries to understand the association of R&D expenditure with macroeconomic characteristics like strengths of a country's institutions, physical and financial infrastructures, quality of governance, human and physical capitals, and absorptive capacities.

Section III
Stylised Facts

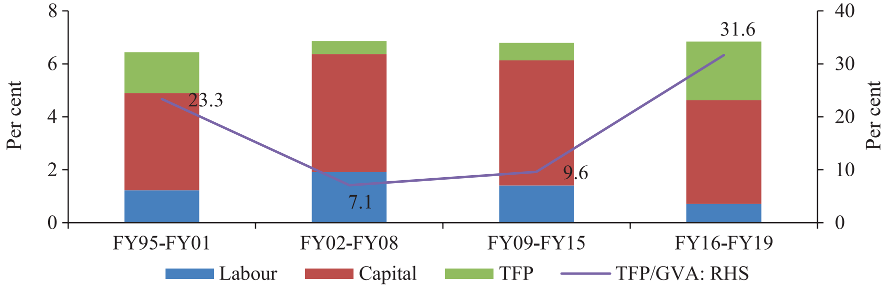
Better productivity performance of a nation can be directly linked with higher innovation activities (Hall, 2011). To set the context of our paper, we first compare the total factor productivity (TFP) indices for the years 2014-19 with the base year 1950 for major countries (Chart 1). It shows that India's TFP remained below the major developed and emerging economies in this period. In terms of productivity contribution to output growth, during 1995-2001, TFP accounted for about 23 per cent of the aggregate GDP growth in India (Chart 2). This ratio fell to below 10 per cent between 2002 and

Chart 1: Total Factor Productivity (Base=1950): 2014-19



Note: In Chart 1, contributions of labour and capital are estimated by multiplying the year-on-year growth in factor inputs with their income share in GVA. TFP growth is the residual term. Labour and capital are adjusted for their quality.
Source: Authors' calculation based on KLEMS database and Penn World Table 10.0.

Chart 2: Contribution of Factor Inputs and TFP to GVA Growth (India): 1995-2019

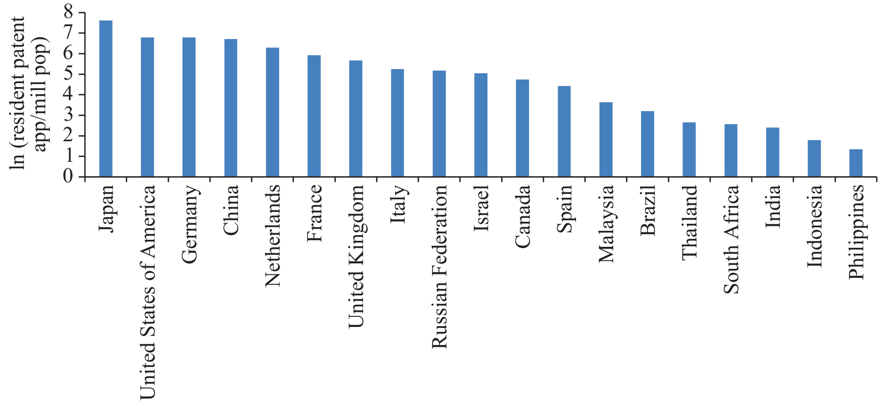


Note: In Chart 1, contributions of labour and capital are estimated by multiplying the year-on-year growth in factor inputs with their income share in GVA. TFP growth is the residual term. Labour and capital are adjusted for their quality.
Source: Authors' calculation based on KLEMS database and Penn World Table 10.0.

2015. Notably, between 2000 and 2011, India witnessed a significantly high rate of growth in aggregate GDP, barring two years of the Global Financial Crisis. This incremental growth was driven largely by factor accumulation, mainly the capital stock. The role of technological progress and productivity in aggregate growth has been, in fact, muted in recent decades.

Chart 3 indicates that India ranks very low in terms of patent applications. The filing of Intellectual Properties (IP) in categories of trademarks and industrial designs during the last decade has remained far below that of other

Chart 3: Resident Patent Application (2014-19 average)



Source: World Intellectual Property Organization (http://data.uis.unesco.org/#).

major economies (Table 1). Although the levels of patent applications have been lower in India than in other countries, but opportunities do remain. The Intellectual Property Patent and Trademark filings by India have grown on an average by 9.8 per cent and 8.5 per cent per year in the year 2007 and 2019, respectively, much faster than the developed countries such as the USA, the UK, Japan, and Germany. In the category of Industrial design too, India has experienced an annual average growth of 6.8 per cent during the same period (Table 1).

The innovation process in India is plagued by low investment. The R&D expenditures in India stood at 0.68 per cent of GDP between 2014 and 2018, compared with, for example, over 2 per cent for both China and Singapore, and over 3 per cent for Japan and Israel (Chart 4a)[2]. The participation by

Table 1: IP Fillings (Residents+ Abroad)
(in '000)

Types	Year	2007	2010	2014	2017	2018	2019	Annual Average Growth between 2007 and 2019 (per cent)
Patent	India	10.5	14.9	22.4	28.0	30.0	34.1	9.8
	China	161.3	308.3	837.8	1306.1	1460.2	1328.1	17.6
	USA	437.7	433.1	509.5	525.5	515.2	521.7	1.5
	UK	50.1	50.9	52.6	53.8	56.2	54.8	0.8
	Japan	508.3	468.4	466.0	460.8	460.4	453.8	-0.9
	Germany	163.9	173.7	179.5	176.4	180.1	178.4	0.7
Trademark	India	125.1	181.6	218.8	262.0	319.2	348.7	8.5
	China	656.7	1054.8	2147.4	525.9	606.8	642.8	-0.2
	USA	780.7	726.3	902.1	975.0	1024.9	1071.3	2.6
	UK	310.8	298.3	432.4	421.2	438.7	440.1	2.9
	Japan	206.6	194.4	220.4	275.2	270.5	279.0	2.5
	Germany	574.9	629.9	656.6	742.3	748.5	765.8	2.4
Industrial Design	India	4.8	5.0	7.4	9.2	10.5	10.9	6.8
	China	262.4	421.4	575.3	722.1	825.8	900.7	10.3
	USA	76.9	86.9	111.2	128.1	132.4	133.5	4.6
	UK	54.0	51.2	57.0	65.6	55.7	54.9	0.1
	Japan	68.4	67.6	70.3	71.5	68.1	66.8	-0.2
	Germany	109.4	118.6	128.7	130.9	125.1	124.6	1.1

Note: Applications by residents includes application filed with an IP office by an applicant residing in the country/region in which that office has jurisdiction.
Source: World Intellectual Property Organization.

[2] See Table A1 in the Appendix for historical data.

Chart 4a: R&D Expenditure (2014-18 average)

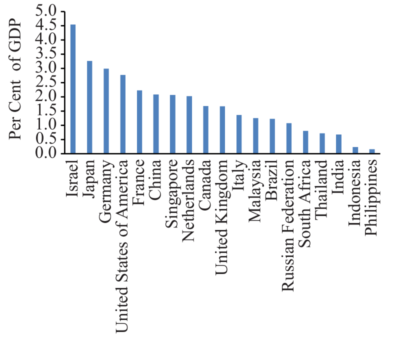
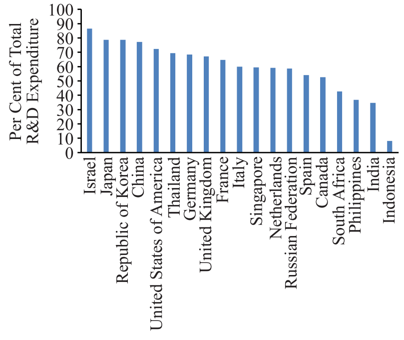


Chart 4b: R&D by Business (2014-18 average)



Source: World Intellectual Property Organization (http://data.uis.unesco.org/#).

industries and corporations particularly is remarkably low, as compared to the other emerging economies (Chart 4b). Herstatt *et al.* (2008) mentioned that the industrial sector devoted only 0.47 per cent of its sales turnover to R&D efforts during most of the early 2000s. Perhaps, one possible explanation of why R&D expenditure in India in relation to its GDP is lower than the other emerging economies is the low participation of industries and corporates in the R&D activities. Moreover, it was observed that in India, the linkages between industry and academia are far from optimal (Forbes, 2016). Often, universities lack adequate resources and incentives - plagued with limited interaction with the industries and markets (CII, 2007). One of the major challenges in scaling up innovation in India, therefore, is to ensure the larger participation of industries and corporates in R&D activities.

Section IV
Macro Economic Factors affecting Innovation

The seminal work by Solow (1956) pointed out that technological progress is the primary factor which results in sustained growth in total factor productivity. In the empirical literature, the aggregate R&D expenditures and the number of patent applications have continued to remain predominant indicators of how a country makes effort towards technological progress (see OECD, 2015). In this vein, our paper attempts to understand the recent progress made in innovation. We emphasise on two questions: (i) what the broad patterns in R&D expenditures across the major economies are and where exactly does India stands; and (ii) how do the R&D expenditures across the countries compare when we consider the differences in their socio-economic factors. A large body of empirical literature including Jones (1981), North (1980, 1981), Fischer *et al.* (1996), Easterly and Levine (2003), Rodrik *et al.* (2004), Beck and Laeven (2006), *etc.* suggest that good institutions promote innovation and foster economic growth. Furman *op. cit.* (2002) explains that better institutions promote R&D productivity by enhancing IP protection, enhancing openness to international trade and investment that enable technological diffusion from globally frontier firms to domestic leaders (OECD, 2015), creating an environment for better collaboration between different types of institutions and fostering competition, *etc*. This literature adequately argues why institutions might be associated with innovation capabilities. Hence, in our subsequent discussions, we focus on several measures of institutions to draw upon the cross-country variations in R&D expenditures.

As regards the role of investment and finance, this can be broadly divided into two aspects. First, how the country fares with the rest in terms of its initial conditions. This can be demonstrated through the availability of good physical infrastructure, *e.g.,* roads, railways, communication, *etc.* that facilitate the movement of goods, people, and ideas. Second, how much the country can support the further development of these infrastructure facilities, that is measured by the development of financial infrastructure. In this regard, Huffman (2007, 2008) suggested theoretical frameworks that demonstrate the role of investment-specific technological progress in the aggregate growth process by incorporating innovation into endogenous growth theories. The simulations by Bishnu *et al.* (2016) extend support for the investment-led innovation and growth process suggested by Huffman (2008), drawing upon the role of efficient taxation of capital on innovation processes. This motivates us to look at the variables like FDI, physical and financial infrastructure, and corporate tax rates in explaining the variation in R&D expenditures.

The works of Lucas (1988) built on Uzawa (1965) proposed a theoretical framework where technological change is being driven by human capital in an economy, where human capital is associated with better utilisation of existing knowledge and technologies. Hartwig (2014) extends support to the Uzawa-Lucas hypothesis and highlights the cross-country differences in public education expenditure as a factor behind variations in economic growth among the OECD countries. This motivated us to look at variations in school enrollments and public expenditures across countries and compare them with their aggregate R&D expenditures. Furman *op. cit.* (2002) suggested that the per-capita GDP and the downstream commercialisation *i.e.,* the share of high-tech exports as a percentage of GDP act more as the factors driving the demand for improved technologies, and therefore are included in our estimates too. Based on the available estimates, we too expect positive relationships of per-capita GDP and the high-tech exports' share in GDP with the aggregate R&D expenditures. Our empirical estimations are motivated by Furman *op. cit.* (2002), which provide estimates for the effects of these above-mentioned factors, namely the institutions, physical capital and human capital, on innovation outcomes.

An analysis of macroeconomic characteristics affecting innovation suggests that India's lower rank in gross expenditure on R&D as per cent of GDP (8^{th} out of 11) in recent years is broadly consistent with the country's weaker relative position in terms of its institutions, infrastructure, human capital and per-capita income among the emerging economies. It is worth noting that although India's rank is very low in terms of aggregate R&D expenditure, it is relatively better placed in terms of institutions (7^{th}), infrastructure (4^{th}), and financial development (5^{th}). The government's endeavour in enhancing human capital is visible through considerable expenditure on education. India ranks 7^{th} out of 11 economies in terms of government expenditure on education as a percentage of GDP despite its low rank in per-capita GDP. India ranks slightly better in aggregate R&D spending (8^{th} out of 11) as compared to business participation in R&D (9^{th} out of 10 -Table 2).

India lags behind several peer-economies in the protection of intellectual property and minority shareholders' interest, time taken to start a business, the corporate taxation policy, *etc.* (Table 3). India also lags in auditing and reporting standards and efficacy of corporate boards. Notably, the country is placed significantly ahead of other emerging economies in university-academia collaboration, ethical behaviour of firms, efficiencies of the legal framework in challenging regulation and settling disputes, and in protecting investors.

Table 2: Macroeconomic Characteristics and Innovation (2014-2018 average)

Country	R&D Exp (% of GDP)	R&D Exp by Business (% of Total)	Institution related to Business GCI Rank (World)	Infrastructure GCI Rank (World)	Financial Development GCI Rank (World)	School Enrollment, Tertiary (% Gross)	Fiscal Balance (% of GDP)	Govt. Spending on Education (% of GDP)	GDP Per Capita (Logarithm)
Brazil	1.2	-	92	79	54	43.1	-8	6.2	9.6
China	2.1	77.3	62	32	31	47.2	-3.2	1.9	9.5
India	0.7	34.6	52	66	36	34.5	-6.8	3.8	8.7
Indonesia	0.2	8.2	49	73	53	26.9	-2.3	3.4	9.3
Israel	4.5	86.5	26	22	23	64.4	-1.9	5.9	10.5
Malaysia	1.2	50.8	25	31	15	44.1	-2.6	4.8	10.2
Philippines	0.2	36.9	96	95	41	35.6	-0.2	2.5	9
Russia	1.1	58.7	75	51	89	81.1	-1.3	4.1	10.2
Singapore	2.1	59.5	3	1	3	85.9	4	2.9	11.4
South Africa	0.8	42.6	60	65	17	49.7	-4.3	6	9.4
Thailand	0.7	69.4	65	63	14	21.7	-0.1	4.1	9.7
India's rank among 11 EMEs	8	9	7	4	5	9	10	7	11

Notes: i) GCI: Global Competitiveness Index.
ii) A higher figure for the rank indicates a weaker position.
Source: Global Competitiveness Reports, various issues; IMF, OECD, and WIPO.

India ranks 63rd within a set of 190 countries[3] on Ease of Doing Business[4], and has improved its ranking by 79 positions in five years from 2014 to 2019. Despite improvements in the Ease of Doing Business rank, Indian companies face challenges in the procurement of construction permits. The number of

[3] Based on an average DTF score, 2019. DTF is an abbreviation of Distance to Frontier, which scores a country's performance in each parameter in comparison to the best and worst country. The best-performing country is considered as the 'frontier' in each parameter and in each year. A higher DTF score would indicate that a country is close to the frontier as compared to the countries with low scores.

[4] The Ease of Doing Business Index 2020 developed by the World Bank provides scores to countries based on an array of institutional parameters which describe the ease with which a corporation sets up and conducts businesses. The parameters include the time required and procedural complexities in setting up new businesses, tax rates, access to power, access to finance, ease in conducting cross-border trades, *etc*.

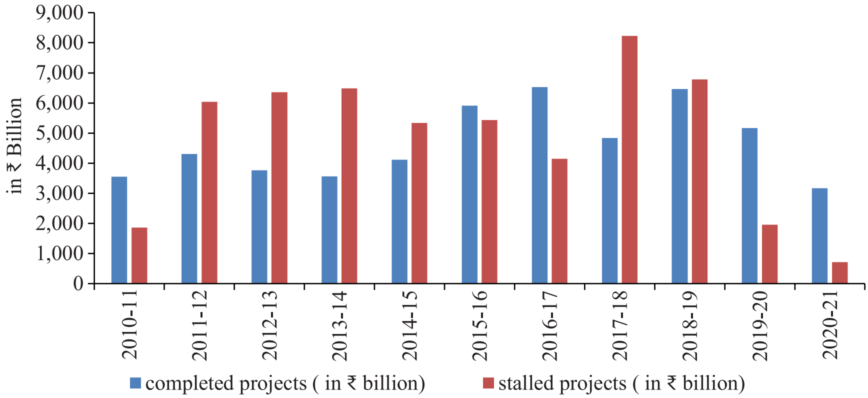
Table 3: Institutions Affecting Business and Innovation: World Ranking of Emerging Economies (Average 2014 to 2018)

Country	IP Protection	Investor Protection	Minority Shareholders' Interest	Univ.-Industry collaboration	Auditing & reporting standards	Efficacy of Corporate boards	Challenging Regulations	Settling disputes	Ethical behaviour of firms	Days to start business	Total tax rate (% of profits)
Brazil	78	40	67	67	60	75	101	117	124	136	134
China	57	101	56	31	75	106	47	48	54	118	131
India	52	15	56	38	83	95	34	42	51	110	125
Indonesia	47	58	44	30	76	61	42	48	44	122	42
Israel	24	9	27	5	21	56	33	39	38	74	37
Malaysia	25	4	16	12	27	23	16	17	24	39	75
Phillippins	71	114	49	58	47	40	76	95	64	117	93
Russia	110	75	115	56	103	67	94	91	68	66	106
Singapore	4	2	7	6	5	8	15	1	3	5	15
South Africa	26	15	9	30	8	11	18	17	45	109	34
Thailand	111	25	34	43	48	75	66	55	90	110	35
India's rank among 11 EMEs	6	5	9	7	10	10	5	5	6	7	9

Note: A higher figure for the rank indicates lower performance.

Source: Global Competitiveness reports, various issues.

Chart 5: Status of Investment Projects



Source: Centre for Monitoring Indian Economy (CMIE), various years.

'stalled' projects[5] also corroborate the fact that there exist impediments which hinder the progress of businesses in India. Based on the data released by the Centre for Monitoring Indian Economy (CMIE), the number of completed projects declined in 2019 -20 and 2020-21 as compared to previous years (Chart 5). Almost 1/5th of those projects are 'stalled' due to various reasons, such as 'land acquisition problems', and 'lack of environmental clearances'.

Section V
Empirical Model, Data and Methodology

V.1 Methodology

Available literature suggests that innovation activities are largely driven by the strengths of a country's institutions, physical and financial infrastructures, quality of governance, human and physical capitals, and 'absorptive capacities' (Furman *et al.*, 2002; Castellacci and Natera, 2013). In this section, we examine whether the differences in innovation activities across a set of developed and emerging countries can be explained by their differences in these characteristics. We estimate an econometric model to test whether certain country-specific characteristics can explain the cross-country

5 The Centre for Monitoring Indian Economy (CMIE) defines 'stalled' projects as the projects which are under implementation (*i.e.*, already started) but are stalled due to several policy and non-policy related reasons. Data has been collected from CMIE.

variations in R&D expenditures. Our first empirical specification broadly follows Furman *et al. op. cit.* (2002) except that we replace the number of patent applications as used in the mentioned study with R&D expenditure as per cent of a country's GDP as the dependent variable in the model.

Model 1:

The model is as follows:

$$R\&D_{it} = \beta_0 + \beta_1 easeinno_{it} + \beta_2(easeinno_{it} * pcgdp_{it-2}) + \beta_3 fdi_{it} + \beta_4(fdi_{it} * pcgdp_{it-2}) + \beta_5 fiscal_{it} + \beta_6 pcgdp_{it-2} + \beta_7 exp_{it-2} + \alpha_i + \mathrm{T}_i + u_{it} \quad ...(1)$$

where, subscripts *i* and *t* represent country and year, respectively. Our data is panel data that consists of annual estimates of R&D expenditure and some country characteristics for 10 emerging economies[6] and 11 developed economies[7] between 2007 and 2016. The explanatory variable *easeinno* summarises the qualities of a country's institutions *viz* the quality of governance, physical infrastructure, and financial infrastructure. This variable is a linear combination of country scores on the qualities of institutions, physical infrastructure, and financial infrastructure as provided by the World Economice Forum. The explanatory variables *fdi* and *fiscal* are net foreign direct investment (FDI) inflows as per cent of a country's GDP to approximate a country's openness to foreign technologies, and fiscal balance as per cent of GDP as a proxy measure of the government's fiscal space while proxies for fiscal space towards undertaking expenditure on R&D, respectively. The variable *pcgdp* is the log of real per capita GDP at purchasing power parity, which is a proxy for a country's 'absorptive capacity'. According to Castellacci and Natera (2013), higher aggregate income creates demand for improved goods and services in the long run,

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[6] Brazil, China, India, Indonesia, Israel, Malaysia, Philippines, Russia, South Africa, and Thailand.

[7] Canada, Hong Kong, France, Germany, Italy, Japan, Netherlands, Singapore, Spain, the UK, and the USA. Countries are selected based on the Gross Expenditure on R&D (source: UNESCO) in our sample. These countries, together with the developing countries incurred the largest R&D expenses in US$ (Purchasing Power Parity) between 2010 and 2015.

incentivising innovation. So, in the long run, we should observe a positive association between R&D expenditure and the country's per capita GDP. The variable *exp* is the exports of high-tech manufactured goods as per cent of a country's GDP. According to Furman *op. cit.* (2002), innovation "influences downstream commercialisation, such as achieving a high market share of high-technology export markets". In the long run, therefore, one can expect some positive association between 'downstream commercialisation' and aggregate innovation activities. We use exports of high-tech manufactured items as per cent of GDP as a measure of 'downstream commercialisation'. We also include interaction terms of all these explanatory variables with the 2-years lagged per capita real GDP at purchasing power parity to see if these effects vary depending on the stage of development (Furman *et al.*, 2002; World Bank, 2018). In our panel data, we control for any unobserved time-invariant country-specific characteristics through the country-specific dummy variable a_i and unobserved year-specific shocks that are common across all countries by year-specific dummy variable T_t.

There can be potential bi-directional causality between R&D expenditure and per capita GDP and between R&D expenditure and exports of high-tech manufactured products (Mowery and Oxley, 1995; Furman *et al.,* 2002). In order to avoid this problem, we have included only second lags of both the variables *pcgdp* and *exp* in our set of explanatory variables. We used only the contemporaneous form of the other variables like institutions and infrastructure as they evolve over a very long period of time and thus are less likely to be correlated with any shocks to the innovation at period t.

Model 2:

In the second model, we replace the dependent variable R&D with R&Dbus which measures the percentage share of R&D expenditure by the private corporate sector in a country's aggregate R&D expenditure. The explanatory variables, set of countries and the sample period, however, remain same as in Model (1). Model (2) takes the following form:

$$
\begin{aligned}
R\&Dbus_{it} = {} & \beta_0 + \beta_1 easeinno_{it} + \beta_2 (easeinno_{it} * pcgdp_{it-2}) + \\
& \beta_3 fdi_{it} + \beta_4 (fdi_{it} * pcgdp_{it-2}) + \beta_5 fiscal_{it} + \beta_6 pcgdp_{it-2} + \\
& \beta_7 exp_{it-2} + \alpha_i + T_i + u_{it} \qquad \ldots(2)
\end{aligned}
$$

In our models, the dependent variables are in percentage form*, i.e.,* R&D expenditure as per cent of GDP, or per cent of aggregate R&D expenditure coming from the private corporate sector. Hence these variables vary between 0 and 1. As the assumption of normally distributed residuals would no longer be valid, the statistical tests on ordinary least square coefficients would become invalid. Therefore, we provide maximum likelihood estimates for these models that are consistent and asymptotic normal (Gourieroux and Monfort, 1981), enabling us to interpret the standard tests of statistical significance.[8]

The issue of endogeneity could arise due to the correlation of error term with any of the explanatory variables, *viz.,* the FDI inflows, the fiscal balances, exports and per-capita GDP. This occurs when some unobserved factor determining the dependent variable (R&D expenditures in this case) is also correlated with these explanatory variables. In most empirical research, it becomes difficult to directly control for these factors, and therefore, they become part of the error term, in turn making the error term correlated with the regressors. The presence of this 'endogeneity', would make the coefficients biased and inconsistent. The scope of research are also not free from this issue. In the presence of endogeneity, we could have used a Generalised Method of Moments (GMM) or any other instrumental variable approaches. However, in our case, we could not use them since we have data only for a limited number of years. So, we use the following steps to make sure that our estimates are free from biases as much as possible. First, in a panel setup, we use year-specific dummy variables as regressors that account for any year-specific unobserved shocks. So, any unobserved common shocks across all countries are accounted for. Second, any factor that consistently influences the regressors could be very well related to the characteristics of the institutions in that country evolving over time. In most empirical research, it becomes challenging to quantify the time-varying characteristics of the institutions and, therefore, they remain missing from the regressions. However, the unique feature of the data that we use is that it enabled us to directly control for the institutions over time, that

[8] In our model we do not emphasize on any casual inference as establishing causal inference would require building models with adequate lags of dependent variable and independent variables. Due to insufficient vintage of the data (only about 11 years), we are not in a position to do that. Therefore, we restricted our inferences to the long-run association only, while paying significant attention to any biases due to 'endogeneity' of the explanatory variables.

we disscuss in the next sub-secton. Since this variable captures a large part of the institutional qualities over time, the presence of any unobserved factor affecting the other macroeconomic variables *viz.* FDI and fiscal balance are minimised. Therefore, in our belief, we reduce the possibilities of ending up with endogeneity on FDI and fiscal balance to a large extent. Third, we have used the second lags of exports and per-capita GDP as our regressors. Any contemporaneous unobserved shocks would not have any correlation with the two-years lagged exports and per-capita GDP. Therefore, these two coefficients are likely to be free from the bias that may occur due to endogeneity.

V.2 Data

The data for the empirical analysis is obtained from multiple sources. The explanatory variable *easeinno* is a linear combination of country scores on the quality of institutions, physical infrastructure, and financial infrastructure. The scores on the quality of physical and financial infrastructures are directly available from several rounds of Global Competitiveness Reports published by the World Economic Forum. For country score on the quality of institutions, we take the average of individual scores on the following aspects: protection of intellectual properties, minority shareholders' interest, investor strength, efficiencies of legal frameworks in settling disputes and challenging regulations, ethical behaviour of firms, the strength of auditing and reporting standards, the efficacy of corporate boards, taxes on profits, number of days to start businesses, and university-industry collaboration. The country scores on each of these aspects of the institutional quality are directly available from the Global Competitiveness Reports. Finally, we take a linear combination of the constructed country score on the quality of institutions, and the country scores on the physical and financial infrastructures obtained from the Global Competitiveness Reports. We use 0.88, 0.59 and 1.00 as the weights for country scores on financial infrastructure, physical infrastructure, and institutions, respectively. To obtain these weights, we use a principal component analysis (PCA) for these variables across all countries from the period 2007 to 2016. These weights are the corresponding factor loadings from this PCA. Therefore, our constructed explanatory variable *easeinno* is an underlying common factor that summarises variations in the quality of institutions, financial and physical infrastructure.

We obtain net FDI inflows as per cent of GDP from the World Development Indicators, World Bank and gross fiscal balance as per cent of GDP from the IMF's World Economic Outlook database. We obtain real per capita GDP at purchasing power parity from the World Development Indicators database, World Bank. The export of high-tech manufactured goods is obtained from the UNComtrade database and includes chemicals (except Pharmaceutical, fertilisers, and explosives), electrical equipment, electronics, rail, automobile, ships and aircraft equipment, clocks, watches, musical instruments, toys, and games accessories[9]. We exclude exports of items, such as explosives, weapons, *etc.*, where cross-border applies.

Section VI
Results

We present the estimation results from the first model (equation (1) in the previous section) in Table 4. Our estimates in Table 4 suggest that the availability of better institutions and infrastructure are associated with higher aggregate R&D spending as per cent of GDP. The estimated coefficients of *easeinno* are positive and statistically significant in both Models 1 and 2. The interaction of *easeinno* with lagged per-capita real GDP suggests that the richer countries generally tend to have a lower impact of additional improvement in their institutions and infrastructure on their innovation activities than the developing countries. In other words, developing countries tend to benefit more from their institutional reforms and infrastructure up-gradation, than their developed counterparts. Higher net FDI inflows as per cent of GDP are estimated to be positively associated with higher aggregate R&D expenditure as per cent of GDP for the set of countries and the coefficient is robust in all the specifications. The interaction of this variable with lagged per-capita real GDP suggests that the richer countries generally tend to have a lower impact of FDI inflows on their innovation activities than the developing countries. The aggregate R&D expenditure is estimated to be positively associated with both 'absorptive capacity' measured by real per capita GDP and 'downstream commercialisation' measured by the share of high-tech manufacturing products as per cent of a country's GDP. Our estimates suggest that a better fiscal

[9] HS Codes 28, 29, 85-92 and 95 are taken as high-technology items.

Table 4: Macroeconomic Characteristics and R&D Expenditure-Cross Country Evidence

	(1) Baseline Model	(2) Additional Controls
Dependent Variable: R&D Expenditure as per cent of GDP		
Factor: Ease of Innovation	**1.05*** (0.28)**	**1.04*** (0.27)**
Ease of innovation interacted with Log of per capita real GDP at PPP(-Lag 2)	-0.12*** (0.028)	-0.11*** (0.027)
Net FDI inflows as per cent of GDP	**0.33*** (0.087)**	**0.38*** (0.085)**
Net FDI inflows as per cent of GDP interacted with Log of per capita real GDP at PPP-Lag 2	-0.031*** (0.0081)	-0.036*** (0.0079)
Fiscal balance as per cent of GDP	0.0098* (0.0054)	0.0093* (0.0052)
Exports of high-tech manufactured goods as per cent of GDP(-Lag 2)	**0.011*** (0.0032)**	**0.011*** (0.0031)**
Log of per capita real GDP at PPP(-Lag 2)	**2.38*** (0.33)**	**2.43*** (0.32)**
Tax on Business		0.0049** (0.0025)
Time to Start Business		-0.10*** (0.035)
Number of observations	192	192
LR chi^2	267.9	282.32
Prob> LR chi^2	0.00	0.00

Notes:

(i) ***, ** and * indicate statistical significance of the coefficients at 1, 5 and 10 per cent, respectively. Standard errors are in parentheses.

(ii) PPP: Purchasing Power Parity.

(iii) We carried out Hausman specification tests following Hausman (1978) that failed to reject random effects. The unit root tests for the explanatory variables suggested that all are stationary at their levels. For the dependent variables, as there are missing observations, no formal test for unit root could be performed. Hence, we include the deterministic trend in all our models. The deterministic trends, however, turned out to be statistically insignificant and is not reported.

balance, or a lower fiscal deficit, is associated with higher R&D expenditure as per cent of GDP. However, the coefficient has a high standard error, which indicates that the relationship may vary significantly across countries. We observed a positive association between corporate tax rate and aggregate

R&D expenditure, but the coefficient is very small. This finding indicates that the tax rate may not be a deterrent to higher R&D expenditure. Lastly, the higher time required to start a business is associated with reduced aggregate R&D expenditure as per cent of GDP.

In the previous section, we have discussed the issues of probable biases in these estimates that can arise due to several factors such as two-way causalities, the unobserved factors that strongly influence both R&D and the regressors, *etc*. We have also discussed how we make our best attempts to overcome them. Now, even if we are left with any unobserved factor that may be positively associated with the aggregate R&D expenditures, can also be assumed to have a positive association with the explanatory variables. When there is a positive correlation between the explanatory variables and the error terms, the estimated coefficients tend to be biased downward. In our case, our estimated coefficients in Table 4 are positive, even with a negative bias. Had we been able to completely remove the endogeneity, the coefficients would have been higher (or more positive). Therefore, in our present case, despite any possible endogeneity issue, the evidence suggest that higher aggregate R&D expenditures are generally associated with better institutions, higher exports, per-capital GDP and FDI inflows. As a study focused mostly on examining whether cross-country variation in R&D expenditures are consistent with the country-characteristics, we tolerate some degree of endogeneity as long as it does not hamper the main takeaway on the public policy guidance.

The estimated coefficients from the second model (*i.e.,* equation (2) in the previous section) are provided in Table 5. In this model, we regress the same set of explanatory variables as in the previous model (*i.e.,* equation (1)) on R&D expenditure by the private corporate sector as per cent of total R&D expenditure in a country. Unlike in Table 4, our estimates in Table 5 do not suggest any significant association of business participation in overall R&D activities with the country's institutions, infrastructure, and 'absorptive capacities'. In an alternative specification in Table 5 (model 3), we control for the stochastic trend in the dependent variable. The coefficients of the other dependent variables, however, do not show much improvement. The 'downstream commercialisation', on the other hand, is estimated to be positively associated with higher participation by businesses in R&D. The

Table 5: Macroeconomic Characteristics and Business participation in R&D-Cross Country Evidence

	(1) Baseline Model	(2) Additional Controls	(3) With R&D Lag
Dependent Variable: Share of Private Corporate in Aggregate R&D			
Factor: Ease of Innovation	-8.84 (7.91)	-8.06 (7.79)	-10.9* (6.34)
Ease of innovation interacted with Log of per capita real GDP at PPP- Lag 2	0.71 (0.79)	0.62 (0.77)	1.01 (0.62)
Net FDI inflows as per cent of GDP	4.31* (2.53)	3.11 (2.53)	3.14* (1.88)
Net FDI inflows as per cent of GDP interacted with Log of per capita real GDP at PPP- Lag 2	-0.40* (0.24)	-0.29 (0.24)	-0.29* (0.18)
Fiscal balance as per cent of GDP	0.29* (0.17)	0.28* (0.17)	0.19 (0.12)
Fiscal balance as per cent of GDP - Lag 2	0.048 (0.15)	0.10 (0.15)	-0.071 (0.11)
Exports of high-tech manufactured goods as per cent of GDP- Lag 2	**0.28***** **(0.090)**	**0.28***** **(0.089)**	**0.24***** **(0.062)**
Log of per capita real GDP at PPP - Lag 2	1.71 (9.19)	0.69 (9.05)	-6.65 (6.69)
Business R&D as per cent of GDP- Lag 2			**0.61***** **(0.068)**
Tax on Business		-0.082 (0.070)	0.027 (0.050)
Time to Start Business		1.99** (1.01)	0.099 (0.73)
Number of observations	181	181	174
LR chi^2	160.0	166.18	229.43
Prob> LR chi^2	0.00	0.00	0.00

Notes:

(i) ***, ** and * indicate statistical significance of the coefficients at 1, 5 and 10 per cent, respectively. Standard errors in parentheses.

(ii) We carried out Hausman specification tests following Hausman (1978) that failed to reject random effects. The unit root tests for the explanatory variables suggested that all are stationary at their levels. For the dependent variables, as there are missing observations, no formal test for unit root could be performed. Hence, we include the deterministic trend in all our models. The deterministic trends, however, turned out to be statistically insignificant and is not reported.

coefficients are observed to be robust and statistically significant in alternative specifications. The coefficients of net FDI inflows and fiscal balance, both as per cent of GDP, are not found to be robust across different specifications.

Section VII
Role of Public Policy in Promoting Innovations

The Government of India has played a promotive role in creating social and institutional infrastructure to foster innovations in the country, which can be divided broadly into two categories; first, in-house research carried out by several departments within the government and second, modernising National Innovation Systems to develop social and institutional infrastructure to create fair opportunities for innovations by commercial entities. India's domestic institutions like the Indian Space Research Organization, Defence Research and Development Organisation, Centre for Development of Advanced Computing, *etc.* have achieved remarkable milestones of international standards. The government of India has created six departments, *viz.* the department of atomic energy, biotechnology, earth science, science and technology, scientific and industrial research, and the department of space, dealing exclusively with matters of innovations. Additionally, the ministries such as Defence, Agriculture and Farmers' Welfare, Chemicals and Petrochemicals, *etc.* have carried out major R&D operations in the past. Together, these efforts have not only fostered technological progress in the concerned fields but also have built up a macro-environment which encourages innovations by the industries.

The government's major role in the innovation system rests in formulating policies that are conducive to innovation, reward industrial quest for innovative products, create institutional frameworks which support basic and advanced research in universities as well as industrial R&D, encourage innovations in small and medium scale enterprises, invite and incentivise foreign direct investment, to name a few. In this direction, the government of India has analysed and modified its policy stances from time to time to foster the ease of doing business, expanding operations, and thereby creating innovation opportunities.

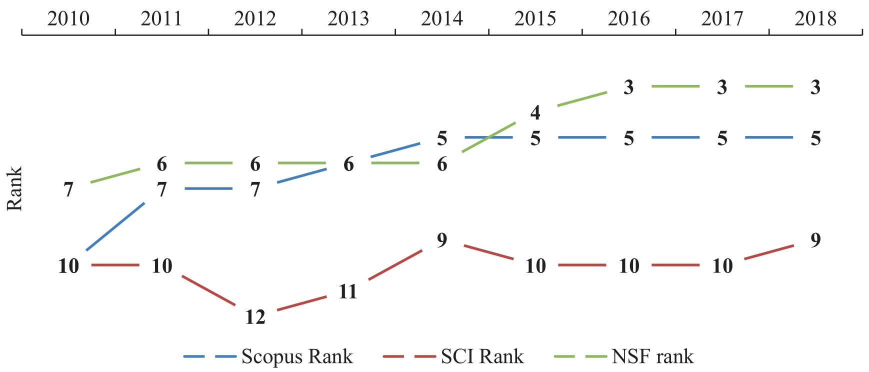
The government of India embarked on a path of 'liberalisation' way back in 1991, progressively reduced barriers to cross-border movements of goods, services and financial resources; and relaxed many of the internal barriers such as 'industrial licenses', which earlier controlled the setting up of new businesses and the expansion of existing ones. The Indian government has consistently worked towards providing appropriate legal framework by enacting laws to address emerging issues in the field of innovation. An example of this was enacting the 'Electronic Commerce Act' as early as 1998 and the 'Information technology Act' in 2000, which sought to 'provide legal recognition for transactions carried out by means of electronic data interchange' (Herstatt *et al*., 2008). Undoubtedly, these early measures helped India to become one of the leading exporters of Information Technology services in 21st country. Similarly, in the field of biotechnology, the government enacted the 'Environment (protection) Act' as early as 1986 to formulate legal protection for the sector. India has also taken decisive steps towards protecting the Intellectual Property Rights (IPRs) of the innovators by making several treaties with advanced countries, and multinational institutions concerning the IPRs. India's pool of skilled labour is often cited as the single largest asset (Herstatt *et al.,* 2008). The Indian government has also set a path for greater collaboration with foreign research institutions, such as the German Academic Exchange Service (DAAD), and the German Research Foundation (DFG), to name a few.

India has consistently featured among the fastest-growing economies in the world since the early 2000s. According to the Global Competitiveness Report 2017-18, India ranked the 3rd largest potential market in the world and 29th for 'innovation' factors.

In terms of research output, India witnessed significant growth in scientific research publications. The number of scientific publications increased by 50 per cent from 90,864 in 2011 to 1,36,238 in 2016 in SCOPUS database; by 36.5 per cent from 47,081 in 2011 to 64,267 in 2016 in Science Citation Index (SCI) database, and by 83.1 per cent from 74,143 in 2011 to 1,35,788 in 2018 in National Science Foundation (NSF) database. In 2018, India ranked 3rd, 5th and 9th in scientific publication output as per the NSF, SCOPUS and SCI databases, respectively (Chart 6).

Through recent initiatives like 'Aatmanirbhar Bharat', 'Make in India', 'Production Linked Incentives (PLI) schemes', there has been a strong push to empower domestic manufacturing sectors and foster innovations. The basic objective of the 'Make in India' initiative is to play a bigger role internationally by enhancing participation within Global Value Chains by leveraging

Chart 6: India's Rank in Scientific Publication



Note: Latest data available as per DST publication is till 2018.
Source: Compiled from R&D Statistics at a Glance, published by DST, Ministry of Science and Technology in 2020.

competitiveness in certain export-oriented activities (OECD, 2014)[10]. However, to achieve this huge investment in R&D is required, including all fields *e.g.,* ICT, data, design, skills, branding, and new organizational processes (OECD, 2014 op. cit). India has launched several significant initiatives like 'Accelerating Growth of New India's Innovations' (AGNi), 'Startup India' mission, and 'Atal Tinkering Labs Initiative for fostering innovation capabilities *etc.* With around 50 thousand startups, India has become the third-largest startup economy after the USA and the UK[11]. As per the Global Innovation Index (by WIPO), India has climbed up to 46th position in 2021, from 81st position in 2015, driven by a vibrant start-up ecosystem. Further, the recently launched 'Science, Technology and Innovation Policy' (STIP), 2020 has the vision to position India among the top three scientific superpowers in the decades to come.

10 https://www.oecd.org/policy-briefs/India-Addressing-Economic-and-Social-Challenges-through-Innovation.pdf

11 Sarker John 2021, September 3, 'India becomes third largest startup ecosystem in the world' Times of India https://timesofindia.indiatimes.com/business/india-business/india-becomes-third-largest-startup-ecosystem-in-the-world/articleshow/85871428.cms

The government has a dominant share (over 60 per cent) in the nation's aggregate R&D spending[12]. There are remarkable efforts made by the government and the industrial bodies to enhance the industry-academia collaboration and encourage innovations in the private sector. Industry associations such as the Federation of Indian Chamber of Commerce and Industry (FICCI), Confederation of Indian Industries (CII), National Association of Software and Services Companies (NASSCOM), Society of Indian Automobile Manufacturers (SIAM), *etc*. have periodically taken lead initiatives in academic collaboration, policy initiatives, process standardisation and improvement. To boost investment in innovation activities, several fiscal incentives are offered by the Government. Financial institutions like Small Industries Development Bank of India (SIDBI) and Industrial Development Bank of India (IDBI) lend support for innovation and entrepreneurship activities. The Technology Development Board (TDB), which is an important stakeholder in the Indian innovation ecosystem, provides soft loans and promotes the equity of Indian industry through the development and commercialisation of indigenous technologies. Biotechnology Industry Research Assistance Council (BIRAC) supports high-risk, early starters from academia, start-ups, or incubators that have exciting ideas in the nascent or planning stage. Several public-private partnership mechanisms such as National Skill Development Corporation (NSDC) and Global Innovation and Technology Alliance (GITA) also provide funding for skill development and bilateral and multilateral joint R&D programs, respectively.

An improved ecosystem of IP protections, industry-academia collaboration and investor protection could pave the way for greater innovation activities in the private sector. Studies highlight that institutions and business sophistication are important pillars to improve innovation performance in developing countries (Acharya and Subramanian, 2009; Acharya *et al.* 2013, 2014). The Economic Survey 2021 rightly emphasised that aspects supported by estimates suggesting that one standard deviation improvement in the rank

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12 Table A1 in appendix.

on 'institution' can lead to an improvement in the innovation output rank by 5 percentage points. Similarly, one standard deviation improvement in business sophistication rank can augment innovation output rank by 3 percentage points.

Section VIII
Conclusion

Though, India lags behind other emerging and developed nations in innovation activities, measured by the number of intellectual property applications for patents, trademarks, and industrial designs, the trend has been on upward trajectory. The low innovation activities are reflected in the country's low aggregate R&D expenditure (as per cent of GDP). Business participation in overall R&D is particularly low in India compared to many other emerging economies. Empirical estimates suggest that the aggregate R&D activities are broadly influenced by the quality of the countries' institutions, physical and financial infrastructures, 'absorptive capacities' for innovation, the extent of 'downstream commercialisation', and degree of openness. Improvements in business regulations and human capital can help in strengthening conditions to promote innovations in India.

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Appendix

Table A1: Gross Expenditure on R&D by Entity-Selected Economies

	2000			2010			2015			2018		
	GERD-Total (% of Total)	GERD-Enterprise (% of GDP)	GERD-Govt. (% of Total)	GERD-Total (% of Total)	GERD-Enterprise (% of Total)	GERD-Govt. (% of Total)	GERD-Total (% of GDP)	GERD-Enterprise (% of Total)	GERD-Govt. (% of Total)	GERD-Total (% of GDP)	GERD-Enterprise (% of Total)	GERD-Govt. (% of Total)
Emerging Economies												
Brazil	1.0			1.2			1.3			1.2		
China	0.9	60.0	31.5	1.7	73.4	18.1	2.1	76.8	16.2	2.1	77.4	15.2
India	**0.8**	**18.0**	**77.9**	**0.8**	**34.8**	**61.1**	**0.6**	**43.6**	**52.5**	**0.7**	**36.8**	**56.1**
Indonesia	0.1	26.3	69.8	0.1	18.8	43.2	0.1	25.7	39.4	0.2	7.3	70.5
Israel	3.9	80.5	3.2	3.9	83.0	2.1	4.3	85.1	1.7	4.9	88.3	1.5
Korea	2.2	74.0	13.3	3.5	74.8	12.7	4.1	77.5	11.7		80.3	10.1
Malaysia	0.5	57.9	25.0	1.0	65.0	6.0	1.3	52.0	19.6	1.0	43.9	13.4
Philippine	0.1	67.8	16.9	0.1	55.2	18.4	0.1	35.7	29.7	-	-	-
Russia	1.0	70.8	24.4	1.1	60.5	31.0	1.1	59.2	31.1	1.0	55.6	34.4
South	0.7	53.7	20.0	0.7	49.7	22.7	0.8	42.7	24.0	-	-	-
Thailand	0.2	43.9	22.5	0.2	41.2	32.7	0.6	70.2	10.0	-	-	-
Advanced Economies												
Canada	1.9	60.3	11.2	1.8	52.0	10.6	1.6	52.1	7.1	1.6	50.9	6.9
Hong Kong	0.5	18.0	1.8	0.7	43.3	4.5	0.8	43.8	4.0	0.9	44.9	4.7
France	2.1	62.5	17.3	2.2	63.2	14.0	2.3	63.7	12.8	2.2	65.4	12.5
Germany	2.4	70.3	13.6	2.7	67.0	14.8	2.9	68.7	14.1	3.1	68.8	13.5
Italy	1.0	50.1	18.9	1.2	53.9	13.7	1.4	58.2	13.1	1.4	62.1	12.7
Japan	2.9	71.0	9.9	3.1	76.5	9.0	3.3	78.5	7.9	3,28	79.4	7.8
Netherland	1.8	55.1	12.0	1.7	47.9	11.7	2.0	56.0	11.9	2.2	67.1	5.8
Singapore	1.8	62.0	14.1	2.0	60.8	10.4	2.2	61.2	11.4	-		-
Spain	0.9	53.7	15.8	1.4	51.5	20.1	1.2	52.5	19.1	1.2	56.5	16.8
UK	1.6	65.0	12.6	1.7	60.9	9.5	1.7	66.0	6.6	1.7	69.1	6.1
USA	2.6	74.2	10.8	2.7	68.0	12.7	2.7	71.7	11.3	2.8	72.6	10.4

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Price Stickiness in CPI and its Sensitivity to Demand Shocks in India

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This study analyses the Consumer Price Index-Combined (CPI-C) data at a disaggregated level by identifying different price-setting methods, *viz.,* maximum retail price (MRP), non-MRP, mixed (both MRP and Non-MRP based items) and fixed (items with administered prices). Based on their price dynamics, it constructs a Sticky Price Index and a Flexible Price Index and finds that the headline inflation is primarily driven by flexible price inflation, while inflation excluding food and fuel largely co-moves with sticky price inflation. The study then analyses the underlying relationship between the sticky price index and output gap in a New Keynesian Phillips Curve (NKPC) framework using data from 2011:Q1-2019:Q4 and compares the results with the Phillips Curve (PC) estimates based on headline CPI-C and the flexible price PC. The results indicate that the sticky price PC is much flatter and the impact of output gap on inflation occurs with a significant lag, suggesting that the sticky price index is less sensitive and slow to adjust to changes in economic slack.

JEL: E3, E31, C38

Keywords: Flexible Price Index, Inflation, K-means Clustering, New Keynesian Phillips Curve, Phillips Curve, Sticky Price Index.

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Introduction

The effectiveness of monetary policy in achieving its ultimate goals hinges on the price-setting behaviour of economic agents. When prices are fully flexible a tightening of monetary policy reduces inflation, but without any effect on output or other real variables. For monetary policy to generate any real output effects, prices must be sticky. In new Keynesian models, monetary policy can become non-neutral because of the widely observed sticky behaviour of price movement (Gali, 2010). Price stickiness, thus, creates scope for monetary policy to pursue the goals of output and employment. It has been found that the output responses of different industries systematically vary depending on the extent to which their prices remain sticky (Henkel, 2020). Not only that, the heterogeneity in the degree of price stickiness across product groups also raises the degree of monetary non-neutrality (Nakamura and Steinsson, 2010). With multiple production sectors in the Indian economy, it could be, therefore, useful to examine the degree of price stickiness in the all India Consumer Price Index - Combined (CPI-C) and its implications for monetary policy.

While a major chunk of the literature in the Indian context in recent times has been devoted largely towards validating the existence of the Phillips curve (PC) relationship in the Indian data (Mazumder, 2011; Behera, *et al*., 2017; Patra *et al*., 2021) and exploring different aspects of inflation forecasting (Dholakia and Kandiyala, 2018; Pratap and Sengupta, 2019; John, *et al*., 2020; Jose *et al*., 2022), little attention has been paid to differences in the price-setting behaviour and related heterogeneity in price dynamics across items in the basket. Literature suggests that the foundations of medium-term inflation forecasting lie in the expectations augmented PC, also referred to as the New Keynesian Phillips Curve (NKPC), wherein the degree of nominal rigidity in prices is one of the key determinants of the slope of the curve (Aucremanne and Dhyne, 2004; Behera and Patra, 2020). This paper, while drawing insights from this literature, intends to examine the degree of price stickiness in the all India CPI-C and decomposes the basket into two separate indices *viz*., a *sticky price index* and a *flexible price index*. To attain this objective, the paper first documents the differences in the price-setting behaviour across 299 CPI-C items on the basis of whether the item comes with the tag of a maximum retail price (MRP), without any MRP tag (non-MRP) or its price is administered/regulated by the government, following which the items are classified into the two sub-indices based on certain important parameters such as 'inflation and its volatility'; and 'price momentum and its volatility'. While studies such as this abound in the case of advanced economies (AEs) [Bils and Klenow, 2004; Dias *et al*., 2004; Aucremanne and Dhyne, 2004; Dhyne *et al*., 2005; Alvarez *et al.*, 2006; Alvarez *et al.*, 2010; Bryan and Meyer, 2010; Millard and O'Grady, 2012; Reiff and Varhegyi, 2013], research in the Indian context is at a nascent stage with a limited number of studies focusing largely on food prices or wholesale price index (WPI) based firm-level price-setting behaviour (Tripathi and Goyal, 2012; Rather *et al*., 2015; Banerjee and Bhattacharya, 2017; Nadhanael, 2020). Based on such classification, the paper further investigates the sensitivity of sticky and flexible price components to output gap under an NKPC framework to better understand the underlying price dynamics which can aid in policy making.

The time-period covered for this study spans over 2011-2019, as the all India CPI-C item level data are available starting from January 2011.[1] The empirical section is based on quarterly data covering the period 2011:Q1-2019:Q4 (recognising a break in the item level data series during March-May 2020 owing to COVID-19 pandemic driven disruptions in data collection and compilation). It is observed that movements in headline inflation sync well with the flexible price inflation, whereas inflation excluding food and fuel (hereafter 'core inflation') shares a significant co-movement with sticky price inflation. Literature in the context of advanced economies has shown that the flexible price index tends to bounce violently from month to month as it responds strongly to changing market conditions, including the degree of economic slack. On the other hand, sticky prices are slow to adjust to economic conditions (Bryan and Meyer, 2010). Therefore, in this regard, while it could be expected that the flexible price index in the case of the Indian CPI would also react faster to the changing macroeconomic conditions, a lesser-known area is when, at what lag and to what extent the sticky price

[1] The all India combined consumer price index (CPI-C) series with base year 2010 was released from January 2011 by the National Statistical Office (NSO). The base year of CPI-C was revised to 2012 from January 2015 in order to align the weighting diagram and item basket with the latest available all India consumer expenditure survey (CES) 2011-12.

index would react to the same. Therefore, this paper tries to fill this gap in the existing literature in the Indian context. The relationship between sticky price index, economic slack and inflation expectations in an NKPC framework is estimated and the results are compared with the headline PC estimation. Overall, the findings indicate that the sticky price PC is much flatter than the headline PC or the flexible price PC, implying that it is less sensitive to changing demand conditions.

The rest of the paper is organised as follows. Section II discusses the extant literature on the relevance of this study for monetary policy, while providing the theoretical underpinnings on why certain prices are sticky. Section III provides a disaggregated analysis of item level CPI-C data in India and presents the approach used in the construction of the two sub-indices. Section IV lays out the theoretical framework for the empirical section along with discussing the methodology and empirical results. Section V concludes the paper.

Section II
Literature Review

II.1 *Evidence on Price Rigidity and Its Significance for Monetary Policy*

Assessing the extent of price rigidity is crucial for the conduct of monetary policy. PC theories based on sticky prices and imperfect information indicate that shifts in nominal aggregate demand lead to real output fluctuations depending on the extent of price rigidity in an economy (Kiley, 2000). In the absence of price stickiness, the real effect of monetary policy disappears (Banerjee, *et al*., 2020). Moreover, the impact assessment of any shock in the economy depends on the price/wage rigidities prevalent in the economy (Baudry *et al.,* 2004; Bils *et al.,* 2003).

Since the adoption of inflation targeting (IT) in several economies, understanding the pricing behaviour of different items in the basket of the target price index has received greater attention. Moreover, as microeconomic rigidity often gives rise to aggregate nominal rigidity, there have been many studies, largely empirical, documenting the microeconomic pricing behaviour, in particular the frequency of microeconomic price adjustments, centred on specific products; market structure; as well as items in the CPI basket

(Caballero and Engel, 2006).[2] A few of them have categorised items into sticky and flexible price indices and explored the insights obtained therefrom in understanding the inflation process while concluding that the sticky price index can be an useful indicator for IT central banks (Bryan and Meyer, 2010; Reiff and Varhegyi, 2013).

In terms of the frequency of price change, a number of studies reveal that many of the commodity prices are typically sticky and undergo revisions may be once in a year. For instance, one of the pioneering works in this area looked at 38 US news-stand magazine prices from 1953 to 1979 and reported that prices remained unchanged for a duration in the range of 1.8 years to 14 years (Cecchetti, 1986). Table 1 summarises the evidence on price stickiness both in the context of the advanced economies as well as in EMEs, in particular India.

Table 1: Evidence on Price Stickiness - A Summary of Findings Based on the Available Literature *(Contd.)*

Author/s	**Objective of the Study**	**Country (Period of Analysis)**	**Methodology**	**Key Findings**
Cecchetti (1986)	To investigate the determinants of nominal price change frequency.	US (1953-1979)	Fixed effects logit specification to the price change rule implied by a firm-level target threshold model.	Magazine prices remained unchanged for a duration in the range of 1.8 years to 14 years. Higher inflation leads to more frequent price adjustment and that the real cost of price changes varies with the size of a real price change.
Kashyap (1995)	To examine the size, frequency, and synchronisation of price changes for twelve selected retail goods.	12 mail order catalogue goods in US (1953-1987)	Statistical techniques such as mean, standard deviation and OLS regression.	Nominal prices are typically fixed for more than one year, although the time span between price changes is very irregular; prices change more often during high inflation periods and the magnitude of change is highly dispersed.

2 The literature has focussed on two aspects of sticky price models – *'time dependent'* (Taylor and Calvo models) where prices are set for a number of periods or each period a fixed fraction of firms have an opportunity to adjust prices to new information and *'state dependent'* (state of the economy) where firms choose when to change prices depending on 'menu costs' (Dotsey *et al.*, 1999). Stickiness of prices also has an impact on the output-inflation trade-off. Costly price-setting may make it inefficient to change prices at each instance of demand fluctuation (Parkin, 1986).

Table 1: Evidence on Price Stickiness - A Summary of Findings Based on the Available Literature *(Contd.)*

Author/s	Objective of the Study	Country (Period of Analysis)	Methodology	Key Findings
Baudry *et al.* (2004)	To document consumer price rigidity in France.	Price records used for computing French CPI, (July 1994-February 2003)	Frequency approach	Average duration of price stickiness is around 8 months; there is considerable sector-wise heterogeneity in price stickiness and price-setting; presence of both time dependent and state dependent nature of price-setting behaviour exist amongst retailers.
Bils and Klenow (2004)	To examine the frequency of price changes.	US -BLS (1995-97)	Measures of central tendency and weighted least squares regression	Price changes are frequent with half of prices lasting less than 4.3 months. Even excluding temporary price cuts (sales), half of prices last 5.5 months or less. Frequency of price change differs across goods. Compared to the predictions of popular sticky-price models, actual inflation rates are far more volatile and transient for sticky-price goods.
Aucremanne and Dhyne (2004)	To examine the degree of price rigidity in Belgian consumer prices.	Micro data on Belgian CPI (1989-2001)	Frequency approach	Each month nearly 17 per cent of the prices change on average and the median duration of a price spell is close to 13 months. The majority of price changes are price increases, but price decreases are not uncommon, except for services.
Dias *et al.* (2004)	To identify the stylised features of price setting behaviour in Portugal.	Micro-datasets underlying CPI and industrial production price index for Portugal (1992-2001)	Frequency approach	Monthly frequency of price changes – both at the consumer and at the producer level – is slightly below 0.25. There is a considerable degree of heterogeneity in product price setting behaviour.
Baumgartner *et al.* (2005)	To analyse patterns and determinants of price rigidity in Austrian CPI.	Individual price records of Austrian CPI (1996-2003)	Frequency approach	On an average, price remains unchanged for around 10-14 months. The typical size of price increase (decrease) is 11 (15) per cent.

Table 1: Evidence on Price Stickiness - A Summary of Findings Based on the Available Literature *(Contd.)*

Author/s	Objective of the Study	Country (Period of Analysis)	Methodology	Key Findings
Álvarez *et al.* (2006)	To present original evidence on price setting in the euro area at the individual level.	Micro data on CPI and PPI and survey data for Euro area	Summary of Inflation Persistence Network (IPN) studies	Prices in the Euro area reveal a higher degree of stickiness as compared to that in the US; factors such as macroeconomic conditions (overall inflation scenario), sectoral characteristics (degree of competition, cost structure, implicit and explicit contracts), time factors (such as seasonality) and specific shocks (including changes in tax structure) play a major role in price-setting and rigidity.
Dhyne *et al.* (2005)	To document patterns of price setting at the retail level in Euro area.	10 Euro area countries' price records underlying CPI (January 1996- different period for each country)	Frequency approach	The average euro area monthly frequency of price adjustment is 15 per cent, lower than in US. There exists substantial cross product heterogeneity.
Fougere *et al*. (2005)	To examine heterogeneity in price stickiness in French CPI.	Individual CPI quotes for French CPI (July 1994-February 2003)	Competing-risks duration model	Considerable asymmetry is found in the probability of a price change, *i.e.*, the determinants for price increases differ from that of price decreases.
Vilmunen and Laakkonen (2005)	To examine the prevalence of price stickiness in Finnish CPI.	Finnish CPI; January 1997 to December 2003	Central tendencies and inverse of the frequency of price change approach.	Prices of unprocessed food products and energy related consumer goods change more frequently. Further, the mean duration of price spells is generally six months.
Caballero and Engel (2006)	To study the relation between the frequency of microeconomic adjustment and aggregate price	US - BLS (1998-2005)	Generalized Ss model	The degree of price flexibility varies three times as much as the frequency of microeconomic adjustment over the business cycle. Also in generalized Ss models,

Table 1: Evidence on Price Stickiness - A Summary of Findings Based on the Available Literature *(Contd.)*

Author/s	Objective of the Study	Country (Period of Analysis)	Methodology	Key Findings
	flexibility in a generalised Ss setup			strategic complementarities reduce aggregate price flexibility for any given frequency of microeconomic price adjustment, but proportionally less so than in Calvo-type models.
Boivin *et al*. (2009)	To analyse the effect of macroeconomic and sectoral differences on price rigidity.	Disaggregated US CPI and PPI (1976- May 2005)	FA-VAR	In response to macroeconomic and monetary disturbances prices appear to be sticky, while prices are flexible in response to sector-specific shocks.
Bryan and Meyer (2010)	To compute two subindices - sticky-price CPI and flexible-price CPI.	US - CPI (1983-2009)	Frequency of adjustment	Sticky prices appear to incorporate expectations about future inflation to a greater degree than flexible prices; flexible prices respond more to economic slack. Sticky-price measure seems to contain a component of inflation expectations, which may be useful to gauge inflation ahead.
Alvarez *et al*. (2010)	To identify the basic features of price setting behaviour at the producer level in Spain.	Spanish-micro data for PPI (1991-1999)	Time series regressions.	Prices do not change often but do so by a large amount. Cost structure and the degree of competition affect price flexibility; Further producer prices are more flexible than consumer prices.
Millard and Grady (2012)	To investigate the information content in relatively sticky-price sectors against relatively flexible-price sectors.	UK CPI (1997-2010)	DSGE	Relatively flexible prices react more to deviations of output from trend than stickier prices; sticky prices tell about firms' inflation expectations.

Table 1: Evidence on Price Stickiness - A Summary of Findings Based on the Available Literature *(Contd.)*

Author/s	Objective of the Study	Country (Period of Analysis)	Methodology	Key Findings
Reiff and Varhegyi (2013)	To build a theory-based (*i.e.*, not purely statistical) underlying inflation indicator for Hungary	Store level retail prices of Hungary (1998-2011)	Simple autoregressive model.	Hungarian sticky price inflation index has a forward-looking component, as it has favourable inflation forecasting properties on horizon of 1-2 years to core inflation. Sticky price inflation index is a useful indicator for inflation targeting central banks.
Erlandsen (2014)	To examine the information content in sticky and flexible prices in Norway.	Norway CPI (2003-September 2014)	Time series forecasting	Sticky prices contain more information about inflation expectations in the medium term than flexible prices.
India-specific Studies				
Ghani (1991)	To evaluate the role of rational expectations in price setting behaviour in India.	WPI (1963–1984)	General price equation	Prices respond fully to anticipated changes in demand, while unanticipated changes affect output as India has a large informal sector where prices are flexible.
Tripathi and Goyal (2012)	To examine how relative price shocks can affect the price level and inflation.	WPI (April 1971-April 2010)	NKPC	Average price increase over time is greater than average price decrease and at an aggregate level, inflation depends on the distribution of relative price changes; an average Indian firm changes prices about once a year and 66 per cent of the Indian firms are forward-looking in their price-setting behaviour.
Chong *et al*. (2013)	To compare the role of macroeconomic and sector-specific factors in price movements in China and India.	PPI for China (February 2001- December 2008), WPI for India (June 1996-October 2008)	FA-VAR	Prices in India respond more promptly to macroeconomic and monetary policy shocks and that the rural CPI responds more sharply than the urban CPI when facing sector-specific shocks.

Table 1: Evidence on Price Stickiness - A Summary of Findings Based on the Available Literature *(Concld.)*

Author/s	Objective of the Study	Country (Period of Analysis)	Methodology	Key Findings
Rather *et al*. (2015)	To examine whether price adjustment of firms is asymmetric.	WPI (April 1993-August 2010)	Threshold cointegration framework	Strong asymmetry in price adjustment of firms in India; shocks that increase firms' desired prices cause quicker and larger rise in prices, whereas shocks that lower desired prices cause smaller or no fall in prices.
Banerjee and Bhattacharya (2019)	To evaluate the stickiness in price adjustments.	CPI-IW (2006-October 2016)	Indirect frequency approach.	Food prices reveal a higher frequency of price change *vis-à-vis* non-food prices. When small price changes are ignored, food and non-food sector record around similar frequencies of price changes and the durations of price spells among the major subgroups of CPI-IW.
Nadhanael (2020)	To study price-setting behaviour within the food sector both from a macro and micro perspective in an emerging economy context.	Price Information System, Department of Agriculture and Co-operation, Government of India (2005-2018)	Frequency based approach and the Menu cost model	Food prices in India exhibit varying degrees of price stickiness across product groups; differences in productivity processes, market power and menu costs could account for the differences in price stickiness.

In the Indian context, the literature is rather limited, with some of the recent studies focusing on the price stickiness in food items based on the consumer price index for industrial workers (CPI-IW) data (Banerjee and Bhattacharya, 2019; Nadhanael, 2020). However, none of the studies relate to disaggregated CPI-C data to analyse price stickiness or the price formation process in general.[3] The current study, using CPI-C, adds to this sparse empirical literature for assessing empirically the frequency of price adjustments and generating measures of sticky and flexible price indices along with examining the determinants of sticky prices in a NKPC framework.

II.2 *Why are Certain Prices Sticky - Theoretical Underpinnings*

As Blinder (1993) states, *"One could literally fill many volumes with good empirical studies of wage and price stickiness, and many more with clever theories purporting to explain these phenomena. Yet, despite all this work, the range of admissible theories is wider than ever, and new theories continue to crop up faster than old ones are rejected."*

Literature suggests an array of theories that could explain why certain prices are sticky. Table 2 provides a summary of such theories and their chief proponents.

In contrast to the theories that provide the micro foundations to the observed phenomenon of macroeconomic price rigidity in a NKPC framework, Mankiw and Reis (2002) and in their further subsequent works have built another side to the story through their sticky information model, which suggests the prevalence of informational frictions among price-setters. For instance, a study by Zbaracki *et al*., (2004) on the costs associated with changing prices at a large manufacturing firm in the US shows that only a small percentage of these costs are the physical costs of printing and distributing price lists. Far more important are the "managerial and customer costs," which include costs of information gathering, decision-making, negotiation and communication. Therefore, if firms face costs of collecting information and choosing optimal plans, then it could be more natural to assume that their adjustment process is time contingent. Subsequent literature has revealed that macro-models with sticky prices in an environment of sticky information are more consistent with micro and macro empirical evidence embodied in a PC framework (Knotek II, 2010).

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3 The analysis based on CPI-C assumes significance as headline inflation based on CPI-C is the nominal anchor under the flexible inflation targeting (FIT) monetary policy framework in India. Further, CPI-C provides price indices for 299 items comprising both food and non-food products. While there are other data sources that provide high frequency price data on primarily food items, similar data sources for prices of non-food items remain scarce.

Table 2: Theories on Price Stickiness

Theory	Proponent/s	Conclusion
Cost-based pricing theory	Gordon (1981) Blanchard (1983)	Prices are based on input costs and prices do not rise until costs rise. As costs rise and percolate through the input-output table and from across products, there can be significant delays in price adjustments.
Theory on inventories	Blinder (1982)	Manufacturing firms draw down (build-up) their inventories when demand rises (falls), rather than increase (decrease) their product prices.
Menu cost theory	Mankiw (1985) Knotek II (2010)	Firms face explicit costs of price adjustment whenever they change prices. These costs lead to state-dependent pricing decisions and firm-level price rigidity.
Cyclical behaviour of prices and costs	Hall, Blanchard, and Hubbard (1986)	Over a business cycle, marginal costs and mark-ups that firms face may not change, thus keeping product prices sticky. There could also be implicit/explicit nominal contracts that may lead to price stickiness.
Theory of coordination failure	Ball and Romer (1987) Cooper and John (1988)	Some firms might like to adjust their prices to changing macroeconomic conditions but hesitate to do so until other firms move first.
Structure of firms and organisational complexities	Blinder (1993)	Large firms' price changes could be slowed down due to difficulties in implementing administrative actions in large, hierarchical organisations.
Sticky information model	Mankiw and Reis (2002)	The prevalence of informational frictions among price-setters could make the price adjustment process time contingent.

Section III
Stylised Facts

The all India CPI-C with base year 2012 has a total of 299 items in the basket,[4] selected based on the Modified Mixed Reference Period (MMRP) data of Consumer Expenditure Survey (CES) conducted in 2011-12 [68th

4 CPI-C with base year 2010 had 318 items, while CPI-C with base year 2012 has 299 items. Item level data in the new base year series are available from January 2014. Therefore, in order to generate a longer time series, the common items in the two series were used to backcast the CPI-C series till January 2011.

round of National Sample Survey (NSS)].[5] These items are classified into 6 major groups, which are 'food and beverages', 'pan, tobacco and intoxicants', 'clothing and footwear', 'housing', 'fuel and light' and 'miscellaneous'.[6] In terms of weights in CPI-C, food and beverages group account for 46 per cent of the share, while the fuel and light group constitutes around 7 per cent. The remaining 47 per cent is generally termed as CPI-core in the policy-making parlance. The basket is, thus, a mixture of a wide variety of items, some of which are consumer durables (like television, washing machine, utensils), some are perishables (like vegetables and fruits) and others are services (like health, house rent and education), with goods constituting a significant share of 77 per cent. An important aspect of such a heterogeneous mix of items is the difference in their price-setting methods.

(i) *Pricing-based Classification of CPI-C*

A snapshot of the CPI-C data reveals stark differences in the movements of price indices across groups (Chart 1a). While the food index reflects significant volatility, which is largely a result of seasonal factors and supply-side shocks that generally impact food prices, the core index is comparatively steadier. Moreover, within food group, price indices of items sold under the public distribution system (PDS), like PDS-rice and PDS-wheat, change infrequently as their prices are fixed/administered by the government, whereas the non-PDS items (which also include rice and wheat) are sold at market prices. Further, perishable items, such as vegetables and fruits, are generally sold unpacked and price discovery is mostly restricted to the local markets or *mandis* through auctioning by traders. In addition, the fuel and light group comprises items whose prices are impacted by international price movements and/or fixed/regulated by the government or its various agencies with government policies having a direct impact on their prices [such as

[5] In MMRP, the consumer expenditure data are gathered from the households using the recall period of: (a) 365-days for clothing, footwear, education, institutional medical care, and durable goods; (b) 7-days for edible oil, egg, fish and meat, vegetables, fruits, spices, beverages, refreshments, processed food, pan, tobacco and intoxicants; and (c) 30-days for the remaining food items, fuel and light, miscellaneous goods and services including non-institutional medical care; rents and taxes (NSSO, 2014; Rangarajan *et al*., 2014). The weighting diagrams of these items in CPI-C are derived on the basis of average monthly consumer expenditure of an urban/ rural household obtained from the same survey.

[6] The National Statistical Office (NSO), Ministry of Statistics and Programme Implementation (MoSPI) is the primary data source for CPI-C.

liquified petroleum gas (LPG) and electricity], alongside items whose prices are market determined (such as firewood and chips). CPI-core, comprising both goods and services, is extremely heterogeneous in its composition with the price indices of items displaying a varied mix of pricing. Services, such as railway fares and porter charges, do not have MRP but are much less volatile. In contrast, household durable goods are generally priced at MRP and hardly display spatial price differences. Their prices are set by the firms based on criteria like cost considerations, market structure (degree of competition) and demand elasticity. Furthermore, items such as petrol and diesel are fixed by the oil marketing companies (OMCs) and are also impacted by the excise duties, cess and value added tax (VAT) fixed and revised by the union and state governments from time to time, while prices of gold and silver are determined by international price movements. In sum, therefore, the price-setting methods within CPI could be very different not only across different items within a group, but also between items within the same product category.

Taking into consideration such differences in the nature of price-setting across items within CPI-C, this paper classifies the complete basket of CPI-C on the basis of price-setting: MRP; non-MRP; a combination of MRP and non-MRP (referred to as 'Mixed'[7]); and Fixed/Regulated pricing (Annex Table A1).[8] The classification reveals that non-MRP items comprise a major share (46 per cent) in CPI-C followed by the MRP items (30 per cent) [Chart 1b]. CPI-goods have items across all the four different price-setting categories, whereas in the case of services, price-setting is either fixed or non-MRP based (Chart 1c). Moreover, non-MRP items comprise a major share in the fuel and light group followed by food and beverages (Chart 1d). The pricing of items within the fuel and light group is either fixed or non-MRP based. CPI-core has a major share of items with MRP based pricing.

From the above sets of classification, it is clear that the movements in MRP and non-MRP based indices would have a key role to play in explaining

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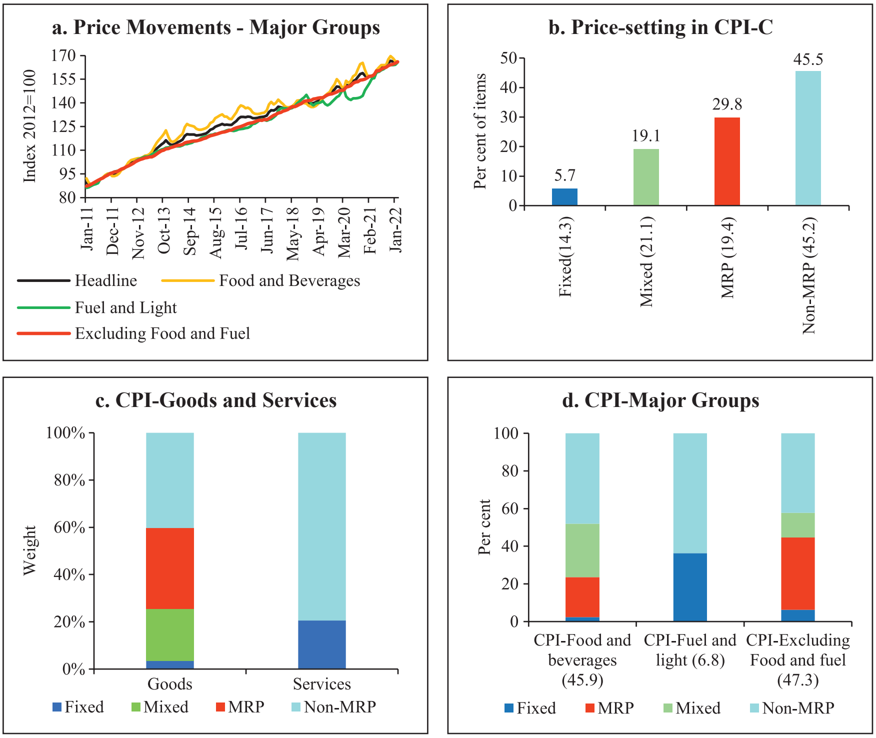
7 Items such as rice and milk can be sold in packed form with an MRP tag as well as in loose form without the MRP tag. As NSO collects price data for most popular item in a market, it can be a mix of both MRP and non-MRP based price-setting from different markets.

8 While there could be concerns related to subjectivity behind the classification of the items under the different pricing methods (*viz*., MRP, non-MRP, a combination of MRP and non-MRP (Mixed), and Fixed/Regulated), in the absence of any proper documentation available with respect to such a classification, the method employed in the paper seemed to be the appropriate as well as a feasible one for research purpose.

Chart 1: Price Movements and Price-setting within CPI-C



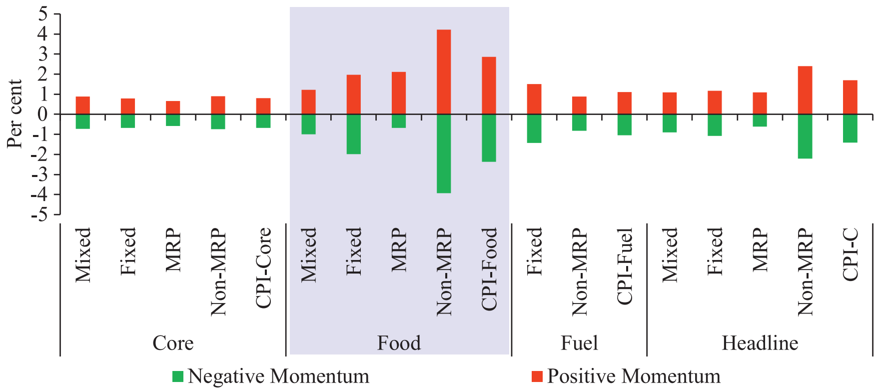
Note: Figures in parentheses indicate weights in CPI-C.
Source: NSO; and Authors' calculations.

the dynamics of overall inflation as these constitute three-fourth of the consumption basket. MRP based classification also includes items such as manufactured food products like edible oils (mostly sold in packed form with MRP tag), where both global prices and government-directed trade policies (particularly, alterations in import duties) have a major impact on prices. But the frequency of their price revisions, given that they are sold at MRP, in response to changes in global prices and government policies, can impart stickiness to their prices.

(ii) *Direction and Frequency of Price Change*

In terms of the average price movements, the food group shows the highest positive and negative momentum, followed by the fuel group (Chart 2), which could be largely attributed to the higher share of non-MRP based price-setting in these groups. Interestingly, however, average price increases

Chart 2: Average Momentum in CPI during February 2014 to February 2020[9]



Source: NSO; and Authors' calculations.

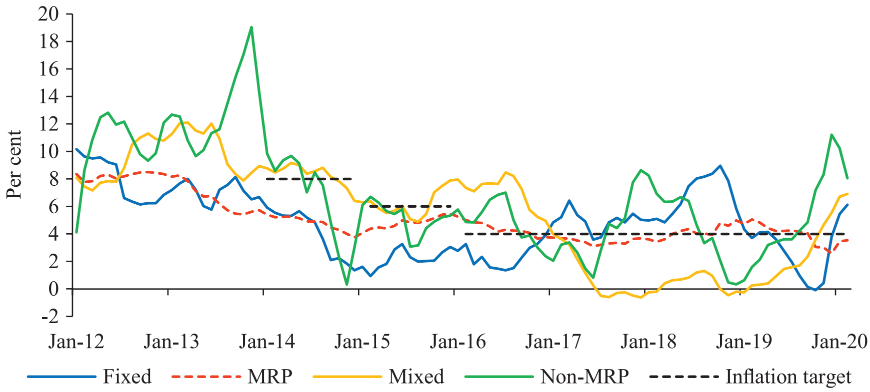
(positive momentum) and price decreases (negative momentum) broadly display similar order of magnitude, indicating that they are largely symmetric.

Surprisingly, the only exception to this pattern are the MRP based items in the food group, which show a higher average positive momentum as compared to the average negative momentum, reflecting downward rigidity in the prices of manufactured/packaged food items, which largely belong to the organised retail market. A price rise in the case of a packaged food item owing to certain adverse supply shocks could be easily passed on to the consumers. However, when such adverse shocks wane, the benefits may not be shared with the consumers by lowering product prices or moving back to the pre-shock price levels. This could be possible in food group given their low elasticity of demand as compared with the other household consumption items. Additionally, there is not much visible difference between the average momentum of the four categories in the core group. This is due to the fact that the core group has a high share of services items and most of the items are not subject to the kind of supply shocks that are common in the food group.

Further, movements in inflation across the four different pricing-based indices clearly show that inflation in MRP based items has the least fluctuation. Since the formal adoption of flexible inflation targeting (FIT) in India in 2016,

[9] Note that these are not the average of annualised momentum. Data period starts from January 2014, implying the availability of momentum from February 2014. Momentum refers to the month-on-month growth rate of the CPI.

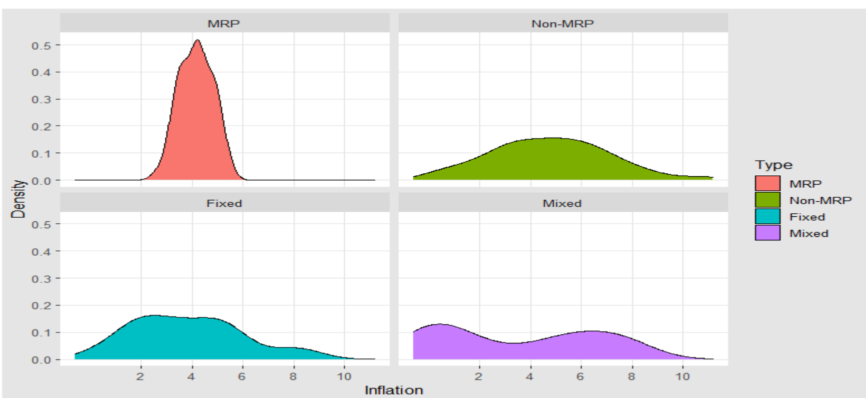
Chart 3: Inflation in CPI-Pricing based Indices



Source: NSO; and Authors' calculations.

inflation in MRP based items has broadly hovered around the medium-term target of 4 per cent, while inflation across the other indices has recorded significant fluctuations on either side of the target (Chart 3). Alternatively, it is found that the distribution of inflation in the case of the MRP based items is strikingly different with much lesser variance, thus, revealing a heavier concentration of inflation around its mean; whereas the rest have much wider and heavier tails indicating the presence of extreme inflation prints (Chart 4). Further, in terms of volatilities of momentum, inflation and change in inflation, the MRP based items exhibit the lowest volatility as compared to the others (Annex Table A2).

Chart 4: Kernel Density Plots



Source: NSO; and Authors' calculations.

Thus, the above nuances of the CPI-C data indicate that there are some price indices which do not change often and are sticky in nature, while the rest fluctuate more often and are thus, flexible. Therefore, based on these observations, the two sub-indices have been constructed within CPI-C, which are: *CPI-sticky price index* and *CPI-flexible price index*.

(iii) *Sticky and Flexible Price Indices*

Based on the observed characteristics of the MRP based pricing index, it forms the sticky price index-1 with a share of 19.4 per cent in CPI. Further, considering the fact that the services items within CPI have a lesser frequency of price change along with a lower volatility of inflation and change in inflation[10], the CPI-sticky price index-2 is constructed by clubbing together 'MRP' and 'services', resulting into a combined share of 42.8 per cent in CPI-C. The counterparts of these two indices are termed as the flexible price indices. Table 3 provides the statistical properties of these indices in detail.

Table 3: Pricing-based Aggregate Indices in CPI-C – Summary Statistics (January 2011-February 2020)

Pricing-based Aggregate Indices	Composition	Momentum[11] (per cent)		Inflation (per cent)		Change in Inflation (percentage points)
		Mean	Std. Dev.	Mean	Std. Dev.	Std. Dev.
Sticky Price Index-1	MRP (19.4)	0.42	0.23	5.03	1.58	0.28
Sticky Price Index-2	MRP+Services (42.8)	0.48	0.29	5.78	1.79	0.33
Flexible Price Index-1	Fixed+Mixed+Non-MRP (80.6)	0.49	0.79	6.08	3.13	0.92
Flexible Price Index-2	Fixed Goods+Non-MRP Goods+Mixed (57.2)	0.47	1.04	5.95	3.78	1.21

Note: 1. Figures in parentheses indicate weights in CPI-C.
2. Standard deviation (Std. Dev.) indicates volatility.

Source: NSO; and Authors' calculations.

10 CPI-services (January 2011-February 2020) – mean inflation: 6.39 per cent, inflation volatility: 2.13 per cent, mean momentum: 0.53, momentum volatility: 0.42, change in inflation volatility: 0.51 percentage point.

11 The study considers price indices rather than actual prices for the construction of the sticky and the flexible price indices, which limits the scope for looking at the actual frequency of price change as indices change almost every month, while actual prices may remain fixed for a considerable duration. This is reflected in the similar mean momentum across the indices, although the volatility in momentum is much different in the sticky price indices as compared to the flexible price indices. Therefore, parameters such as inflation and its volatility as well as momentum and its volatility are used which help us to bring out the differences in terms of price stickiness across the various items in CPI-C.

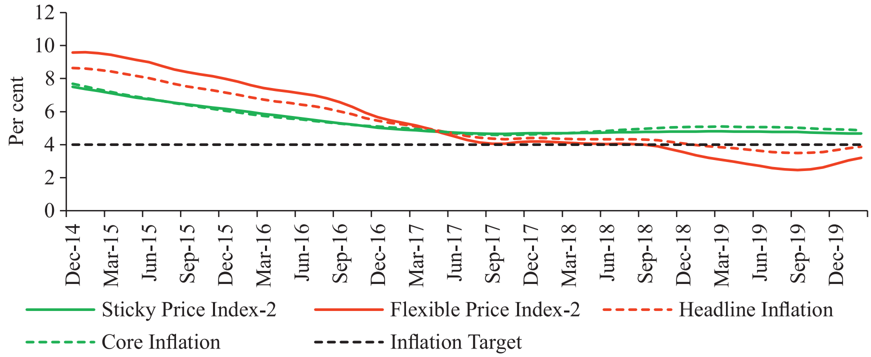
It may be observed that the sticky price indices have lower average momentum and inflation as compared to the flexible price indices. Additionally, they also record much lesser volatility in terms of various volatility parameters. Furthermore, it is observed that headline inflation is primarily driven by the movements in the flexible price inflation, while core inflation broadly aligns with the sticky price inflation (Chart 5). Moreover, chart 5 also reveals that while headline inflation eased significantly over the years (up to Q4:2019) in line with a fall in inflation in both sticky and flexible price indices, the extent of easing in core inflation, however, has been relatively less. The observed relative stability in core inflation is largely on account of its composition - a larger share of MRP-based items and services. Accordingly, while average headline inflation moved towards the target of 4 per cent, mean core inflation has stayed higher than the target inflation.

Correlation coefficients indicate that inflation in flexible price index-1 has the highest correlation with headline inflation, whereas inflation in sticky price index-2 has the highest correlation with core inflation (Annex Table A3).

(iv) *Machine Learning Approach to Generate Sticky and Flexible Price Indices: An Alternative Approach*

As an alternative approach to generate flexible and sticky price indices, a K-means clustering[12] is performed on the 299 items of CPI-C. The approach

Chart 5: Inflation across CPI-based Aggregate Price Indices (3-years Rolling Average)



Source: NSO; and Authors' calculations.

12 It is an unsupervised machine learning (ML) technique.

here is to identify two clusters of the items from the basket corresponding to flexible and sticky prices using two key data features - inflation volatility and frequency of price change during January 2014 to February 2020. Items having less inflation volatility and lower frequency of price change are expected to be classified under the sticky price cluster, while items having higher inflation volatility as well as higher frequency of price change are expected to fall under the flexible price cluster.[13]

Based on the results of the K-means clustering (K being set to 2), items are classified into sticky and flexible price clusters. These ML-based indices are then compared with pricing-based indices constructed in the previous section. Results show that the two indices move together, thereby providing further credence to our derived pricing-based measures of sticky price indices. In terms of their relationship with headline and core inflation, while headline inflation follows the ML-based flexible price index directionally, magnitude-wise the latter is more volatile (Chart 6a), indicating that the latter is primarily capturing the extreme volatile items of the basket. Further, the sticky price index-2 generated earlier tracks core inflation much better than the ML-based sticky price index (Chart 6b).[14] This implies that core inflation is largely influenced by the price movements in the MRP-based items and services.[15]

Therefore, in the subsequent section, we consider the sticky price index-2 towards estimating the sticky price PC as it largely captures the

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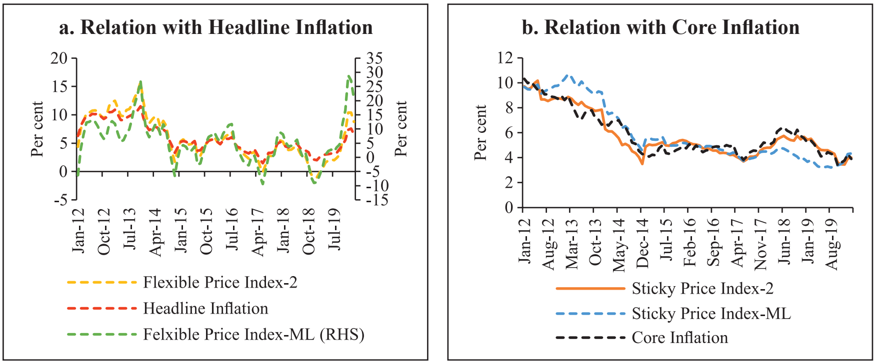
13 Another K-means clustering was performed on 275 CPI items relying on the same features from January 2011 to December 2013 (among the 318 items in the old base year 2010, 275 items could be mapped as common items in the new base year 2012). Using suitable linking factors, the two series are then combined to generate one complete series starting from January 2011. Although the classification of 37 items changes when using the old base data, any observed change at the level of aggregate index is negligible.

14 Correlation coefficients between the two ML based indices and headline/core inflation are also compared with the correlation coefficients obtained earlier. The comparison indicates that the ML-based sticky and flexible price indices have a lower correlation with core and headline inflation, respectively (Annex Table A3).

15 The K-means algorithm classifies an overwhelming number of items in the sticky price cluster (236 items in the current base). Majority of the items which have been identified as MRP (except 5 out of 89) fall under the sticky price cluster as per this classification. Moreover, 11 out of 17 items in the Fixed classification fall under sticky price cluster, which are primarily services. Since the classification by this method is heavily skewed towards the sticky price cluster, this study considers and relies on indices constructed purely based on the observed underlying data characteristics [as provided in Section III - (iii)] for the empirical analysis.

Chart 6: ML-based Flexible and Sticky Price Indices *vis-à-vis* Headline and Core Inflation



Source: NSO; and Authors' calculations.

underlying price movements that are less transient in nature. This implies that any sustained increase in its inflation could indicate building up of persistent price pressures in the economy and therefore, may need constant monitoring.

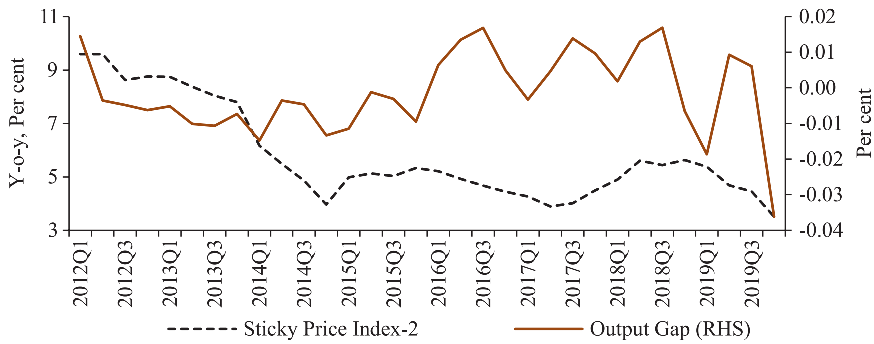
Section IV
Empirical Evaluation

(i) *Sticky Price Index and Its Sensitivity to Output Gap*

Having derived the two sub-indices of CPI-C, in this section we primarily focus on the dynamics of sticky price index. Literature provides ample evidence that sticky prices may not respond to each instance of demand fluctuation and that price stickiness has an impact on output-inflation trade-off (Parkin, 1986; Bryan and Meyer, 2010), which may lead to the non-neutrality of monetary policy (Gali, 2010). Such literature in the Indian context, however, is limited. Therefore, this section studies the linkages between domestic demand conditions/measures of economic slack and the CPI-based sticky price index in a NKPC framework. The sticky-price index-2 is used for this purpose.

A cursory look at the data reveals that the sticky price inflation does not have a very close correspondence with the economy-wide measure of slack, which is output gap (Chart 7).

Chart 7: Sticky Price Inflation and Output Gap



Note: Output gap is calculated as log of actual series less its Hodrick-Prescott filtered trend*100 (based on seasonally adjusted real GDP).

Source: NSO; and Authors' calculations.

Further, pair-wise contemporaneous correlation between quarter-on-quarter (q-o-q) change in sticky price index and output gap turns out to be negative (Annex Table A4). Therefore, dynamic correlations (cross-correlations) are computed to check for any delayed positive association (Annex Chart A1). Results show that changes in sticky price index lag changes in output gap with a significant delay of 2 years and more.

Theoretical Framework and Methodology

In order to further validate the relationship between sticky price index and demand conditions (proxied by output gap), we base our empirical framework on the insights drawn from the NKPC[16] in standard macroeconomic theory. The NKPC, an extension of the original PC with its theoretical micro

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[16] The NKPC has its origins in the works of Fischer (1977) and Taylor (1979). It hinges on inflation being primarily a forward-looking process, according to which current inflation is driven by expectations of future real economic activity rather than past shocks. It, thus, implies that monetary policy can affect inflation through the management of inflation expectations (Mavroeidis *et al*., 2014) and expectations change as the world is not frictionless, rather imperfections and factor market rigidities could be the norm. In the marginal cost formulation of the NKPC, the fundamental relations are the conditions linking unit labour cost to inflation. The circumstances under which the output gap becomes the appropriate forcing process in the PC are in cases of price stickiness accompanied by a competitive and flexible labour market, as discussed in Erceg *et al.,* (2000) and Galí, *et al.,* (2001). The marginal cost formulation of the PC is the more general relationship, and this is stressed by Galí, *et al.,* (2001) and Gagnon and Khan (2001).

foundations, has received widespread acceptance in the monetary policy domain and has been widely adopted by central banks globally as the key price determination equation in macro-models. Given this backdrop, a purely forward-looking NKPC resembles equation (1) below:

$$\pi_t = \beta E_t(\pi_{t+1}) + \lambda x_t + u_t \quad \ldots (1)$$

where, π_t is inflation at time period t, $E_t(\pi_{t+1})$ is inflation expectations at time period t and x_t represents a proxy for marginal cost or demand conditions[17] prevailing in the economy. The disturbance term u_t can be interpreted as measurement error or any other combination of unobserved cost-push shocks, such as shocks to the mark-up or input prices (*eg*., an oil price shock).

The principle micro foundation that is inherent in the NKPC framework is the existence of price rigidity, wherein in a microeconomic environment consisting of identical monopolistically competitive firms, firms face constraints on price adjustment[18]. Literature suggests that even under rational expectations, partial rigidities in the form of information lags or nominal rigidities in prices and wages play a significant role in explaining the observed relationships between inflation and unemployment (Taylor, 1980). Given these facets and empirical difficulties in fitting a purely forward-looking NKPC in the US inflation data, equation (1) underwent modifications that included lagged inflation terms, often termed as *'intrinsic inflation persistence'* (Mavroeidis *et al*., 2014). While Gali and Gertler (1999) introduced lagged terms of inflation under the assumption that a fraction of firms updates their prices using some backward-looking rule of thumb, Fuhrer and Moore (1995) relied on the staggered wage contracts to do the same. Some of the newer studies assumed that firms that are unable to re-optimise upon their prices as in the Calvo model often index their prices to past inflation (Christiano *et al*., 2005; Sbordone, 2005). Thus, the introduction of intrinsic inflation persistence in the

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17 Marginal cost variable is replaced with the output gap in NKPC estimation as according to Gali and Gertler (1999), in the standard sticky price framework without variable capital there is an approximate log-linear relationship between the output gap and marginal cost. Even with variable capital, simulations suggest that the relation remains very close to proportionate.

18 Calvo (1983) assumes that nominal individual prices are not subjected to continuous revisions; and price revisions are not synchronous. Rotemberg (1982) assumes that changing prices could be costly for firms possibly due to the difficulties that it could pose on consumers.

PC framework drove the emergence of the *'hybrid NKPC'*, which resembles equation (2) below:

$$\gamma(L)\pi_t = \gamma_f E_t(\pi_{t+1}) + \lambda x_t + \eta\omega_t + u_t \text{ ...(2)}$$

where, $\gamma(L) = 1 - \gamma_1 L - \gamma_2 L^2 - \cdots - \gamma_l L^l$ is a lag polynomial, x_t represents a proxy for marginal cost or demand conditions prevailing in the economy,[19] ω_t denotes additional controls, and u_t is an unobserved shock. $\gamma_f = 0$ gives back the backward-looking PC (which does not incorporate inflation expectations) and in particular, Gordon (1990)'s triangle model where inflation is explained by three key factors – demand [proxied by the level and change in output gap (x_t)], supply [represented by exogenous shift variables indicating the impact of supply-side shocks like oil price shocks, import price shocks and price controls (ω_t)] and inflation inertia represented by the lagged inflation terms [$\gamma(L)$]. Equation (2) is a more general specification of the hybrid NKPC.[20]

Importantly, the inflation expectations term in equation (2), which is supposed to be an endogenous variable in the system and in fact is unobservable, poses estimation issues in the NKPC framework. Therefore, to correct for such estimation anomalies, literature has come to a consensus on different methods to deal with the inflation expectations variable while estimating the NKPC. These methods include: (i) replacing expectations with actual inflation outcomes and use appropriate instruments (generalised instrumental variables (GIV) framework) [McCallum, 1976; Hansen and Singleton, 1982; Roberts, 1995; Gali and Gertler, 1999]; (ii) deriving expectations in a particular reduced-form model (vector autoregression (VAR) framework) [Fuhrer and Moore, 1995; Sbordone, 2002]; and (iii) using direct measures of expectations (available through inflation expectations surveys) [Roberts, 1995]. Relying on survey-based inflation expectations avoids the need for modelling inflation expectations using statistical/econometric methods, though some researchers feel that the procedure allows for non-rational price setting, the understanding of which is rather limited or at a relatively nascent stage. Therefore, survey-based measures of inflation expectations can be considered as one of the useful

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[19] x_t is stated as the main forcing variable in Mavroeidis *et al.,* (2014).

[20] Hybrid NKPC specifications in Gali and Gertler (1999), Sbordone (2005), and Christiano *et al.,* (2005) include only one lagged term of inflation.

ways to look at the intuition behind price-setting being partially forward-looking, partially backward-looking as well as responding to economy-wide aggregate demand conditions. Therefore, considering survey-based inflation expectations in the NKPC framework yields the following representation:

$$\pi_t = \beta\pi^s_{t+1|t} + \lambda x_t + \eta\omega_t + u_t + \beta\varepsilon_t \quad ...(3)$$

where, $$\varepsilon_t = E_t(\pi_{t+1}) - \pi^s_{t+1|t} \quad ... (3.1)$$

Equation (3.1) implies that the deviation of the survey-based expectations from the actual inflation expectations (which in reality, are unobservable) may be influenced by a combination of factors such as measurement errors and news shocks, the latter arising when survey responses are based on a restricted/ smaller set of information set as compared to the one the agents in the model use. Model identification would depend on the properties of the survey-based error term as well as on the correlation between $\pi^s_{t+1|t}$ and ω_t. Some researchers treat $\pi^s_{t+1|t}$ as an exogenous variable in the system. Alternatively, $\pi^s_{t+1|t-1}$ instead of $\pi^s_{t+1|t}$ is used in the model estimation as it is certainly pre-determined (usually measured within the quarter) and therefore, can be treated as exogenous (Rudebusch, 2002; Adam and Padula, 2011).

Against this backdrop, equation (4) below forms the base for the empirical framework attempted in this section.

$$\gamma(L)\pi_{sticky,t} = \beta\pi^s_{t+4|t} + \lambda x_t + \eta\omega_t + u_t + \vartheta\varepsilon_t \quad ...(4)$$

where, $\gamma(L) = 1 - \gamma_1 L - \gamma_2 L^2 - \cdots - \gamma_l L^l$ is a lag polynomial, $\pi_{sticky,t}$ represents CPI-based sticky price inflation, $\pi^s_{t+4|t}$ represents survey-based one-year ahead inflation expectations of the households as obtained from the Inflation Expectations Survey of the Households conducted by the RBI, x_t represents demand conditions/economic slack prevailing in the economy and is proxied by output gap.[21] and ω_t denotes additional control variables taking into account various supply-side shocks such as domestic and global input cost conditions and nominal exchange rate (INR-USD) movements.

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[21] Since the purpose of the paper is to estimate the sensitivity of the sticky price index to the demand conditions in the economy, we do not consider additional control variables denoted by ω_t in our base model. However, as a robustness check for our results we have re-estimated the base model using additional controls as indicated in the paper, the results of which are presented in the Annex.

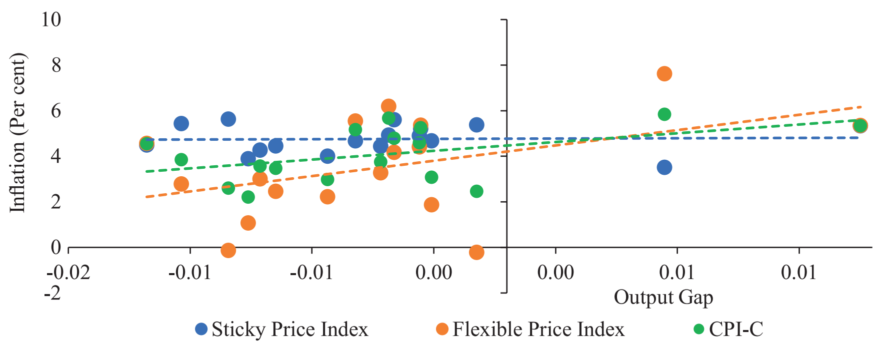
$u_t + \vartheta\varepsilon_t$ is the residual where ε_t is as given by equation (3.1). Equation (4) is estimated using the ordinary least squares regression technique. Based on the available literature related to the treatment of the survey-based measure of inflation expectations (Rudebusch, 2002; Adam and Padula, 2011), $\pi^s_{t+4|t-1}$ instead of $\pi^s_{t+4|t}$ is used in the model estimation as it is pre-determined and therefore, is treated as exogenous. Given the smaller sample period, this was considered to be an appropriate way of treating inflation expectations in the modelling framework.

(ii) *Empirical Estimation and Results*

Before proceeding for the PC estimation, we first look at the relationship between economic slack (represented by output gap) and the sticky price index-2 and compare that to CPI- C and flexible price index. The slope of the trendline in the case of the sticky price index is flatter as compared to that in the headline CPI-C, while the flexible price index has the steepest slope, indicating its larger reaction to fluctuations in demand conditions in the economy (Chart 8). Therefore, estimation of PC for these indices would enable us to validate this graphical observation.

Based on the outlined framework in the previous sub-section [equation (4)], empirical exercise using quarterly data for the sample period 2011:Q1-2019:Q4 is conducted. Data sources used in the empirical exercise are provided in Annex Table A5.1 and variable representation and description are provided

Chart 8: Disaggregated CPI Phillips Curves – Scatter Plots



Note: The chart plots output gap at t-15 lag given the delayed association between output gap and sticky price index as also revealed by the cross-correlation plots.
Source: NSO; RBI; and Authors' estimates.

in Annex Table A5.2. All variables are converted to their natural logarithms, wherever applicable, and then de-seasonalised using US Census X-13ARIMA method, after which they are used in their first-differenced forms (*i.e.,* q-o-q change) in the model because of their non-stationarity. Stationarity of the variables are tested by employing the augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests of unit roots, the results of which are provided in Annex Table A6.

Results presented in table 4 indicate that output gap has a positive and significant impact on the changes in sticky price index and the magnitude of impact turns out to be 0.04 per cent. However, the impact of output gap happens with a significant lag of around 3 years.[22] Given the average duration of business cycles to be around five years in India (with an overall range of 2-8 years),[23] prices that are sticky may undergo revisions once/twice during such cycles, which could have been possibly reflected in the empirical results obtained. With regard to inflation expectations, results indicate that changes in inflation expectations positively impact sticky price changes with significant lag. The estimated impact turns out to be 0.01 per cent with a lag of 8 quarters.[24] The results also point to a significant presence of intrinsic persistence as reflected by the coefficients of the lagged changes in the sticky price index.

Having obtained the estimates for the sticky price PC, we now compare the results with the headline PC and the flexible PC estimates (Table 4; columns 2 and 3). The results show that the sticky price PC is much flatter and slower to respond to changes in demand conditions as compared to the headline PC estimates, while the flexible PC is the steepest indicating its larger reaction to fluctuations in demand conditions in the economy, thus, re-validating Chart 8.

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22 Another paper that establishes the PC relationship in the context of India using CPI-C data, although on headline inflation, shows that the impact of output gap on headline inflation occurs with a lag of around 2 years [Jose, *et al*., 2022]. Other studies that show the delayed impact of output gap on inflation include Fisher *et al*. (1997).

23 See Behera and Sharma (2019).

24 Inflation expectations are on y-o-y basis. In the model change in inflation expectations has been incorporated, which makes the explanatory variable in percentage points. Therefore, the coefficient corresponding to the q-o-q change in inflation expectations is multiplied by 100 for impact comparison purpose across variables.

Table 4: Regression Results

	Dependent Variables $\Delta(ln\ Y_i)$		
Explanatory Variables	***Sticky Price Index*** **(1)**	***CPI-C*** **(2)**	***Flexible Price Index*** **(3)**
Constant	0.003* (0.001)	0.01*** (0.002)	0.01*** (0.003)
$\Delta(ln\ Y)_{i,t-1}$	0.02 (0.10)	0.17 (0.11)	0.23 (0.14)
$\Delta(ln\ Y)_{i,t-3}$	0.36** (0.09)	0.37** (0.15)	-
$\Delta(ln\ Y)_{i,t-12}$	0.21** (0.05)	-	-
$\Delta(one-year\ ahead\ inflation\ expectations)_{t-j}$	0.0001* (0.0000)	0.001* (0.0004)	0.001* (0.001)
$(Output\ Gap)_{t-k}$	0.04** (0.01)	0.19* (0.10)	0.35* (0.18)
No. of Observations	36	36	36
Sample Period	2011Q1-2019Q4	2011Q1-2019Q4	2011Q1-2019Q4
Adjusted R-squared	0.99	0.57	0.38
B-G Serial Correlation LM Test: F-Statistic	3.51	0.21	0.66
B-P-G Heteroscedasticity Test: F-Statistic	0.45	0.50	0.40

Notes: 1. *, ** and *** represent significance levels at 10 per cent, 5 per cent and 1 per cent, respectively. The variables used in the model were transformed to their natural logarithms and seasonally adjusted before incorporating them in the model. Figures in parentheses indicate heteroscedasticity-consistent standard errors. Δ represents q-o-q change in the variables.

2. Separate period dummies for appropriate quarters were incorporated in the specifications as exogenous variables in order to enhance model performance.

3. The lag structure is as follows: j is 7 in (1), 8 in (2) and 3 in (3); k is 13 in (1) and 6 in (2) and (3). In addition, specification 1 also contains 14th lag of output gap which turned out to be insignificant and specification 2 also consists of 4th lag of dependent variable and 5th lag of output gap.

Overall, the results indicate that the sticky price PC is much flatter as compared to the headline PC followed by the flexible PC, reflecting its meek reaction to changing demand conditions. Additionally, the results also highlight the contribution of intrinsic persistence in imparting price stickiness as indicated by a significantly higher coefficient of its own lags. As a robustness check, another set of regression specification was estimated using control variables such as exchange rate changes, average retail prices of petrol and diesel across four metro cities of India (Kolkata, Delhi, Mumbai and Chennai) as a proxy for input cost pressures, as well as rainfall deviation from the long period average and retail prices of primary vegetables in the case of the flexible price equation. The results (Annex Table A7) are broadly in line with those obtained in Table 4.[25]

Section V
Conclusion

In new Keynesian models, monetary policy can become non-neutral because of the widely observed sticky behaviour in prices. Price stickiness, thus, creates scope for monetary policy to pursue the goals of output and employment.

While literature in the Indian context has been devoted largely to validating the presence of the PC and exploring different aspects of inflation forecasting, research on differences in price-setting methods and related heterogeneity in price dynamics at the disaggregated level of the all India CPI has been limited. This paper, therefore, addresses this void in the existing literature and analyses CPI-C at a disaggregated level on the basis of the different price-setting methods. The study first classifies the items based on four different price-setting methods – MRP; non-MRP; a combination of MRP and non-MRP (termed as 'Mixed'); and Fixed/Regulated – and then using this classification and certain parameters such as 'price momentum and its volatility' and 'inflation and its volatility' constructs two separate indices, *viz*., Sticky Price Index and Flexible Price Index.

The results show that the sticky price index constitutes around 43 per cent of the overall CPI-C basket and by construction records lower average

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[25] The results also indicate the significance of input cost pressures and changes in nominal exchange rate (INR-USD) in determining changes in the sticky price index. Simple line plots (Annex Chart A2) also show a lagged co-movement between these variables and sticky price inflation. Further, annex Table A4 provides the contemporaneous correlation on q-o-q change between the sticky price index and the other control variables. Results indicate that the q-o-q change in the sticky price index shares statistically significant and positive correlation with exchange rate changes.

In the case of the flexible price index, the average retail prices of tomato, onion and potato (DCA TOP) and rainfall deviation from its long period average (LPA), turn out to be the two major factors influencing its dynamics because the food group constitutes a major share of the flexible price index.

momentum and inflation as well as much lesser volatility compared to the flexible price index. Furthermore, it is observed that headline inflation is primarily driven by the movements in the flexible price inflation, while core inflation broadly aligns with the sticky price inflation.

PC estimates based on the NKPC framework indicate that the sticky price PC is much flatter as compared to the PC based on headline CPI-C and the flexible price PC. Therefore, the results imply that the sticky price PC is less sensitive to changing conditions of economic slack. Additionally, the impact of output gap occurs with a significant lag of around 3 years, suggesting that the sticky price index is slow to adjust to changes in economic slack. Given the average duration of business cycles to be around five years in India, prices that are sticky may undergo revisions once or twice during such cycles, which could possibly be the underlying reason behind the slow and lagged adjustment to output gap. With regard to inflation expectations, results indicate that changes in inflation expectations positively impact sticky price changes, although with some lag. Furthermore, the results reveal a higher degree of intrinsic persistence in the sticky price index, which explains a major part of its stickiness. All of these together imply that in a situation when the sticky price inflation turn upwards, it may remain elevated for a considerable period of time because of its high intrinsic persistence, thus, posing risks for inflation turning generalised. Therefore, monetary policy should remain wary of the underlying inflationary pressures which may be observed by a careful monitoring of the sticky price index. Therefore, from the perspective of India's monetary policy, analysing movements in the sticky price index could be an important aid in gauging the underlying price pressures in the economy (whether transitory or permanent) and the pricing power of firms, thus providing a deeper understanding of the overall inflation dynamics.

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Annex

Table A1: Classification of Items

S. No	MRP	Non-MRP	Mixed	Fixed
1	medicine [non-institutional] (4)	house rent; garage rent (9.5)	milk: liquid (litre) (6.4)	tuition and other fees [school; college; etc.] (2.9)
2	mustard oil (1.3)	cooked meals purchased (no.) (2.4)	rice_other sources (4.4)	electricity (std. unit) (2.3)
3	refined oil [sunflower; soyabean; saffola; etc.] (1.3)	firewood and chips (2.1)	wheat/atta_other sources (2.6)	petrol for vehicle (2.2)
4	tea: leaf (gm) (1)	fish; prawn (1.3)	sugar - other sources (1.1)	telephone charges: mobile (1.8)
5	biscuits; chocolates; etc. (0.9)	chicken (1.2)	arhar; tur (0.8)	bus/tram fare (1.4)
6	washing soap/soda/ powder (0.9)	cooked snacks purchased [samosa; puri; paratha; burger; chowmein; idli; dosa; vada; chops; pakoras; pao bhaji; etc.] (1.2)	dry chillies (gm) (0.6)	LPG [excl. conveyance] (1.3)
7	motor cycle; scooter (0.8)	gold (1.1)	turmeric (gm) (0.5)	taxi; auto-rickshaw fare (0.6)
8	toilet soap (0.6)	potato (1)	ghee (0.5)	rice_PDS (0.4)
9	books; journals: first hand (0.6)	saree (no.) (0.9)	jeera (gm) (0.4)	kerosene PDS (litre) (0.3)
10	motor car; jeep (0.5)	tea: cups (no.) (0.9)	moong (0.3)	school bus; van; etc. (0.2)
11	papad; bhujia; namkeen; mixture; chanachur (0.5)	monthly charges for cable TV connection (0.8)	dhania (gm) (0.3)	railway fare (0.2)
12	hair oil; shampoo; hair cream (0.5)	goat meat/mutton (0.8)	masur (0.3)	wheat/atta_PDS (0.2)
13	bidi (no.) (0.4)	doctors/surgeons fee-first consultation [non-institutional] (0.8)	urd (0.3)	telephone charges: landline (0.2)
14	foreign/refined liquor or wine (litre) (0.4)	cloth for shirt; pyjama; kurta; salwar; etc. (metre) (0.7)	leather boots; shoes (0.2)	water charges (0.2)
15	powder; snow; cream; lotion and perfume (0.4)	onion (0.6)	gram: split (0.2)	diesel for vehicle (0.1)
16	toothpaste; toothbrush; comb; etc. (0.4)	domestic servant/cook (0.6)	leather sandals; chappals; etc. (0.2)	sugar - PDS (0.1)
17	country liquor (litre) (0.4)	private tutor/coaching centre (0.6)	gamchha; towel; handkerchief (no.) (0.2)	diesel (litre) [excl. conveyance] (0)
18	groundnut oil (0.3)	tomato (0.6)	other petty articles (0.2)	-

Table A1: Classification of Items *(Contd.)*

S. No	MRP	Non-MRP	Mixed	Fixed
19	rubber/PVC footwear (0.3)	shirts; T-shirts (no.) (0.6)	besan (0.2)	-
20	cigarettes (no.) (0.2)	other vegetables (0.6)	tamarind (gm) (0.1)	-
21	incense [agarbatti]; room freshener (0.2)	banana (no.) (0.6)	black pepper (gm) (0.1)	-
22	bed sheet; bed cover (no.) (0.2)	prepared sweets; cake; pastry (0.6)	other washing requisites (0.1)	-
23	electric bulb; tubelight (0.2)	shorts; trousers; bermudas (no.) (0.6)	chira (0.1)	-
24	newspapers; periodicals (0.2)	barber; beautician; etc. (0.6)	gram: whole (0.1)	-
25	curry powder (gm) (0.2)	baniyan; socks; other hosiery and undergarments; etc. (no.) (0.5)	curd (0.1)	-
26	television (0.2)	X-ray; ECG; pathological test; etc. [non-institutional] (0.5)	oilseeds (gm) (0.1)	-
27	salt (0.2)	apple (0.5)	cashewnut (0.1)	-
28	mobile handset (0.1)	dung cake (0.4)	other leather footwear (0.1)	-
29	bicycle [without accessories] (0.1)	hospital and nursing home charges (0.4)	peas [Pulses] (0.1)	-
30	mosquito repellent; insecticide; acid etc. (0.1)	palak/other leafy vegetables (0.4)	bucket; water bottle/ feeding bottle and other plastic goods (0.1)	-
31	sports goods; toys; etc. (0.1)	eggs (no.) (0.4)	maize and products (0.1)	-
32	PC/Laptop/other peripherals incl. software (0.1)	cloth for coat; trousers; suit; etc. (metre) (0.4)	raisin; kishmish; monacca; etc. (0.1)	-
33	bread [bakery] (0.1)	tailor (0.4)	cereal substitutes: tapioca; etc. (0)	-
34	shaving blades; shaving stick; razor (0.1)	stationery; photocopying charges (0.4)	other dry fruits (0)	-
35	suji; rawa (0.1)	brinjal (0.4)	ragi and its products (0)	-
36	pickles (gm) (0.1)	grinding charges (0.3)	dates (0)	-
37	refrigerator (0.1)	mango (0.3)	almirah; dressing table (0)	-
38	sanitary napkins (0.1)	garlic (gm) (0.3)	maida (0)	-
39	cold beverages: bottled/canned (litre) (0.1)	groundnut (0.3)	other furniture and fixtures [couch; sofa; etc.] (0)	-

Table A1: Classification of Items *(Contd.)*

S. No	MRP	Non-MRP	Mixed	Fixed
40	other beverages: cocoa; chocolate; etc. (0.1)	residential building and land [cost of repairs only] (0.3)	gram products (0)	-
41	matches (box) (0.1)	ladys finger (0.3)	other rice products (0)	-
42	coconut oil (0.1)	green chillies (0.3)	chair; stool; bench; table (0)	-
43	other packaged processed food (0.1)	beef/buffalo meat (0.3)	other metal utensils (0)	-
44	rug; blanket (no.) (0.1)	other tobacco products (0.3)	other crockery and utensils (0)	-
45	tyres and tubes (0.1)	coconut (no.) (0.3)	headwear; belts; ties (no.) (0)	-
46	vanaspati; margarine (0.1)	cauliflower (0.2)	coir; rope; etc. (0)	-
47	umbrella; raincoat (0.1)	gourd; pumpkin (0.2)	walnut (0)	-
48	beer (litre) (0.1)	jowar and its products (0.2)	cloth for upholstery; curtains; tablecloth; etc. (metre) (0)	-
49	coffee: powder (gm) (0.1)	kurta-pajama suits: females (no.) (0.2)	goods for recreation and hobbies (0)	-
50	air conditioner; air cooler (0.1)	kerosene other sources (litre) (0.2)	carpet; daree and other floor mattings (0)	-
51	fruit juice and shake (litre) (0.1)	coat; jacket; sweater; windcheater (no.) (0.2)	glassware (0)	-
52	lubricants and other fuels for vehicle (0.1)	ginger (gm) (0.2)	candy; misri (0)	-
53	zarda; kimam; surti (gm) (0)	other fuel (0.2)	other cereals (0)	-
54	pillow; quilt; mattress (no.) (0)	cabbage (0.2)	bedding: others (0)	-
55	torch (0)	stainless steel utensils (0.2)	knitting wool (gm) (0)	-
56	shaving cream; aftershave lotion (0)	other footwear (0.2)	small millets and their products (0)	-
57	inverter (0)	school/college uniform: boys (0.2)	any other personal goods (0)	-
58	milk: condensed/ powder (0)	other consumer services excluding conveyance (0.2)	-	-
59	sewai; noodles (0)	pan: finished (no.) (0.2)	-	-
60	candle (no.) (0)	grapes (0.2)	-	-
61	baby food (0)	frocks; skirts; etc. (no.) (0.2)	-	-

Table A1: Classification of Items *(Contd.)*

S. No	MRP	Non-MRP	Mixed	Fixed
62	washing machine (0)	beans; barbati (0.1)	-	-
63	sauce; jam; jelly (gm) (0)	school/college uniform: girls (0.1)	-	-
64	mineral water (litre) (0)	ingredients for pan (gm) (0.1)	-	-
65	electric fan (0)	cinema: new release [normal day] (0.1)	-	-
66	mosquito net (no.) (0)	lemon (no.) (0.1)	-	-
67	ice-cream (0)	orange; mausami (no.) (0.1)	-	-
68	electric batteries (0)	washerman; laundry; ironing (0.1)	-	-
69	butter (0)	other fresh fruits (0.1)	-	-
70	water purifier (0)	other medical expenses [non-institutional] (0.1)	-	-
71	chips (gm) (0)	watch man charges [other cons taxes] (0.1)	-	-
72	VCR/VCD/DVD player (0)	lungi (no.) (0.1)	-	-
73	other cooking/ household appliances (0)	other entertainment (0.1)	-	-
74	CD; DVD; audio/ video cassette; etc. (0)	bajra and its products (0.1)	-	-
75	other durables [specify] (0)	silver (0.1)	-	-
76	plugs; switches and other electrical fittings (0)	muri (0.1)	-	-
77	radio; tape recorder; 2-in-1 (0)	peas [Vegetables] (0.1)	-	-
78	honey (0)	gur (0.1)	-	-
79	camera and photographic equipment (0)	coconut: copra (0.1)	-	-
80	electric iron; heater; toaster; oven and other electric heating appliances (0)	leaf tobacco (gm) (0.1)	-	-
81	bathroom and sanitary equipment (0)	parwal/patal; kundru (0.1)	-	-
82	suitcase; trunk; box; handbag and other travel goods (0)	carrot (0.1)	-	-

Table A1: Classification of Items *(Contd.)*

S. No	MRP	Non-MRP	Mixed	Fixed
83	lock (0)	flower [fresh]: all purposes (0.1)	-	-
84	sewing machine (0)	other pulses (0.1)	-	-
85	lighter [bidi/ cigarette/gas stove] (0)	shawl; chaddar (no.) (0.1)	-	-
86	pressure cooker/ pressure pan (0)	guava (0.1)	-	-
87	family planning devices (0)	internet expenses (0.1)	-	-
88	clock; watch (0)	air fare [normal]: economy class [adult] (0.1)	-	-
89	stove; gas burner (0)	other intoxicants (0.1)	-	-
90	-	dhoti (no.) (0.1)	-	-
91	-	radish (0.1)	-	-
92	-	pan: leaf (no.) (0.1)	-	-
93	-	toddy (litre) (0.1)	-	-
94	-	bedstead (0.1)	-	-
95	-	spectacles (0.1)	-	-
96	-	kurta-pajama suits: males (no.) (0.1)	-	-
97	-	pork (0.1)	-	-
98	-	clothing [first-hand]: other (0.1)	-	-
99	-	papaya (0)	-	-
100	-	watermelon (0)	-	-
101	-	green coconut (no.) (0)	-	-
102	-	rickshaw [hand drawn and cycle] fare (0)	-	-
103	-	sweeper (0)	-	-
104	-	other educational expenses [incl. fees for enrollment in web-based training] (0)	-	-
105	-	Monthly Maintainance charges (0)	-	-
106	-	coal (0)	-	-
107	-	other pulse products (0)	-	-
108	-	earthenware (0)	-	-
109	-	other milk products (0)	-	-
110	-	photography (0)	-	-
111	-	coffee: cups (no.) (0)	-	-
112	-	other nuts (0)	-	-
113	-	clothing: second-hand (0)	-	-

Table A1: Classification of Items *(Contd.)*

S. No	MRP	Non-MRP	Mixed	Fixed
114	-	kharbooza (0)	-	-
115	-	other ornaments (0)	-	-
116	-	khesari (0)	-	-
117	-	coke (0)	-	-
118	-	other conveyance expenses (0)	-	-
119	-	hotel lodging charges (0)	-	-
120	-	leechi (0)	-	-
121	-	hookah tobacco (gm) (0)	-	-
122	-	others: birds; crab; oyster; tortoise; etc. (0)	-	-
123	-	cheroot (no.) (0)	-	-
124	-	jackfruit (0)	-	-
125	-	horse cart fare (0)	-	-
126	-	pineapple (no.) (0)	-	-
127	-	VCD/DVD hire [incl. instrument] (0)	-	-
128	-	charcoal (0)	-	-
129	-	singara (0)	-	-
130	-	porter charges (0)	-	-
131	-	club fees (0)	-	-
132	-	berries (0)	-	-
133	-	snuff (gm) (0)	-	-
134	-	pears/nashpati (0)	-	-
135	-	steamer; boat fare (0)	-	-
136	-	library charges (0)	-	-
Items	**89**	**136**	**57**	**17**
Weight	**19.4**	**45.2**	**21.1**	**14.3**

Table A2: Volatility (Standard Deviation: January 2011 to February 2020)

Price Indices	Momentum	Inflation	Change in Inflation
MRP	0.2	1.6	0.3
Non-MRP	1.2	3.9	1.5
Mixed	0.5	3.8	0.6
Fixed	0.6	2.5	0.8

Source: NSO; and Authors' calculations.

Table A3: Correlation between Headline/Core Inflation and Inflation in Sticky and Flexible Price Indices

Indices	Headline Inflation	Core Inflation
Sticky price index-1	0.76***	0.90***
Flexible price index-1	0.99***	0.72***
Sticky price index-2	0.81***	0.95***
Flexible price index-2	0.97***	0.63***
Sticky price index-ML	0.92***	0.89***
Flexible price index-ML	0.75***	0.28***
Headline Inflation	*1.00****	*0.77****

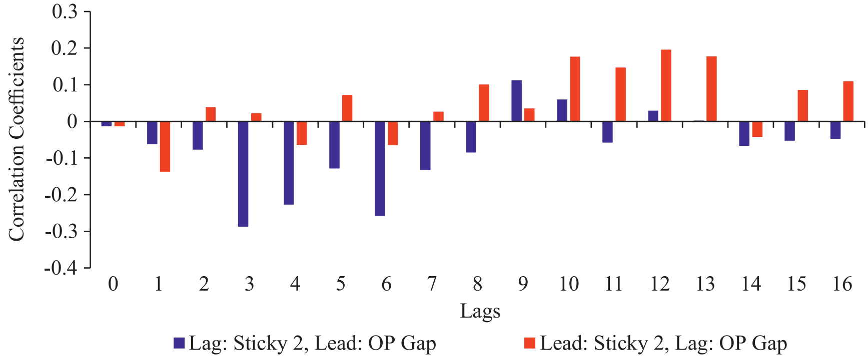
Note: Coefficients are significant at 1 per cent level of significance.
Source: NSO; and Authors' calculations.

Table A4: Contemporaneous Correlation Coefficients (on Q-o-Q change)

Variables	Sticky Price Index 1	Sticky Price Index 2
Sticky Price Index-1	1.00	0.88***
Sticky Price Index-2	0.88***	1.00
Flexible Price Index-1	0.42**	0.64***
Flexible Price Index-2	0.35**	0.56***
Inflation Expectations (1 year ahead)	0.51***	0.50***
Inflation Expectations (3 months ahead)	0.45***	0.46***
Output Gap	-0.34**	-0.26
Petrol and Diesel Retail Prices	0.15	0.22
Global Non-Fuel Price	-0.26	-0.28
Exchange Rate (INR-USD)	0.38**	0.40**

Note: ***, ** and * indicate significance at 1 per cent, 5 per cent and 10 per cent levels of significance, respectively.

Chart A1: Dynamic Correlations: Sticky Price Index-2 and Output Gap
(on Q-o-Q Change)



Source: Authors' estimates.

Table A5.1: Data Sources

S. No.	Variables	Source
1.	CPI-C	National Statistical Office (NSO), Ministry of Statistics and Programme Implementation (MOSPI), GoI
2.	INR-USD Exchange Rate	Database on Indian Economy (DBIE), RBI
3.	Petrol and Diesel Retail Prices	Indian Oil Corporation Limited (IOCL)
4.	Global Non-fuel Price Indices	World Bank Pink Sheet Database
5.	Rainfall Deviation from LPA	India Meteorological Department (IMD)
6.	Inflation Expectations	Inflation Expectations Survey of Households (IESH), RBI
7.	Real Gross Domestic Price (GDP) [Base year: 2011-12=100]	NSO, MoSPI, GoI
8.	Tomato-Onion-Potato (TOP) prices	Department of Consumer Affairs (DCA), Ministry of Consumer Affairs, Food and Public Distribution, GoI
9.	Rural Wages	Labour Bureau, Ministry of Labour and Employment, GoI

Table A5.2: Variable Description and Representation

S. No.	Variables	Representation
1.	CPI-C and other derived indices	Y
2.	INR-USD Exchange Rate	Nominal exchange rate
3.	Petrol and Diesel Retail Prices: average retail prices of petrol and diesel across four metro cities of India (Kolkata, Delhi, Mumbai and Chennai)	RetailPrice_Petrol&Diesel
4.	Rainfall Deviation from the long period average (LPA)	Rain Dev from LPA
5.	Inflation Expectations	One-year ahead households' inflation expectations
6.	Output Gap: Calculated as log of actual seasonally adjusted real GDP series less its Hodrick-Prescott filtered trend*100.	Output Gap
7.	Tomato-Onion-Potato (TOP) prices: Average of retail prices	DCA TOP

Table A6: Unit Root Test Results

De-seasonalised Variables	**ADF Test**		**PP Test**	
	log(x)	**Δ log(x)**	**log(x)**	**Δ log(x)**
Sticky Price Index-1	-3.50*	-3.65**	-3.22*	-3.65**
Sticky Price Index-2	-4.09**	-3.69**	-3.64**	-3.83**
Output Gap#	-7.45***	-9.53***	-	-
Exchange Rate (INR-USD)	-2.67	-5.84***	-1.87	-6.50***
Global Non-fuel Prices	-1.2	-4.56***	-0.56	-4.58***
Domestic Petrol and Diesel Prices	-2.12	-2.44	-2.24	-5.46***
DCA TOP Prices	-2.91	-6.74***	-3.29*	-6.79***
Rural Wage	-3.81**	-5.61***	-2.31	-3.81**
Non-De-seasonalised Variable	**x**	**Δx**	**x**	**Δx**
Rainfall Deviation from LPA	-5.14***	-6.40***	-5.13***	-14.96***
Inflation Expectations (1year ahead)	-3.2	-6.60***	-3.23*	-7.88***

Note: ***, ** and * indicate significance at 1 per cent, 5 per cent and 10 per cent levels of significance, respectively. #: tested for structural break unit root test.

Table A7: Regression Results - With Controls

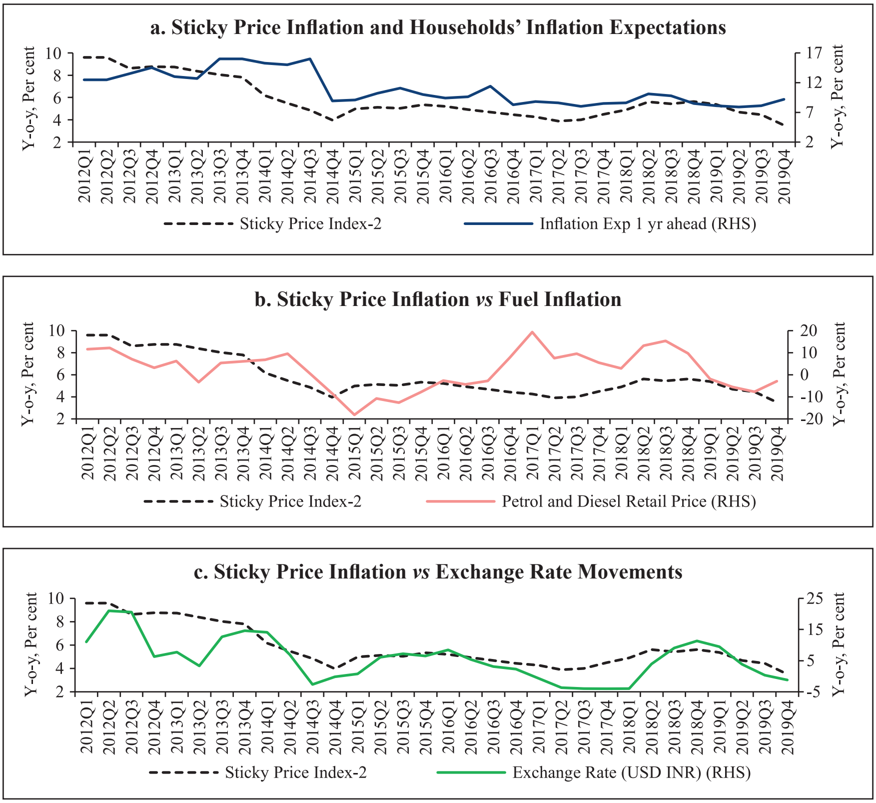
Explanatory Variables	***Dependent Variables*** $\Delta(ln\ Y_i)$		
	***Sticky Price Index* (1)**	***CPI-C* (2)**	***Flexible Price Index* (3)**
Constant	0.0004 (0.001)	0.005** (0.002)	0.007*** (0.002)
$\Delta(ln\ Y)_{i,t-1}$	0.10** (0.03)	0.38*** (0.12)	-
$\Delta(ln\ Y)_{i,t-2}$	-	-	0.15* (0.08)
$\Delta(ln\ Y)_{i,t-3}$	0.10*** (0.02)	-	-
$\Delta(ln\ Y)_{i,t-12}$	0.34*** (0.02)	-	-
$\Delta(one-year\ ahead\ inflation\ expectations)_{t-i}$	0.0003*** (0.0000)	0.001* (0.0003)	0.0002 (0.0003)
$\Delta(ln\ RetailPrice\_Petrol\&Diesel)_{t-j}$	0.03*** (0.002)	0.05** (0.02)	0.003 (0.02)
$(Output\ Gap)_{t-k}$	0.08*** (0.01)	0.21* (0.10)	0.26** (0.10)
$[Dummy\_Output\ Gap^*$ $\Delta(ln\ RetailPrice\_Petrol\&Diesel)]_{t-l}$	0.08*** (0.002)	-	0.06 (0.05)
$\Delta(ln\ Exchange\ rate)_{t-m}$	0.07*** (0.005)	0.10** (0.0003)	0.10*** (0.02)
$(Rain\ Dev\ from\ LPA)_{t-3}$	-	-	0.0002*** (0.0000)
$\Delta(ln\ DCA\ TOP)_t$	-	-	0.06*** (0.01)
No. of Observations	36	36	36
Sample Period	2011Q1-2019Q4	2011Q1-2019Q4	2011Q1-2019Q4
Adjusted R-squared	0.95	0.48	0.82
B-G Serial Correlation LM Test: F-Statistic	0.91	0.71	2.10
B-P-G Heteroscedasticity Test: F-Statistic	0.92	0.76	1.10

Notes: 1. *, ** and *** represent significance levels at 10 per cent, 5 per cent and 1 per cent, respectively. The variables used in the model were transformed to their natural logarithms and seasonally adjusted before incorporating them in the model. Figures in parentheses indicate heteroscedasticity-consistent standard errors. Δ represents q-o-q change in the variables.

2. Separate period dummies for appropriate quarters were incorporated in the specifications as exogenous variables in order to enhance model performance.

3. The lag structure is as follows: i is 8 in (1) and (2) and 1 in (3); j is 2 in (1), 7 in (2) and 5 in (3); k is 13 in (1), 6 in (2) and 7 in (3); l is 5 in (1) and 0 in (3); m is 1 in (1), 5 in (2) and 7 in (3); n1 is 0 in (1), 2 in (2) and 0 in (3). Other controls used were other lags of output gap, respective dependent variables and change in rural wages.

Chart A2: Movements in Sticky Price Inflation, Inflation Expectations, Domestic Fuel Inflation and Nominal Exchange Rate



Source: NSO; RBI; and IOCL.

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Measuring Economic Growth and Productivity: Foundations, KLEMS Production Models and Extensions edited by Barbara M. Fraumeni, 536pp, Academic Press, Elsevier (2020), $125.00 ISBN: 978-o-12-817596-5

Productivity plays a crucial role in driving the potential growth trajectory of an economy. What policies can raise productivity and how it needs to be measured, however, remain debatable in academic and policy discussions. The book "*Measuring Economic Growth and Productivity*" edited by Barbara M. Fraumeni provides a comprehensive perspective on productivity, covering both theory and its related applications. The book is also a tribute to Jorgenson's contributions to the theory of growth accounting, which command an overwhelming influence on researchers pursuing studies on productivity worldwide. The edited volume brings together contributions from top academicians on extension of KLEMS (Capital, Labour, Energy, Material and Services) production models, that ranges from an analysis of trade productivity linkages, and energy and environmental issues to models of welfare and human capital development. Apart from theoretical underpinnings, the book also provides empirical evidence on patterns of productivity trends in both developed and developing economies.

Twenty-two chapters in the volume are categorised under four different themes, namely: (i) theoretical foundation, (ii) cross country estimates of productivity, (iii) methodological refinements and (iv) extension models. Some broad observations and remarks are presented in the conclusion section.

On the first crucial theme, Edward A. Hudson discusses different approaches to explain economic growth and presents a model where growth is driven by demand for innovative products. The paper draws inspiration from Schumpeter "creative destruction" and emphasises the role of innovation in driving output growth. In another topic, Carol Corrado, Jonathan Haskel, Massimiliano Iommi and Cecelia Jona-Lasinio, develop a theoretical model to derive the relationship between innovation, intangible capital and productivity. Based on data for the European countries and the US, the paper investigates the impact of knowledge capital on productivity to find a positive relationship between growth in intangible capital and total factor productivity growth in the post Global Financial Crisis (GFC) period.

A total of nine chapters in the book explain different facets of productivity trends around the world. Khuong M.Vu examines the performance of seven largest emerging E7 countries (namely China, India Indonesia, Brazil, Mexico, Turkey and South Korea) vis-à-vis G7 countries (namely US, Japan, Germany, UK, France, Italy, Canada) on three important parameters – sources of growth, catch up performance, and future growth prospects. It finds that capital accumulation exceeded total factor productivity contribution in both G7 and E7 economies. Further, the E7 economies outperformed G7 countries due to their higher productivity growth as well as greater capital deepening and contributed to about 60 percent of world growth during 2010 to 2017. As compared to the E7, the G7 group accounted for about 20 percent of world growth during the same period. In another chapter Matilde Mas, Andre Hofman and Eva Benages compare the knowledge intensity of industries across American, European and Latin American nations based on measurement of human and physical capital services. They find that developed nations have a higher share of knowledge based gross value added, but the growth in knowledge intensity is fastest in less developed nations, indicating a certain process of gradual convergence.

Among studies on European nations, the chapter by Gang Liu, finds that the slowdown in productivity growth between 1997 to 2014 in Norway originated from declining productivity growth in distribution, finance and business service sectors. Robert Inklaar, Kirsten Jager, Mary O. Mahony and Bart Van Ark highlight that productivity slowdown in the EU region started well before the GFC in 2005. In the European economies, the industries that had benefitted the most from global value chain integration and offshoring activities during 1995 to 2005, experienced larger declines in productivity growth in the subsequent decade, suggesting that the slowdown in global trade was an important factor in depressing productivity growth.

Among studies on the Asian economies, Chi Yuan Liang and Ruel-He-Jheng find that TFP gap in Information and Communication Technology (ICT) industries between the US and the Asian countries became wider during 1995 to 2010. Lower R&D expenses and lower number of patents had led to lower TFP growth in Korea, Taiwan and China as compared with the US. In a comparative study between Japan and Korea, Kyoji Fukao, Tsutomu Miyagawa, Hak Kil Pyo, Keunhee Rhee and Miho Takizawa emphasise increase in investment in ICT that led to an increased demand for middle and low skilled labour in Japan, whereas in Korea the demand for skilled workers increased with the rise in ICT investment. To understand the productive trends of the two giant economies of Asia- i.e., India and China, two separate chapters are devoted in this edited volume. Harry X.Wu, finds that TFP growth slowdown in China began during mid 2000s, following its entry in WTO and increased state intervention to protect strategic industries. The paper finds protection of strategic industries crowded-out private investments and made Chinese industries less capable to adjust to structural shocks of GFC. In contrast to productivity decline in China, for India, K.L.Krishna, Bishwanath Goldar, Deb Kusum Das, Suresh Chand Aggarwal, Abdul A Erumban and Pilu Chandra Das finds TFP growth improved during 2000s, with higher equipment share in total capital stock and greater engagement in backward linkages in GVCs helping Indian industries to enhance their productivity performance.

Four exclusive chapters in the book discuss the statistical refinements brought about by the National Statistical agencies in strengthening developing productivity accounts. For instance, J. Steven Landefeld describes the interactions between growth theory and the development of US National accounts. It presents how the US National account systems has improved beyond GDP measurement and included supplementary accounts that capture distribution of income, production accounts of energy, natural resources enabling better assessment of economic welfare. On a related issue, Chapter by Lucy P Eldridge, Corby Garner, Thomas F. Howells, Brain C. Moyer, Mathew Russell, John D. Samuels, Erich H. Strassner and David B. Wasshausen discuss the joint research work by two institutions namely the US Bureau of Economic Analysis (BEA) and the Bureau of Labour Statistics (BLS) in developing industry level production accounts for the US for the time period 1947 to 2016. Ilya Voskoboynikov, Derek Burnell and Thai Nguyen report in another chapter the development and progress of KLEMS framework in two resource rich countries - Australia and Russia. It highlights the role of the Australian Bureau of Statistics (ABS) in developing Gross Output based KLEMS data in Australia. For Russia it mentions the recent methodological developments in the KLEMS framework and records that the contribution of the National Research University of Higher School of Economics and University of Groningen.

Nine other chapters in the book look beyond the traditional growth decomposition debate and aim at linking productivity theories with trade, inflation, climate change and economic welfare. Richard J. Goettle, Mun S. Ho and Peter J. Wilcoxen develops an intertemporal general equilibrium model to find the macro economic impact of carbon tax under three revenue cycling options-lump sum redistributions, capital tax reductions, and labor tax cuts. The paper finds that welfare gains are obtained under capital tax reductions and labour tax cuts when emission accounting is viewed from top down rather than bottom up accounting standard. Here when sectors buys energy inputs at common price the accounting standard is classified as top down or supply side accounting. Whereas when different sectors pay different price then that is labeled as bottom up or demand side accounting. Jing Cao, Mun S.Ho and Wenhao Hu use another Computable General Equilibrium (CGE) framework to assess if carbon tax can help achieve the Paris climate change target for China. Koji Nomura, Kozo Miyagawa and John D Samuels provide benchmark estimates of price differentials between Japan and the US based on a price accounting model. They find that Japanese industries are more price competitive in manufacturing whereas US industries are more price competitive in services. Marshall Reinsdorf and Paul Schreyer measure consumer inflation in a digital economy and suggest adjustment in consumption deflator in OECD countries to account for cost savings from digital economy. Ana Aizcorbe, David M. Byrne and Daniel E. Sichel attempt to develop a quality adjusted price index of digital products which shows a faster decline in adjusted deflator of smartphones over the last two decades than the currently published official measures in the US.

On trade and productivity linkages, Marcel P. Timmer and Xianjia Ye extends the KLEMS framework to incorporate GVC model and find that productivity growth in GVCs would be overestimated when the standard assumption of perfect competition is used in global factor markets. In another chapter , Kun Young Yun presents the Dynamic General Equilibrium model to evaluate the welfare effects of tax policy in the US and finds that welfare gains are the maximum when capital is efficiently allocated across the entire private sector and the labour income tax is flattened.

On welfare related issues, Daniel T. Slesnick discusses the limitations of GDP as a measure of social welfare and develops a consumption based social welfare function which can be used as a benchmark to compare real per capita GDP. In the last chapter by Barbara M. Fraumeni and Michael S. Christian study the trend of economic growth and productivity in the US by incorporating an expanded accounting system that incorporates for changes in human capital by gender.

Despite being a compendium of several well researched articles, the book overall leaves behind some unsettled issues that would require its readers to refer to other literature on the subject. First, TFP growth as a 'residual', besides technological progress may reflect a myriad of factors that influence growth. These includes implication of changes in government policies, external shocks, measurement errors and shifts in production possibilities (Hulton 2001). Second, the book includes chapters on welfare issues, but does not cover much on labour productivity estimates. Studies have shown that in the long run, nation's ability to increase the standard of living of its people depends on its ability to increase the output per worker. Third, on the empirical chapters in the volume, there is no clear explanation as to why the rapid progress in ICT and digital technologies does not halt the slowdown in productivity statistics worldwide.

To sum up, this book brings together recent productivity related studies covering both advanced and emerging market economies which have so far been analysed in isolation. This precious compilation is a useful resource for researchers and policymakers who are interested in studying the dynamics of productivity growth and the role of policy in fostering the productivity led growth of an economy.

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Foundations of Post-Schumpeterian Economics: Innovation, Institutions and Finance by Beniamino Callegri, 270 pp., Routledge (2020), £96.00

The COVID-19 pandemic was feared to unleash waves of bankruptcies globally, which was largely prevented through counter-pandemic policy stimulus. The pandemic also created opportunities for start-ups to proliferate and scale up as unicorns through innovations. This has brought to the fore the significance of Schumpeterian creative destruction to the post-COVID world. The book offers a reconstructed narrative of Schumpeterian economic thoughts that could be viewed as relevant to the contemporary works. The book tries to link Schumpeter's economic theory to philosophy, drawing insights from works by Henry Bergson, a French philosopher and Georgescu-Rogen, an economist. The book gives a comprehensive review of Schumpeter's major economic contributions including his theory of economic development and capitalist crisis, thereby highlighting how reviving Schumpeter's original contributions can be integrated into the ongoing academic debates.

This book is divided into three sections. In the first section, the author explores Schumpeter's theory from a philosophical perspective. The second section describes in detail the economic theory propounded by Schumpeter, including his theory of economic development, capitalist crisis and business cycle. The last section attempts to link Schumpeter's theory of development to economics of evolution.

The first chapter explains how Schumpeter visualized social science. According to Schumpeter, 'the object of study of social science is one indivisible whole', wherein society, culture and economy are all connected and cannot be separated from each other. The author highlights the monism in Schumpeter's study of social science by discussing the connection between social and natural process. The author supports this unified interpretation of social science by citing Bergson's and Rogen's philosophies. For instance, Rogen's intuitive continuum refers to a seamless whole in which nature, space and time cannot be separated from each other. When this intuitive continuum is applied to Schumpeter's indivisible whole, it strengthens its monist interpretation. In the second chapter, the author explores Schumpeter's concept of rationality in social science. He discusses the various meanings of rationality distinguished by Schumpeter, including subjective and objective rationality. The former refers to the established social norm, and the latter refers to the independent free will which is detached from the social norm. Innovation and creative action emerges from the individual free will. The author then links Schumpeter's innovation to Bergson's creative evolution, which relates life with creation. Bergson argued that it is intelligence which leads to the creation of new things, whereas instinct finds solution based on old existing knowledge perceived by the mind. The author argues that Schumpeter's rationality is analogous to Bergson's instinct and intelligence. The author further argues that Schumpeter introduced a social component within rationality leading to the rejection of an individualist view of social process.

In the second section, the author highlights the key contributions of Schumpeter to social science. Schumpeter's theory of development discusses how innovation originates and is financed in capitalist economies. This is explained in the book through four components of economic development - circular flow, innovation, novelty and money. The book explains how the process of economic development encounters cycles of prosperity, recession and depression and provides a detailed analysis of Schumpeter's model of business cycle through three approximations. In the first approximation, development is introduced into the circular flow as an exceptional single event to which the economic system adapts physiologically. This model illustrates how development leads to an alternative cycle of prosperity and recession. In a perfectly competitive market with full employment of resources, the entrepreneur borrows money to introduce innovation and purchase productive services. Since resources are fully employed, this leads to a rise in price of productive services, thereby generating windfall profits for old firms. Once the innovative output is introduced into the market, entrepreneurial profits also emerge for the new firms. This refers to the prosperity phase. Eventually, competitiveness among the older firms increases, which in turn puts a downward pressure on prices leading to the phase of recession. Overtime, the system adapts to innovation, leading to a new circular flow identical to the old one but with new lower prices. The lower prices reflect the rise in real incomes brought by innovations. The second approximation shows how development leads to booms and depression. The phase of prosperity and recession in the first approximation gives rise to a secondary wave. In the prosperity phase, the windfall profit is used to increase consumption. The economic agents adapt to higher profits and as demand increases permanently, firms increase their investments to increase supply. This leads to a temporary self-sustaining boom accompanied by rising prices. Eventually, competition breaks the spell leading to losses and putting a sudden end to the boom, which in turn can also lead to a crisis and subsequent slowdown in economic activity. Finally, in the third approximation model, instead of a single developmental process, there are multiple development processes occurring simultaneously in different economic sectors. The book concludes this section by discussing the causes and consequences of a crisis. The author argues that Schumpeter considers crisis as capitalist in nature and assumes it as the capitalist variant of the process of development. Although development in itself can follow a linear trajectory, capitalism is inherently cyclical. The ultimate driver of a crisis is the decentralized capitalistic planning, and that crisis is destructive in nature. It implicates the people who have nothing to do with the crisis such as workers and leads to wastages, necessitating the need for state intervention to manage the booms, recession, and crisis. The book also discusses the role of institutions in managing a crisis and describes the inability of Schumpeter's competitive capitalism to find a permanent solution to a crisis. This occurs because under competitive capitalism, the adaptive, creative and speculative activities are operationalised by different agents leading to inconsistent planning. Hence, the interactions between these agents give rise to booms, recession and depressions. The author discusses an alternative institution proposed by Schumpeter, which is trustified capitalism where all the activities are confined to a single entity: the oligopolistic innovative firm. This, in turn, creates a condition for co-respective competition, which is defined as the market configuration in which there is complete coordination among competitors to minimise the destructive effect of development at all the stages. Trustification reduces instability and eventually eliminates inconsistent and decentralised planning. This alternative institution, if fully realised, can provide a permanent solution to the capitalistic business cycle.

The last section summarises some of the ongoing Schumpeterian debates. It provides a historical review of the trajectory of Schumpeterian economics since his demise, illustrating the scope of his legacy and the corresponding opportunities offered by the post-Schumpeterian synthesis. The author argues that Schumpeter influenced the theoretical discourse on growth, development and innovation, and sheds light on the sustained efforts made during 1950s to integrate Schumpeter's thoughts into the mainstream economics. The subsequent rise of neo-classical, neo-Keynesian and neo-Schumpeterian school of thought during the 1960s, and the decline of Schumpeter's influence is ascribed to its lack of interest in capital theory and concern for policy, complexity of concepts and the assumption of instability. The book then revisits the revival of Schumpeter during the 1980s and 1990s. During these decades the focus of Schumpeterian debate shifted to the evolutionary premise of his theory that the economic process evolves and is determined by both individuals and the society. The author tries to link neo-Schumpeter's meso level analysis of economic development to Schumpeter's original approach. According to the meso level analysis, development comprises three stages: origination, diffusion and retention. During the origination phase, the agent develops a new rule and assembles resources needed for its realization. In the diffusion phase, this rule gets adapted throughout the economic system. In the retention phase, the rule is enforced and identically replicated. The author argues that the origination phase is similar to Schumpeter's idea of leadership in which free will leads to the emergence of a new ideas. The diffusion phase refers to the rest of Schumpeter's development process in which a new idea is integrated into the economic system. Therefore, the author argues that the meso approach is strongly Schumpeterian, pointing to the evolutionary nature of Schumpeter's theory. The author then elaborates on the evolutionary framework by discussing the theory of General Darwinism (GD), which refers to the study of evolution of all living systems including the social system. The author establishes compatibility of Schumpeter's evolutionary perspective with GD by showing that Schumpeter's theory satisfies the conditions which are relevant for any evolutionary theory to remain compatible with GD. The author, thus, argues that Schumpeter's theory is Darwinian in nature. The last chapter concludes the book by providing a scope for hybridization of Schumpeterian and Keynesian economics. It gives a detailed discussion on

Schumpeter meeting Keynes (S+K) family of agent-based models and agent-based stock flow consistent models (AB-SFC), offering a cross fertilization between the two. These models highlight the dependence of Schumpeter's engine of economic growth on Keynesian demand management, and show that any drain in demand becomes an obstacle for investments by firms. The book highlights the role of demand management for economic development and the limitation of exclusive supply side focus as done by Schumpeter.

The author has lucidly narrated the philosophical stance inherent in Schumpeter's work. The main aim of this book is to delineate the philosophy underpinning Schumpeterian theory; however, it is found vividly only in the first section of this book. In the second and third sections of the book, the author focuses on Schumpeter's core economic theory where the philosophical interpretation is largely missing. The stated purpose of the book is also to set the ground for post-Schumpeterian economics to take the centre stage, but there is hardly any mention of what constitutes this school of thought and how the post-Schumpeterian economics is different from that of Schumpeter. Nonetheless, the book is an important contribution to the literature on Schumpeterian economics and can meet the expectations of students and scholars of evolutionary economics. Given the lingering uncertainty surrounding the post-COVID permanent scarring effects on economies, the evolutionary approach highlighted in this book could help in exploring the possibilities for durable recovery in growth and the role of policy interventions for managing the shape and speed of recovery.

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