An Analysis of Heterogeneity in Inflation Expectations across Cities in India

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Abstract

The Inflation Expectations Survey of Households, conducted by the Reserve Bank of India (RBI), indicates that there is considerable disparity in inflation expectations across cities in India. Why do cities exhibit heterogeneous inflation expectations despite coming under a central monetary policy umbrella? Using seemingly unrelated regression, our results indicate that "information friction" plays an important role in explaining disparity in inflation expectations across cities. Additionally, the effects of macro-level factors vary from city to city, thereby accentuating expectations dispersion. The findings indicate that the monetary policy-related communication by the RBI should increase in order to address the "information friction".

Keywords: Inflation Expectation, Heterogeneity, India.

JEL Classification: C23, D84, E31

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1. Introduction

Inflation expectations are an important marker for monetary policy makers in any economy. With inflation targeting being the explicit goal of many central banks around the world, including India, tracking and analyzing inflation expectations is of primary importance. As pointed out by Rajan (2014), anchoring inflation expectations is essential for achieving inflation targeting. Inflation expectations anchoring is feasible through monetary policy provided the policy makers are aware of how inflation expectations among the general public are formed, to begin with.

In September 2005, the Reserve Bank of India initiated the Inflation Expectations Survey of Households (IESH) across various cities in the country. During the recently concluded round of the survey in December 2017, people across various age groups and professions were surveyed across 18 cities of the country.

Each round of IESH provides evidence of inflation expectations variability for all categories, i.e. current inflation, 3-month ahead inflation and one-year ahead inflation. The IESH summary tables mention that the factors that cause this variability are-city, gender, and age-group, out of which city seems to be the most dominant factor across all categories.

One finds it curious that despite having a central monetary authority and being exposed to the same set of macroeconomic shocks at the economy-wide level, various regions/cities of the same economy exhibit variations in inflation expectations. This leads us to the question that what might be the cause(s) of this dispersion in inflation expectations across cities in India?

We find this question relevant in the Indian context since "heterogeneity in inflation expectations might affect the behavior of economic agents and become relevant for economic welfare and policy through a number of channels" (Gnan et al., 2011). Mankiw et al. (2003) and Townsend (1983) show that the disagreement among agents about inflation expectations is important in understanding the macroeconomic dynamics of an economy. As pointed out by Gnan et al. (2011), using models of imperfect information, Phelps (1970), Lucas (1973), Woodford (2002) and Sims (2003), show that the real costs of nominal movements may be

related to heterogeneity in inflation expectations. Further, outcomes in asset markets models are altered if inflation expectations do not converge (Acemoglu et al., 2007), and heterogeneity in inflation expectations can lead agents to bet against each other, thereby leading to overinvestment in real assets while delaying and distorting monetary policy actions (Sims, 2009).

The existing literature documents studies on heterogeneity in inflation expectations among agents based on their socio-economic and demographic characteristics. Bryan and Venkatu (2001a) in their study based on Ohio consumers find that women perceived higher rate of inflation for recent and past year and also predicted a higher rate of inflation for future in comparison to men. Studies based on survey data of U.S. (Bryan and Venkatu, 2001b; Souleless 2004; Pfajfar and Sontoro, 2008; Bruine de Bruin et al., 2010), New Zealand (Leung 2009), England (Blanchflower and MacCoille, 2009), and Ireland (Duffy and Lunn, 2009), all find that individuals with lower household income tend to have higher inflation expectations than those with higher income, although a study of South African consumers finds the opposite pattern (Kershoff, 2000). In a recent paper by Easaw et al. (2013), they investigate the heterogeneous inflation expectations behavior of various demographic groups in Italy and conclude that households absorb the inflation forecasts made by the professional forecasters, forecasts vary with gender and the level of education, etc.

All studies mentioned above have focused on agent-based inflation expectations based on individual responses at the micro-level and their corresponding socio-economic and demographic features. So far, we could not locate any study that looks at city-level heterogeneity in inflation expectations and the possible macro-level factors that might explain the former.

This paper analyses heterogeneity in inflation expectations across 12 cities in India between 2008 and 2017. The sample period commences from 2008 when 12 cities were surveyed (instead of four cities before that), and it ends with the latest available survey data in 2017. We decompose our analysis into three parts. In the first part, we present the extent of city-level dispersion in inflation expectations at each survey round. Further, we map city-level economic characteristics with expected inflation and find that cities with a high level of

economic activity and high inflation rates, record higher expected inflation. In the second part of our work, we trace how this disagreement regrading inflation expectations vary over the business cycle. We find that this disagreement in inflation expectations among cities increases during the times of economic boom and recession, and with the rise in inflation. These results are aligned with the findings of Mankiw et al. (2003) who present some stylized facts about inflation expectations disagreement in the context of macroeconomic business cycles. Lastly, we investigate the source(s) of heterogeneity in inflation expectations following a model proposed by Hubert (2015) and Hubert and Maule (2016) and conclude that the presence of information friction is the main source of heterogeneity. Additionally, macro-level variables like the interest rate, exchange rate, economic policy uncertainty, and oil prices, have varying degrees of effect on each city, thereby accentuating the dispersion in city-level inflation expectations. These results point to the fact that the RBI should increase its monetary policyrelated communication with the general public so that the information friction is lowered.

The contribution of this paper to the existing literature is as follows. First, this study is an application of the relatively recent IESH survey data (compared to similar surveys that have been conducted in the developed countries for decades now) that has not been explored much in the Indian context. Given that the sample size of the time-series data of this survey is not too large (less than fifty observations as of now), this work considers the panel dimension of the data which has been not explored hitherto.

Second, the literature on inflation expectations heterogeneity is replete with studies that look at the socio-economic characteristics of individual respondents and identify specific groups based on gender, ethnic origin, income, etc. who exhibit expectations heterogeneity. However, there is no study thus far that investigates heterogeneity at the city or regional level. Coibion and Gorodnichenko (2015) comment that for the success of the inflation targeting policy in an economy, it is imperative to understand the nature of heterogeneity in inflation expectations; not just from the point of view of socio-economic differences, but also from the geographical angle. This is especially true in the case of a diverse country like India. The above-mentioned authors further point out that regional heterogeneity in inflation expectations might be a result of economic disparities and expectations would eventually converge over time as the political and economic situation stabilizes. However, they also mention the possibility that heterogeneity in expectations across regions might also be due to the fact that agents receive the same news/signals about the economy and yet process the same information differently. In such a case, the heterogeneity in expectations would persist, thereby making policymakers' attempts for achieving monetary policy targets difficult. In this aspect, our analysis adds to the understanding of regional inflation expectations heterogeneity.

Another novel feature of our work is the use of nightlights as a proxy for city-level economic activity in the absence of any data on city-level income. The growing literature in this area presents evidence of a strong relationship between the economic activity of a region with satellite-based nightlight data. Ghosh et al. (2010) and Henderson et al. (2012), find a strong correlation between GDP and nightlight at the national and sub-national levels. Chen and Nordhaus (2011), Michalopoulos and Papaioannou (2013) and Papaioannou (2013) use nightlights as a proxy for income and economic growth. Prakash et al. (2015) use nightlights as a proxy for constituency-level economic activity in the absence of income data at such a disaggregated level. In this context, our work that uses nightlights as a proxy for city-level income is an addition to this literature.¹

The rest of the paper is structured as follows. Section 2 gives an overview of the Inflation Expectations Survey of Households (IESH) conducted by the Reserve Bank of India. Section 3 presents the theoretical background for this empirical study. Section 4 describes the data sources, followed by a discussion of the results in Section 5, and Section 6 concludes.

2. An Overview of Inflation Expectation Survey of Households (IESH)

Surveys specifically designed for recording inflation expectations of the general public have been in place for a while in several countries. The Michigan Consumer Survey of the US, the Reserve Bank of New Zealand's Household Inflation Expectations Survey, the Bank of England Survey of Inflation Sentiments, etc. are some of the well-known sources of information on inflation expectations. In line with these surveys, the Reserve Bank of India (RBI) initiated the Inflation Expectation Survey of Households (IESH) from September 2005, although the survey data was made publicly available from September 2006. This quarterly

¹ See Donaldson and Storeygard (2016) for a detailed description of use of satellite data in economics.

survey presents quantitative and qualitative data on current perception and near future expectation of inflation of the general public in India.

The initial two rounds of the survey were based only on qualitative questions on the expectation of general price rise in relation to the inflation rate. Apart from expectation on general price products, the expectation on prices of food products, non-food products, household durables housing, and services were also collected. The questions asked in the survey were on five different scales: (i) price increase similar to current rate; (ii) price increase more than the current rate; (iii) price increase less than the current rate; (iv) no change in price; (v) decline in prices. The survey covered 2000 households, 500 each from four metro cities viz., New Delhi, Kolkata Mumbai, and Chennai which were a representation of four geographical zones (North, East, West, and South respectively).

Gradually, from the third round onwards the reach of the survey was enhanced. The geographical coverage of the IESH expanded by incorporating eight more cities, taking it to a total of twelve cities. The selection of cities was done in a manner such that one metro city and two other cities from each zone (North, South, East, and West) was chosen. The cities from North were Delhi, Lucknow, and Jaipur, from South – Chennai, Bengaluru and Hyderabad from East – Patna, Kolkata and Guwahati and from West – Mumbai, Ahmedabad and Bhopal. The metro cities and non-metro cities were represented by 500 and 250 households each. This increased the overall sample size from 2000 to 4000 households. A major change that occurred in this round of the survey was to add quantitative questions for the expected rate of inflation for three-month-ahead and one-year-ahead. From September 2007 onwards, households' perception about inflation was also added.

From the 30th round (December 2012) onwards four more cities, namely- Kolhapur, Nagpur, Thiruvananthapuram, and Bhubaneswar were added to the list of existing cities surveyed. 250 households from each of these new cities included were surveyed, thereby increasing the total sample to 5000 households across 16 cities. From the 43rd round (March 2016) onwards, Kolhapur was dropped and three more cities-Chandigarh, Raipur and Ranchi, were included

in the sample. At present, this survey is conducted across 18 cities in India and includes around 5500 households.

The survey is designed in a way that it represents not just the geographical diversity in India, but also the socio-demographic diversity. The male and female ratio in the sample is 3:2 and all the respondents are above 18 years. The respondents are further categorized on the basis of their occupation under the following categories- financial sector employees, other employees, self-employed, housewives, retired persons, daily workers, and others. Initially, each category had an equal number of individual representation, but from September 2008 onwards, the representation of "housewives" and "self-employed" categories increased while that of the "other category" decreased. Respondents are also categorized based on their age groups- "up to 25 years", "25 to 30 years", "30 to 35 years", "35 to 40 years", "40 to 45 years", "45 to 50 years", "50 to 55 years", "55 to 60 years", and, "60 years and above".

Having mentioned the major features of the Inflation Expectations Survey of Households, we next outline the theoretical model that is employed to study the reasons for inflation expectations heterogeneity across cities in India.

3. The Model

In trying to understand why there is heterogeneity in inflation expectations across agents (across cities), we have to start with the question "how inflation expectations are formed, to begin with?". As pointed out by Coibion and Gorodnichenko (2015), ".... how those expectations are formed, and how best to model this process, remains an open question. From the simple automatons of adaptive expectations to the all-knowing agents of modern full-information rational expectations models, macroeconomists have considered a wide variety of frameworks to model the expectations formation process, yielding radically different results for macroeconomic dynamics and policy implications". The authors further point out that in recent times, rational expectations models with information friction can account for otherwise puzzling empirical observations compared to full information rational expectations models.

There are two dominant schools of thought on modelling information friction in rational expectations models. One school of thought is based on the "sticky information" analysis proposed by Mankiw and Reis (2002) which suggests that all agents do not update their expectations at each period since acquiring information is costly. If all agents were to update their expectations at all times, then that would be equivalent to a full information rational expectations model. In a similar spirit, Carroll (2003) suggests an epidemiological model of inflation expectations whereby in each period, some agents update their information based on a common source like the forecasts by professional forecasters, inflation-based news, etc. Akin to Mankiw and Reis (2002), Carroll too assumes that not all agents update their expectations each period since only a fraction of the population pays attention to the opinion of experts or follow the relevant news. To put it succinctly, the above two variants of sticky information can be represented by the following equations:

$$E_t \pi_{t+h} = \lambda_1 R E_t \pi_{t+h} + (1 - \lambda_1) E_{t-1} \pi_{t+h}$$
(1)

$$E_t \pi_{t+h} = \lambda_2 SPF_t \pi_{t+h} + (1 - \lambda_2)E_{t-1}\pi_{t+h}$$
(2)

where, $E_t \pi_{t+h}$ is household inflation expectations for horizon h, RE_t is the rational forecast and SPF_t is survey of the professional forecast. $E_{t-1}\pi_{t+h}$ represents the lagged household inflation expectations. In both equations, the inflation expectations of households are a weighted average of the fraction of the population who update their expectations and the remaining population who continue with their previous beliefs about future inflation expectations.

The other school of thought on why inflation expectations vary across agents is based on the "noisy information" models by Woorford (2001) and Sims (2003). These models are based on the premise that agents continuously update their beliefs or their information set but observe only noisy signals about the true state of the economy (Hubert, 2015). The observed stickiness or inertia in expectations is these models, are a result of agents' inability to process all available information since internalizing noisy information at all times is not possible. In such models, forecasts are formed via a Kalman filter and are a weighted average of the agents' prior beliefs and the new information received (Hubert and Maule, 2016). This is represented

by equation (3) below, where $E_t \pi_{t+h}$ is a weighted average of the fraction of the population who do not update their inflation expectations from past values $(E_{t-1}\pi_{t+h})$ and the remaining population who update their information about inflation expectations based on the information included in vector X_t .

$$E_t \pi_{t+h} = (1 - \xi) E_{t-1} \pi_{t+h} + \xi X_t + \epsilon_t$$
(3)

Hubert (2015) and Hubert and Maule (2016) combine the above two types of inflation expectations formation in a single equation, as in equation (4) below, by expressing private forecasts made by individuals (π^{PF}) as a linear combination of past inflation forecast (π^{PF}_{t-1}) and a vector Λ_t that captures new information between time period *t*-*l* and *t*.

$$\pi_{t,h}^{PF} = \beta_0 + \beta_1 \pi_{t-1,h}^{PF} + \beta_A \Lambda_t + \varepsilon_t \tag{4}$$

Hubert (2015) and Hubert and Maule (2016) suggests that this vector Λ_t might include "a rational forecast, a newspaper forecast, a professional forecast, the central bank interest rate and/or other variables that might affect future inflation".

Equation (4) forms the core of our empirical analysis since the inflation expectations in the Indian context do not follow full information rational expectations (Mohanty (2012), and authors' own calculations). Following Hubert (2015) and Hubert and Maule (2016), we model and empirically test for inflation expectations across cities in India and show that inflation expectations heterogeneity at the city-level is indeed due to the presence of information frictions.

Following the literature that looks into the drivers of inflation expectations at the economywide level, we include macroeconomic variables like the real interest rate (repo rate that represents the monetary policy stance for the Indian economy) and the real effective exchange rate (Cerisola and Gelos, 2009). A rise in the interest rate is expected to lead to a decline in aggregate demand, thereby bringing down inflation and expected future inflation. However, the empirical literature, in this aspect provides ample evidence that a contractionary monetary policy shock actually increases inflation in the short run; a phenomenon known as the "price puzzle".

Depreciation in currency is also expected to have a negative impact on inflation expectations. With currency depreciation imports become costlier and might lead to higher inflation and corresponding higher inflation expectations.

Although inflation is considered as a driver for inflation expectations (Cerisola and Gelos, 2009), our tests for Granger causality between inflation and inflation expectations at the citylevel for 12 Indian cities indicate that inflation Granger causes inflation expectations in only one city and not the other way around². Hence, except for the city of Kolkata, where inflation expectations Granger cause inflation, we do not include inflation as an explanatory variable in our analysis.

Next, we include a variable on economic policy uncertainty (EPU) since at the macro-level it has an impact on inflation expectations, as shown by Istrefi and Piloiu (2016).

Lastly, the variable denoting crude oil prices is included in the model following Patra and Kapur (2010) and Behera, Wahi and Kapur (2018) since it is relevant for inflation in the Indian context.

Studies like Celasun et al. (2004a, b) and Cerisola and Gelos (2009) indicate that fiscal policy is a driver of inflation expectations in developing countries. In our regional analysis of inflation expectations heterogeneity, it would have been ideal to include a fiscal policy factor like fiscal deficit (as a percentage of GDP) of the state to which a particular city belongs to, but non-availability of state-level quarterly data of the same limits us from including this variable.

It is also feasible to include the "inflation target" as an explanatory variable, as done by Cerisola and Gelos (2009) for Brazil, to check whether the inflation expectations are anchored

² Granger causality results are not presented in the text. Available upon request.

or not. However, since India formally adopted flexible inflation targeting as an explicit monetary policy objective in June 2016, there are too few data points for a meaningful analysis.

Thus, the full version of equation (4) that we estimate is represented by equation (5) below:

$$E_{t}\pi_{t+1} = \alpha_{0} + \alpha_{1}E_{t-1}\pi_{t+1} + \alpha_{2}Real \ Interest \ Rate_{t} + \alpha_{3} \ Real \ Exchange \ Rate_{t} + \alpha_{4}Policy \ Uncertainty_{t} + \alpha_{5}Oil \ Price_{t} + \varepsilon_{t}, \qquad (5)$$

where, $E_t \pi_{t+1}$ is city-level one quarter ahead inflation expectation, and $E_{t-1}\pi_{t+1}$ is the citylevel inflation expectation from the last quarter. *Real Interest Rate_t* is the difference between the repo rate (which is taken as the nominal real interest rate) and CPI inflation at period *t*, *Real Exchange Rate_t* is the real exchange rate of Indian currency in terms of US dollar at time period *t*, *Policy Uncertainty_t* is an index that captures economic uncertainty for the country and *Oil Price_t* is the crude oil prices.

4. Data

In analyzing the reasons for the disparity in city-level inflation expectations in India, we look at the city-level and all-India level factors. The data sources for these variables are listed below.

Inflation expectations

A detailed description of the data is presented in section 2 above.

Inflation rate

City-level inflation data is available as city-level consumer price index (CPI) for industrial workers (IW) across major cities in India from the Ministry of Labor, Government of India. The data on CPI-IW is available for 78 centers across India, and the prices are collected from 289 markets across these centers. Monthly data for CPI-IW is available with 2000-01 as the base year.

CPI-IW measures a change in the price level of a fixed basket of goods and services consumed by industrial workers. The target group under this category is the average workingclass family belonging to any of the seven sectors of the economy, namely- factories, mines, plantations, motor transport, port, railways, and electricity generation and distribution. The CPI-IW is further decomposed into 5 groups, namely- the Food Group (FG); the Pan, Supari, Tobacco and Intoxicant Group; the Fuel and Light Group (FL); the Housing Group (HG) and, the Clothing, Bedding, and Footwear Group. Each group is assigned different weights while the maximum weight (around 50 percent) is allotted to a food group, followed by the housing group (around 18 percent) and the fuel and light group.

Economic activity

To the best of our knowledge, city-level income data or data on economic activity is not available for India. In the absence of this data, we use the intensity of night lights as a proxy for economic activity.

The satellite data is collected by National Aeronautics and Space Administration's (NASA) Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS) which has taken the picture of Earth every night from 1993 to 2013. Figure 1 shows the nightlight imagery from DMSP for India in 2013. Our data comes from the "India Lights" platform that contains the total light output at night for 20 years at an all-India level, the state-level, the district-level and the village level as well. This dataset has been constructed by the researchers in the University of Michigan in collaboration with World Bank.



Figure 1: Composite of night light imagery from DMSP, 2013 (Source: India Lights API)³

Each satellite observed the earth every night during the local time period between 8:30 pm to 10 pm. The DMSP raster⁴ images have a resolution of 30 arc-seconds, equal approximately to 1 km^2 at the equator. Each pixel of the image is assigned a digital number between 0 to 63, with 0 indicating no light output and 63 as the highest output.

The nightlight output data is extracted from each raster image for each date for the pixel that corresponds to the location for which approximate latitude and longitude is mentioned. The data is further filtered out for too much cloud cover or solar glare, following the recommendations of National Oceanic and Atmospheric Administration (NOAA). The data is then aggregated by taking the median measurement for each location for over a month.

While the application of nightlights data is innovative in this case, there are some caveats pertaining to this data. First, the data is top-coded at 63 which implies that this is the upper boundary. Thus, big cities with the brightest lights might all end up with this maximum number, and that might not change much over time. Second, the value zero might not actually

³ Night lights website link: http://india.nightlights.io.

⁴ A raster consists of a matrix of cells (or pixels) organized into rows and columns (or a grid) where each cell contains a value representing information, such as light. Rasters are digital aerial photographs, imagery from satellites, digital pictures, or even scanned maps.

indicate no-lights, rather it might be so due to clouds, etc. for which no lights could be recorded. Thus, in a time-series for nightlights for a particular city, we might encounter a sudden zero value (with positive numbers before and after that) that does not indicate "no economic activities." Although such values are too few in our sample, we treat them as missing data rather than assigning them a zero value that creates a sudden drop in the series.

Overall, although the nightlights data as a proxy for economic activity has its limitations, in the absence of any other city-level proxy for income or output, this is the best alternative.

Output gap

The output gap at the all-India level is measured by the difference between the real GDP (seasonally adjusted) and its trend obtained by HP filter. The series is seasonally adjusted by using the X-11 algorithm of the US Department of Commerce. The GDP data is taken from the Database of Indian Economy (DBIE) provided by the RBI.

Interest rate

The repo rate is considered as the interest rate in our study. After the implementation of the LAF (liquidity adjustment facility) by the RBI, the repo rate is considered as the single independent monetary policy variable. A real interest rate series is generated by following the Fisher equation where the real interest rate is the difference between the nominal interest rate (repo rate) and the inflation rate (CPI inflation rate).

Real effective exchange rate

The real effective exchange rate is taken from the Database of Indian Economy (DBIE), RBI.

Economic policy uncertainty

We use the economic policy uncertainty (EPU) index by Baker et al. (2016). This index is supposed to capture uncertainty about what policy action the decision makers will undertake, uncertainty about the economic effects of current and future actions and/or inactions (Istrefi and Piloiu, 2016).

EPU⁵ is a monthly newspaper-based index whereby data is collected across seven daily English newspapers in India by counting the number of news articles containing at least one term from each of three term sets. The first set is uncertain, uncertainties, or uncertainty. The second set is economic or economy. The third set consists of policy relevant terms such as 'regulation', 'central bank', 'monetary policy', 'policymakers', 'deficit', 'legislation', and 'fiscal policy'. The data is scaled by the total number of news articles in each newspaper every month, and then it is normalized.

Crude oil prices

The crude oil purchased by the Indian economy is based on the Brent linked prices (Mishra, 2011). Accordingly, we use the Brent-Europe monthly crude oil prices data for our work. The monthly data is from the EIA 4^6 data source, and it is converted to quarterly frequency.

General election at the Centre

Data on the timing of the general elections for the central government are obtained from the Election Commission of India website.

Having outlined the data sources in this section, we next proceed to the following section that discusses the results.

5. Results

We organize our analysis of inflation expectations heterogeneity at the city-level across India in three parts.

The first part presents a statistical summary of city-level inflation expectations in India. This enables us to visualize the extent of inflation expectations heterogeneity in each survey round. Additionally, we analyze if there is any relation between city-specific inflation expectations and the corresponding city-specific features like economic activity, cost of living, etc.

⁵ <u>http://www.policyuncertainty.com/india_monthly.html</u>
⁶ <u>https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=RBRTE&f=M</u>

In the second part of our analysis, we investigate some stylized facts regarding disagreement (about inflation expectations across cities) over the business cycle. In other words, we check if this heterogeneity due to disagreement on inflation expectations across cities in India increase or decrease when the overall economy is doing well, when inflation, in general, is high or when there is a monetary policy shock, etc.

In the third and final part of our work, we investigate the premise (represented by equation (4) in section 3 above) that inflation expectations heterogeneity arises due to the presence of information friction and due to the effect of various macro-level variables that affect each city differently.

5.1 Statistical summary

Table 1 presents a snapshot of the extent of variation in the city-level mean 3-month-ahead inflation expectations collected through the IESH survey. For each survey round, the minimum and the maximum values of inflation expectations across cities are presented to get an idea of the range of disparity, along with the mean and standard deviation. For example, among the 12 cities surveyed in 2009: Q1, the 3-month-ahead inflation expectations displays a great disparity as it ranges from a minimum of 0.8 to a maximum of 15.

Total No. of		Inflation Expectations (3-month-ahead)							
Cities	Quarter	Min.	Max.	Average	Standard Deviation				
	2008Q2	9.0	14.8	11.8	1.8				
	2008Q3	4.7	11.7	8.8	1.9				
	2008Q4	3.5	7.4	5.5	1.4				
	2009Q1	0.8	15.0	6.9	4.2				
	2009Q2	2.1	16.1	9.5	4.9				
	2009Q3	4.2	15.5	11.9	3.4				
	2009Q4	4.4	15.8	10.9	2.9				
	2010Q1	8.4	15.8	11.8	2.2				
	2010Q2	8.3	16.0	12.5	2.2				
12 Cities	2010Q3	7.8	15.6	12.4	2.3				
12 Cities	2010Q4	9.0	16.0	11.8	2.4				
	2011Q1	8.9	15.7	11.7	2.0				
	2011Q2	8.2	16.3	12.4	2.3				
	2011Q3	9.8	16.0	12.5	1.9				
	2011Q4	7.1	15.8	11.9	2.8				
	2012Q1	8.3	15.9	12.2	2.7				
	2012Q2	7.7	15.6	11.6	2.4				
	2012Q3	8.2	14.8	11.8	2.2				
	2012Q4	7.6	14.7	11.2	2.2				
	2013Q1	8.3	15.4	11.7	2.3				
	2013Q2	8.1	15.9	12.9	1.7				
	2013Q3	8.5	14.8	12.1	1. 7				
	2013Q4	7.9	14.6	12.3	1.8				
	2014Q1	7.7	15.0	12.3	2.2				
16 Citian	2014Q2	8.1	15.6	12.7	1.9				
10 Cities	2014Q3	5.5	11.2	8.8	1.7				
	2014Q4	6.9	11.4	9.1	1.2				
	2015Q1	5.9	12.5	10.3	2.1				
	2015Q2	7.3	14.7	10.8	2.2				
	2015Q3	6.6	14.5	10.8	2.5				
	2015Q4	4.3	14.3	8.8	2.9				
18 Cities	2016Q1	5.4	14.0	9.6	2.6				
	2016Q2	6.2	14.5	9.7	2.4				
	2016Q3	5.3	10.8	7.9	1.8				
	2016Q4	3.7	10.0	8.1	1.8				
	2017Q1	6.0	10.5	8.0	1.3				
	2017Q2	4.9	11.1	8.1	1.9				

Table 1: Statistical properties of inflation expectations (mean) 3-month-ahead (Source: Various rounds of IESH, RBI)

Appendix 1 presents the time-series graphs of city-wise 3-month-ahead inflation expectations and city-wise realized inflation of the 12 cities in our sample between 2008: Q2 and 2017: Q2. To address the issue of accuracy of the city-specific expected inflation vis-à-vis the actual or realized city-specific inflation, we check for expectations bias by regressing actual inflation on survey-based expected inflation as in equation (6):

$$\pi_t = \alpha + \beta \pi_t^H + \epsilon_t \tag{6}$$

where, π_t is the realized or actual city-specific CPI-based inflation, π_t^H is the city-specific inflation expectations, and α and β are the intercept and the slope respectively.

This is followed by joint testing of the null hypothesis that the intercept is equal to zero and the slope equals 1. If the null hypothesis is rejected, then the expectations are biased (Theil, 1966).

Cities	α	β	p-value of joint test					
Ahmedabad	4.13 (2.66)	0.43 (0.23)	0.00					
Bangalore	10.59 (1.11)	-0.04 (0.09)	0.00					
Bhopal	9.12 (3.37)	0.09 (0.34)	0.04					
Chennai	3.51 (1.35)	0.54 (0.13)	0.00					
Delhi	9.15 (1.72)	-0.16 (0.17)	0.00					
Guwahati	3.06 (1.74)	0.53 (0.16)	0.00					
Hyderabad	11.34 (2.21)	-0.12 (0.21)	0.00					
Jaipur	14.04 (2.68)	-0.37 (0.22)	0.00					
Kolkata	7.39 (1.43)	0.22 (0.14)	0.00					
Lucknow	14.31 (1.94)	-0.15 (0.17)	0.00					
Mumbai	9.06 (1.29)	-0.04 (0.11)	0.00					
Patna	4.13 (2.66)	0.43 (0.23)	0.00					
NOTE: Standard errors are in parenthesis.								

Table 2: Inflation expectations bias across cities

Table 2 indicates that the all cities, except Bhopal, show evidence of bias in inflation expectations.

As a slight digression, we ask if despite being bias, the city-specific expectation errors can be improved upon. To put this differently, as we observe a pattern in expectations error, can this knowledge be used to make better expectations at the city-level? Following Croushore (2010), we collect the $\hat{\alpha}$ and $\hat{\beta}$ values from equation (6) for each city and generate a new series of expectations data π_t^F by estimating equation (7):

$$\pi_t^F = \hat{\alpha} + \hat{\beta}\pi_t^H + \epsilon_t \tag{7}$$

Croushore (2010) points out that economists in the early 1980s had suggested that for forecasts that are irrational, estimates based on equation (7) would lead to relatively smaller forecast errors than in fact they had. We test this proposition for each city and based on the root mean squared error (RMSE) of the equations presented in Table 3, reach a mixed conclusion.

C:t-	Root Mean Squared Error (RMSE)						
Chy	Model 1 (survey data)	Model 2 (forecast data)					
Ahmedabad	3.35	2.58					
Bangalore	3.31	4.52					
Bhopal	3.10	2.21					
Chennai	3.18	1.66					
Delhi	3.15	3.68					
Guwahati	3.27	2.54					
Hyderabad	3.21	3.05					
Jaipur	3.49	4.04					
Kolkata	3.10	2.10					
Lucknow	3.27	3.95					
Mumbai	3.35	4.05					
Patna	3.30	2.75					

Table 3: Survey-based inflation expectations versus a forecast of inflation expectations

In the 12-city sample that we consider, except for the cities of Bangalore, Delhi, Jaipur, Lucknow, and Mumbai, all other cities, particularly the entire eastern zone, record lower RMSE with the new series of inflation expectations data generated by equation (7).

City-level inflation expectations and city-specific characteristics

Prior to analyzing the factors that explain inter-city heterogeneity in inflation expectations in India, we try and see if there is a correspondence between city-specific characteristics and city-level inflation expectations.

In particular, we check which kind of cities, in terms of economic activity (income) and cost of living (inflation), forecast higher inflation expectations, by estimating equation (8) below. Equation (9) is similar to equation (8), except for using a break-up of various types of CPI inflation. In absence of data on city-level income, we use city-level nightlights as a proxy for standard of living or economic activity.

$$X_{it} = \alpha_i + \alpha_2 Economic Activity_{it} + \alpha_3 CPI Inflation_{it} + \mu_{it}$$
(8)

$$X_{it} = \alpha_i + \alpha_2 Economic \ Activity_{it} + \alpha_3 CPI_FG \ Inflation_{it} + \alpha_4 CPI_FL \ Inflation_{it} + \alpha_5 CPI_HG \ Inflation_{it} + \mu_{it}$$
(9)

Equation (8) represents a fixed-effect panel regression where X_{it} is the inflation expectations of city *i* at time period *t* that is regressed on city-specific economic activity (*Economic Activity_{it}*) and city-specific aggregate inflation rate (*CPI Inflation_{it}*). Equation (9) is another version of equation (8) that uses city-specific inflation rate across various groups like food group inflation (*CPI_FG Inflation*), fuel and light inflation (*CPI_FL Inflation*), and housing group inflation (*CPI_HG Inflation*), instead of aggregate inflation.

	Model 1	Model 2					
Constant	10.12 ^{***} (0.33)	10.16 ^{***} (0.30)					
Economic Activity	0.03 ^{***} (0.01)	0.03 ^{***} (0.01)					
Inflation CPI	0.17 ^{**} (0.08)						
Inflation CPI_FG		0.08 (0.05)					
Inflation CPI_FL		0.14 ^{***} (0.04)					
Inflation CPI_HG		-0.03 (0.03)					
City Fixed Effect	Yes	Yes					
Observations	264	264					
R-Squared	0.06	0.10					
<i>NOTE:</i> ***, **, * denote statistical significance at 1, 5 and 10 percent levels respectively. Standard errors are in parenthesis.							

Table 4: City-level inflation expectations and city-specific characteristics

As indicated in Table 4, cities with higher economic activity and higher cost of living exhibit higher inflation expectations.

5.2 Disagreement in inflation expectations across cities- some stylized facts

The disagreement in inflation expectations across cities is measured by the standard deviation in each cross-section or each round of the survey.

To see how this disagreement behaves vis-à-vis the business cycle and other macroeconomic factors, following Mankiw, Reis, and Wolfers (2003), we regress disagreement on the output gap, inflation rate, and the square of the change in inflation rate (represents inflation shock),

etc. Additionally, as in Dovern et al. (2012), who analyse inflation expectations disagreement across the G7 countries, we include monetary policy shock represented by the square of the change in the interest rate or repo rate. The role of policy uncertainty is included in the analysis by taking into account the economic policy uncertainty index for India. Finally, we include impending general elections (at the national-level) as another explanatory variable since the work by Berlemann and Elzemann (2006) shows that prior to the time of elections, the government becomes especially alert about the state of overall inflation and takes every possible measure to keep inflation expectations under control.

Table 5 presents the pattern of disagreement amongst cities over the business cycle and other macroeconomic factors. As in Mankiw et al. (2003), we conduct this analysis as bivariate OLS regression, followed by multivariate OLS regressions including all the factors mentioned above.

Model	Constant	Output Gap	CPI Inflation	Δ Inflation CPI Squared	∆ Real Interest Rate Squared	Policy Uncertainty	National Election					
Panel A	Panel A: Bivariate Regressions											
1	2.28 ^{***} (0.17)	0.22 ^{**} (0.09)										
2	1.55 ^{***} (0.23)		0.09 ^{**} (0.03)									
3	2.18*** (0.11)			0.04 (0.04)								
4	2.20*** (0.13)				0.02 (0.03)							
5	2.17 ^{***} (0.35)					0.0008 (0.002)						
6	2.21 ^{***} (0.13)						0.59 (0.58)					
Panel B: Regressions controlling for CPI Inflation												
1	1.55 ^{***} (0.21)	0.21 ^{**} (0.10)										
2	1.52 ^{***} (0.25)			0.03 (0.03)								
3	1.54 ^{***} (0.24)				0.01 (0.02)							
4	1.68^{***} (0.24)					-0.002 (0.003)						
5	1.61 ^{***} (0.23)						0.33 (0.46)					
Panel C	Panel C: Multivariate Analysis											
1	1.50 ^{***} (0.23)	0.23** (0.11)	0.08 ^{***} (0.03)	0.03 (0.03)								
2	1.47***	0.26*	0.09**	0.34	-0.27	0.0001	0.24					
	(0.31)	(0.15)	(0.04)	(0.24)	(0.20)	(0.002)	(0.32)					
<i>NOTE:</i> , , , denote statistical significance at 1, 5 and 10 percent levels respectively. Newey-West standard errors are in parenthesis; correcting for autocorrelation up to 4 quarter lags.												

Table 5: Disagreement and the business cycle and other macroeconomic factors

Results indicate that akin to the findings of Mankiw et al. (2003), disagreement across cities increases as the output gap increases. The coefficient of the output gap in all the panels above is both positive and significant, thereby indicating that during the times of recessions and economic booms, disagreement is more across cities when compared to normal times.

Similar to Mankiw et al. (2003), across both the bivariate and multivariate regressions, we find that as inflation rate increases, disagreement across cities increase. As in the findings of Mankiw, in this case, too, the inflation rate is a robust predictor of disagreement.

Akin to the results obtained by Mankiw et al. (2003) regarding the change of inflation rate, we find that disagreement is positively related with the former, but the coefficients are statistically not significant.

The effects of a monetary policy shock (the squared value of interest rate change), economic policy uncertainty and impending national elections, vis-à-vis disagreement, are statistically not significant.

Thus, overall, we find that inflation expectations disagreement across cities in India increases with output gap and inflation, similar to the stylized facts presented in Mankiw et al. (2003) and Dovern et al. (2012).

We conclude this sub-section by quoting Mankiw et al. (2003) that the above findings do not reflect causality and are only indicative in nature. These results give us some direction regarding what to expect in terms of inflation expectations disagreement across cities when pitted against some important macroeconomic factors.

5.3 Estimation Results

Having established the city-specific economic characteristics and their corresponding inflation expectations, and some stylized facts about disagreement across cities vis-à-vis the business cycle and other macroeconomic variables, we now turn our attention to analyze how city-level inflation expectations are formed and if that explains heterogeneity in inflation expectations across cities in India.

To do so, we empirically test the theoretical model presented in Section 3 and in particular we estimate equation (5). We have a panel of 12 cities across 37 quarters, and since N is not greater than T in this case, the dynamic panel estimation method cannot be applied. Instead, we estimate equation (5) using Seemingly Unrelated Regression (SUR) method, which is an appropriate estimation technique when N is small compared to T (Wooldridge, 2010). However, instead of considering all the 12 cities simultaneously, we divide the sample into two sets of SUR as follows.

The first set of SUR estimates equation (5) for the four metropolitan cities in India viz. Delhi, Chennai, Kolkata, and Mumbai, which is also a fair representation of the four zones. Since we are in the SUR framework, any shock common to the cities (say a nation-wide fiscal policy shock or monetary policy shock, etc.) that is not explicitly included in the model, is still taken care of by the system.

In the second set, we club cities based on the respective region they belong to and conduct a region-wise SUR for each of the four regions that consist of three cities each. This regional SUR takes into account any region-specific shock that has not been accounted for explicitly in the model. This also allows us to identify the extent of information friction in each city and the various macroeconomic factors that affect city-level inflation expectations, thereby pinning down the sources of expectations heterogeneity.

Table 6 displays the SUR results pertaining to expectation formation for the four major cities in India. The Breusch-Pagan test for independence with a p-value of 0.00 indicates the presence of common factors across the system.

	IESH_Delhi	IESH_Chennai	IESH_Kolkata	IESH_Mumbai				
Constant	3.37 ^{***} (0.85)	3.26 ^{***} (1.16)	7.27 ^{***} (1.59)	3.48 ^{***} (1.01)				
IESH(-1)	0.27 ^{***} (0.11)	.27 ^{***} 0.48 ^{***} 0.11) (0.14)		0.25 [*] (0.14)				
Real Interest Rate	-0.11 [*] (0.06)	0.18^{*} (0.10)	0.20 ^{**} (0.10)	-0.17 ^{**} (0.08)				
Exchange Rate	-0.04 (0.03)	-0.04 (0.03)	-0.07 (0.04)	-0.07 [*] (0.04)				
Policy Uncertainty	-0.01 (0.01)	-0.01 (0.01)	-0.02 ^{**} (0.01)	0.01 (0.01)				
Oil Price	0.06 ^{***} (0.01)	$\begin{array}{cccc} 0.06^{***} & 0.04^{***} & 0.04^{***} \\ (0.01) & (0.01) & (0.02) \end{array}$		0.05 ^{***} (0.01)				
Adjusted R Square	0.74	0.69	0.47	0.72				
Breusch-Pagan test of	25.52							
p-value	0.00							
NOTE: *** ** and $*$ indicate statis	NOTE: **** and $*$ indicate statistical significance at 1, 5 and 10 percent levels respectively. Standard errors are in							

parenthesis.

Table 6: SUR estimates of inflation expectations across 4 metro cities in India

The lag inflation expectations term is positive and significant across all four metro cities, thereby indicating the presence of information friction. This corroborates that be it the sticky information or the noisy information explanation, there is information friction across cities in India, thereby leading to heterogeneity in inflation expectations.

Apart from that, amongst the factors that drive inflation expectations, we find that the real interest rate affects inflation expectations negatively for the cities of Delhi and Mumbai, positively for Kolkata and Chennai. As per theoretical conclusion, a tightening of monetary policy leads to a fall in future inflation expectations in two metro cities, while a reverse effect that is observed for the other two metro cities is not unusual in empirical studies (Cerisola and Gelos, 2009). The real effective exchange rate is negative and significant for Mumbai and not significant for the rest of the cities. Policy uncertainty is a factor that affects Kolkata

negatively, and for the rest of the cities, it is not significant. As per Istrefi and Piloiu (2016), as the economic uncertainty increases, an economy shrinks and so does inflation and inflation expectations. Oil prices are the only macro-level factor that affects inflation expectations of all cities since it has a positive and significant coefficient.

To sum up the findings for the source(s) of inflation expectations heterogeneity across the four major cities in India, we find that there is a significant presence of information friction across all the four metro cities. Additionally, the macroeconomic factors, along with oil prices, affect each city's inflation expectations differently. Oil price is the only variable that affects the inflation expectations of all cities, thereby indicating that agents, irrespective of their geographical location, pay a great deal of attention to oil prices as an indicator of future inflation.

In the next part of our analysis, we conduct SUR for the four geographical zones in India, where each zone comprises 3 cities each. The zone-specific analysis helps us compare inflation expectations across zones and also captures shocks peculiar to a particular zone of the country.

Table (7) presents the results of zone-specific SUR following equation (5).

For the northern zone, consisting of the cities of Delhi, Lucknow, and Bhopal, the lag of inflation expectations is positive and significant for all except Lucknow (it is significant and positive for Lucknow at a level of significance of 12%). This indicates the presence of information friction due to which a portion of the population does not update their expectations. As far as the effect of macroeconomic variables on inflation expectations is concerned, only oil prices seem to have an impact across all the three cities. The real interest rate has a negative and significant impact for Delhi, the exchange rate has a negative and significant impact for Delhi, the exchange rate has a negative and significant for this region.

Thus, the overall conclusion for the northern zone is that there is the presence of information friction that gives rise to heterogeneity in inflation expectations across cities. Additionally,

while oil prices affect the inflation expectations for all cities, other macro-level factors affect each city differently.

	North Zone: Delhi, Lucknow, Bhopal		South Zone: Bangalore, Hyderabad, Chennai			East Zone: Patna, Kolkata, Guwahati			West Zone: Mumbai, Ahmedabad, Jaipur			
	IESH_	IESH_	IESH_	IESH_	IESH_	IESH_	IESH_	IESH_	IESH_	IESH_	IESH_	IESH_
	Delhi	Lucknow	Bhopal	Bangalore	Hyderabad	Chennai	Patna	Kolkata	Guwahati	Mumbai	Ahmedabad	Jaipur
Constant	3.23 ^{***}	3.17 ^{***}	4.92 ^{***}	2.17 [*]	6.41 ^{***}	2.38 ^{**}	4.72 ^{***}	6.82 ^{***}	8.37 ^{***}	3.00 ^{***}	9.55 ^{***}	5.45 ^{***}
	(0.88)	(1.23)	(1.26)	(1.20)	(1.39)	(1.20)	(1.33)	(1.67)	(1.85)	(1.01)	(1.79)	(1.29)
IESH (-1)	0.30 ^{***}	0.22	0.25 ^{**}	0.48 ^{***}	0.05	0.62 ^{***}	0.26 [*]	0.28 ^{**}	0.24 ^{**}	0.35 ^{***}	0.12	0.24 ^{**}
	(0.11)	(0.14)	(0.12)	(0.19)	(0.14)	(0.14)	(0.14)	(0.13)	(0.13)	(0.13)	(0.13)	(0.12)
Real Interest	-0.11 [*]	-0.01	0.06	-0.37 ^{***}	-0.39 ^{***}	0.11	-0.16 ^{**}	0.19 [*]	0.12	-0.15 ^{**}	0.03	-0.19 ^{***}
Rate	(0.06)	(0.10)	(0.08)	(0.15)	(0.10)	(0.10)	(0.08)	(0.11)	(0.12)	(0.08)	(0.09)	(0.08)
Exchange Rate	-0.04	-0.03	-0.08 ^{**}	-0.02	-0.04	-0.05	0.05	-0.06	-0.08	-0.06 [*]	-0.01	-0.04
	(0.03)	(0.04)	(0.04)	(0.05)	(0.04)	(0.03)	(0.03)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)
Policy	-0.01	0.00	-0.01	0.01	0.00	-0.01	0.00	-0.02 ^{**}	-0.03***	0.01	-0.02***	0.01
Uncertainty	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Oil Price	0.06 ^{****}	0.07 ^{***}	0.04 ^{***}	0.03	0.03 ^{****}	0.03 ^{****}	0.04 ^{***}	0.04 ^{**}	0.04 ^{**}	0.05 ^{***}	0.04 ^{****}	0.03 ^{**}
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
Adjusted R- Squared	0.75	0.61	0.47	0.79	0.58	0.70	0.59	0.47	0.43	0.72	0.23	0.61
Breusch- Pagan test of	9.96		2.40		15.34		21.35					
independence p-value		0.02			0.49			0.00			0.00	
NOTE: ***, **, * denote statistical significance at 1, 5 and 10 percent levels respectively. Standard errors are in parenthesis.												

Table 7: SUR estimates of inflation expectations across four zones in India

The south zone that includes the cities of Chennai, Bangalore, and Hyderabad, shows the presence of information friction, except for the last-mentioned city. This implies, as indicated in the literature, one of the major sources of origin of inflation expectations heterogeneity. Except for exchange rate and policy uncertainty that does not affect any of the cities in this zone, other macro-level factors like the interest rate and oil prices, have some impact on inflation expectations for some cities, but not on all at the same time.

Similar conclusions are drawn from the SUR estimates for the eastern and western zones. Since the lag of expected inflation continues to be positive and significant across these zones (except Ahmedabad), the presence of information friction is yet again validated. Thus, the lack of updating expected inflation is the primary source of expectations heterogeneity, and this finding is in line with the underpinning of the theoretical model (presented in equation (4) in Section 3) that looks at the source of inflation expectations heterogeneity.

Oil prices continue to be a significant macro-level signal that agents might use for forming their inflation expectations. Contrary to the findings of the northern and western zones, these two zones, especially the cities in Eastern India, factor in economic policy uncertainty while forming their inflation expectations. The effect of real interest rate is negative and significant for Patna, Mumbai, and Jaipur while being positive and significant for Kolkata. Exchange rate effect is absent in these zones, except for Mumbai.

To summarize the findings of the reasons for heterogeneity in inflation expectations across cities in India, we conclude that information friction exists at the city-level. The exact nature of this information friction is beyond the scope of this paper but is an interesting question for future exploration. Oil prices are the only macro-level variable that almost all cities take into account while forming their expectations about future inflation. However, for the other macro-level factors like interest rate, exchange rate, and policy uncertainty- different cities pay importance to different factors, thereby leading to more heterogeneity in inflation expectations.

The above findings bring to fore the important role played by the Reserve Bank of India (RBI) in tempering down the heterogeneity in inflation expectations across cities in India.

This is warranted since the success of inflation targeting, which is the explicit monetary policy objective adopted by the RBI, depends on closing in on the inflation expectations gap across cities in India. The presence of information friction indicates that the monetary policy-related communication from the RBI (towards the general public) has to increase significantly. Second, since half of the cities in the sample pay attention to the interest rate (repo rate) in forming their inflation expectations, it implies that the monetary transmission mechanism is working in the right direction, but this mechanism is not as strong as theory predicts it to be. This finding is in line with several studies on monetary transmission mechanism for India that show a weak transmission link (see Mishra, Montiel and Sengupta, 2016, for a list of studies on this topic). Both these findings indicate that if the RBI engages more with the general public in terms of dissemination of monetary policy, the heterogeneity in inflation expectations might be mitigated.

Further, our analysis indicates that city-level characteristic like economic activity and inflation are linked with city-specific inflation expectations. Thus, city-specific factors are taken into account by the agents while forming their expectations about future inflation. At present, the lack of city-level or regional macroeconomic data is a limitation in understanding inflation expectations across regions in India, hence making data available at a disaggregated level might yield useful insights for this kind of work.

6. Conclusion

The Inflation Expectations Survey of Households conducted quarterly by the Reserve Bank of India, indicates that there is considerable disparity in inflation expectations across cities in India. Why do different cities have divergent expectations about inflation despite coming under a central monetary policy umbrella? This work investigates the factors that might contribute towards heterogeneity in inflation expectations across Indian cities. Using a Seemingly Unrelated Regression model for 12 cities (divided on a zonal basis), our results indicate that the presence of information friction plays a significant role in explaining disparity in inflation expectations across cities, while the effect of macro-level variables like interest rate, exchange rate, economic policy uncertainty, and oil prices, vary from city to city, thereby accentuating inflation expectations dispersion. Since India has adopted inflation

targeting as its explicit monetary policy target, inflation expectations anchoring is a necessary pre-requisite to attaining the end objective. In this backdrop, the presence of considerable heterogeneity in inflation expectations across cities due to information friction implies that the RBI should enhance its communication with the general public to attain effectiveness of its central monetary objective. A better understanding of inflation expectations heterogeneity requires access to micro-level data of the survey respondents such that the RBI can target specific groups (gender-wise, age-wise, profession-wise, etc.) for effective communication.

References

Acemoglu, D., Chernozhukov, V. and Yildiz, M. (2007). Learning and disagreement in an uncertain world. NBER Working Paper, 12648.

Baker, S. R., Bloom, N. and Davis, S. J. (2016). Measuring economic policy uncertainty. The Quarterly Journal of Economics, 131(4), 1593-1636.

Behera, H. K., Wahi, G. and Kapur, M. (2018). Phillips Curve relationship in India: Evidence from state-level analysis. Economic Analysis and Policy, 59, 116-126.

Berlemann, M., and Elzemann, J. (2006). Are expectations on inflation and election outcomes connected? An empirical analysis. Economics Letters, 91, 354–359.

Blanchflower, D. G. and MacCoille, C. (2009). The formation of inflation expectations: an empirical analysis for the UK. NBER working paper w15388.

Bruine de Bruin, W., Vanderklaauw, W., Downs, J.S., Fischhoff, B., Topa, G., and Armantier, O. (2010). Expectations of inflation: The role of financial literacy and demographic variables. Journal of Consumer Affairs, 44, 381-402.

Bryan, M. F., and Venkatu, G. (2001a). The curiously different inflation perspectives of men and women. Economic Commentary, Federal Reserve Bank of Cleveland, November.

Bryan, M. F., and Venkatu, G. (2001b). The demographics of inflation opinion surveys. Economic Commentary, Federal Reserve Bank of Cleveland, October.

Carroll, C.D. (2003). Macroeconomic expectations of households and professional forecasters. Quarterly Journal of Economics, 118 (1), 269–298.

Celasun, O., Gelos, R. G. and Prati, A. (2004a) Obstacles to disinflation: what is the role of fiscal expectations? Economic Policy, 19, 441–81.

Celasun, O., Gelos, R. G. and Prati, A. (2004b) Would 'cold Turkey' work in Turkey? IMF Staff Papers, 51, 493–509.

Cerisola, M. and Gelos, G. (2009). What drives inflation expectations in Brazil? An empirical analysis. Applied Economics, 41(10), 1215-1227.

Chen, X. and Nordhaus, W. D. (2011). Using luminosity data as a proxy for economic statistics. Proceedings of the National Academy of Sciences, 108(21), 8589–8594.

Coibion, O. and Gorodnichenko, Y. (2015). Inflation expectations in Ukraine: A long path to anchoring? Visnyk of the National Bank of Ukraine 223, 6-21.

Coibion, O. and Gorodnichenko, Y. (2015). Information rigidity and the expectations formation process: A simple framework and new facts. American Economic Review, 105(8), 2644-2678.

Croushore, D. (2010). An evaluation of inflation forecasts from surveys using real-time data. B. E. Journal of Macroeconomics, 10 (1), 1-30.

Donaldson, D. and Storeygard, A. (2016). The view from above: Applications of satellite data in economics. Journal of Economic Perspectives, 30(4), 171-198.

Duffy, D. and Lunn, P.D. (2009). The misperception of inflation by Irish consumers. The Economic and Social Review, 40(2), 139–163.

Dovern, J., Fritsche, U. and Slacalek, J. (2012). Disagreement among forecasters in G7 countries. The Review of Economics and Statistics, 94(4), 1081-1096.

Easaw, J., Golinelli, R. and Malgarini, M. (2013). What determines households inflation expectations? Theory and evidence from a household survey. European Economic Review 61, 1–13.

Elvidge, C. D., Sutton, P. C., Ghosh, T., Tuttle, B. T., Baugh, K. E., Bhaduri, B. and Bright, E. (2009). A global poverty map derived from satellite data. Computers & Geosciences, 35(8), 1652–1660.

Ghosh, T., Powell, R L., Elvidge, C. D., Baugh, K. E., Sutton, P. C. and Anderson, S. (2010). Shedding light on the global distribution of economic activity. The Open Geography Journal 3, 148-161.

Gnan, E., Lanthaler. J. and Valderrama, M. T. (2011). Heterogeneity in Euro area consumers' inflation expectations: Some stylized facts and implications. Monetary Policy and the Economy, Q2/11, 43-66.

Henderson, J. V., Storeygard, A. and Weil, D. N. (2012). Measuring economic growth from outer space. American Economic Review, 102(2), 994–1028.

Hubert, P. (2015). ECB projections as a tool for understanding policy decisions. Journal of Forecasting, 34, 574-587.

Hubert, P. and Maule, B. (2016). Policy and macro signals as inputs to inflation expectations formation. Bank of England Staff Working Paper No. 581.

Istrefi, K. and Piloiu, A. (2016). Economic policy uncertainty and inflation expectations. Rue de la Banque, (33).

Kershoff, G.J. (2000). Conducting inflation expectation surveys in South Africa. BER Report.

Leung, C. (2009). The demographics of household inflation perceptions and expectations. Reserve Bank of New Zealand: Bulletin, 72(2), June 2009.

Lucas, R. E. (1973). Some international evidence on output-inflation tradeoffs. American Economic Review, 63, 326-334.

Mankiw, G. and Reis, R. (2002). Sticky information versus sticky prices: A proposal to replace the New Keynesian Phillips Curve. Quarterly Journal of Economics, 117 (4), 1295–1328.

Mankiw, G., Reis, R. and Wolfers, J. (2003). Disagreement about inflation expectations. NBER Macroeconomics Annual. 18, 209-270.

Michalopoulos, S. and Papaioannou, E. (2013). Pre-colonial ethnic institutions and contemporary African development. Econometrica, 81(1), 113–152.

Mishra, P, Montiel, P and Sengupta, R. (2016). Monetary transmission in developing countries: Evidence from India. IMF Working Paper WP/16/167.

Mishra, R. (2011) Why India prefers Brent to cheaper US crude oil WTI. http://www.thehindubusinessline.com/industry-and-economy/why-india-prefers-brent-to-cheaper-us-crude-oil-wti/article2359323.ece.

Mohanty, D. (2012). The importance of inflation expectations. Speech delivered at S P Jain Institute of Management & Research, Mumbai, November 9.

Papaioannou, E. (2013). National institutions and subnational development in Africa. The Quarterly Journal of Economics, 129(1), 151–213.

Patra, M. D. and Kapur, M. (2010). A monetary policy model without money for India. IMF Wtaff Papers, WP/10/183.

Pfajfar, D., and Santoro, E. (2008). Asymmetries in inflation expectation formation across demographic groups. Cambridge Working Papers in Economics 0824, Faculty of Economics, University of Cambridge.

Pfajfar, D. and Santoro, E. (2010). Heterogeneity, learning and information stickiness in inflation expectations. Journal of Economic Behavior & Organization, 75 (3), 426–444.

Phelps, E. S. (1970). The new microeconomics in employment and inflation theory. American Economic Review, 59(2), 147-160.

Pinkovskiy, M. and Sala-i Martin, X. (2014b). Lights, camera,... income!: Estimating poverty using national accounts, survey means, and lights. Technical report, National Bureau of Economic Research.

Prakash, N., Rockmore, M. and Uppal, Y. (2015). Do Criminally Accused Politicians Affect Economic Outcomes? Evidence from India. *Mimeo*.

Rajan, R. (2014). "Fighting Inflation", Inaugural speech, Governor, Reserve Bank of India at FIMMDA-PDAI Annual Conference 2014, on February 26, Mumbai.

Reserve Bank of India. (2010). Inflation Expectations Survey of Households. RBI Monthly Bulletin 5, 1161–1226.

Sims, C. A. (2003). Implications of rational inattention. Journal of Monetary Economics, 50, 665–690.

Sims, C. A. (2009). Inflation expectations, uncertainty and monetary policy. BIS Working Paper No. 275.

Souleles, N. S. (2004). Expectations, heterogeneous forecast errors, and consumption: Micro evidence from the Michigan Consumer Sentiment Surveys. Journal of Money, Credit and Banking, 36(1), 39-72.

Theil, H. (1966). Applied economic forecasting. Amsterdam: North Holland.

Townsend, R. M. (1983). Forecasting the forecasts of others. Journal of Political Economy, 91(4), 546-588.

Woodford, M. (2001). Imperfect common knowledge and the effects of monetary policy. NBER Working Paper, No. 8673.

Woodford, M. (2002). Imperfect common knowledge and the effects of monetary policy. Aghion, P., R. Frydman, J. Stiglitz and M. Woodford (eds.). Knowledge, Information and Expectations in Modern Macroeconomics. In honor of Edmund S. Phelps. Princeton. Princeton University.

Wooldridge, J. (2010). Econometric analysis of cross section and panel data. Second Edition. MIT Press.



Appendix I⁷: City-specific Inflation Expectations and CPI Inflation across 12 cities in India

⁷ Data for graphs are taken from various rounds of IESH, RBI.





