Asymmetry and Heterogeneity in Inflation Expectations Survey of Indian Households

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Abstract

This study examines the systematic heterogeneity in the inflation expectations of Indian households using micro-level datasets. Using the quarterly survey data of Inflation Expectations Survey of Households (IESH) from the Reserve Bank of India (RBI), we observe that inflation expectations are persistently biased upwards and are distributed in a dispersed way. We find that the "asymmetric loss function model," in which households incur asymmetric loss from either overestimation or underestimation of the future inflation rate, can explain the observed bias to a certain extent. It is found that the Indian households incur significantly larger losses in the instances of underestimating future inflation compared to the overestimating it. Further, we examine the demographic factors that contributes to the systemic heterogeneity among the respondents of the IESH survey. Expectations are not only biased but systematically dispersed depending up on the status of actual inflation. To explore the relationship between dispersed expectations and inflation period, we made use of the Lacy (2006) measure of index of ordinal variation. We found that the expectations are less dispersed in the inflation acceleration period compared to the inflation deceleration period. Further, we examine the demographic factors that contributes to the systemic heterogeneity among the respondents of the IESH survey and the Consumer Confidence Survey (CCS). The results show that there is systematic heterogeneity in the expectations formation in Indian households. Male, younger, poorer, and people employed in financial sector were found to have lesser expectations that their counterparts. The relationship between expectations and age show an asymmetric inverted-U shape, displaying illiterate and the more literate respondents have lesser expectation for the future inflation. This study broadly identifies inflation experience and information friction as significant reasons for heterogeneous expectations.

Keywords: inflation expectations, systematic heterogeneity, information friction, asymmetric loss function, dispersion, demographic determinants

JEL Classification: C31, D84, E31, J11

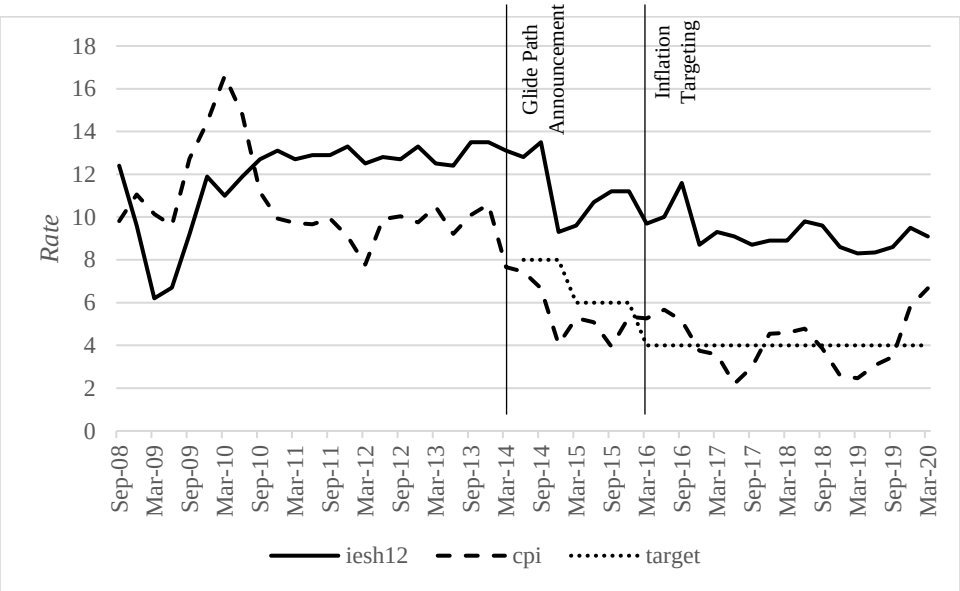
1. Introduction

Heterogeneity in inflation expectations pertains to the variations in future inflation expectations among different individuals or groups within an economy (Apokoritis et al., 2019). Studies have shown that there is often a degree of disagreement among individuals and groups within an economy regarding future inflation, and this disagreement can affect the stability and effectiveness of monetary policy; see, for example (Bryan & Venkatu, 2001; Pfajfar & Santoro, 2010; Saakshi & Sahu, 2019; Souleles, 2004). The level of heterogeneity in inflation expectations is crucial for policymakers as it offers valuable insights into the underlying economic conditions (Reid et al., 2021). This information can be used to shape the design of monetary policy effectively.

In a rational framework, the expectations about inflation have to be equal to the actual inflation for it to be an unbiased forecast (Pfajfar & Santoro, 2010). While this concept finds extensive use in studies concerning the formation of inflation expectations, it has also faced substantial criticism from various quarters (Mlambo, 2012). Research on Indian expectations has indicated that these expectations are *not* formed rationally (Sharma & Bicchal, 2018). Moreover, it has consistently displayed a positive bias in Figure 1. The figure shows a decline in inflation since the beginning of 2014. Similarly does the household inflation expectations. However, a decline in the expectations is not at the rate at which CPI has declined. Moreover, the persistent upward bias is visible throughout the sample period. Studies on other countries also indicate the existence of such a bias. Bryan & Venkatu (2001) studied the survey conducted by the Federal Reserve Bank of Cleveland and Ohio State University in 1998 to find that people over estimated the 12 months ahead forecast by 2.1 points and the perception on current inflation by 3.1 points. Ueno & Namba (2014) find that Japanese households overestimated inflation by 1.5 points. Though the bias in expectation formation is documented, the literature lacks a comprehensive analysis that explains the underlying reasons for this bias.

In this study, our focus lies in examining the heterogeneity in inflation expectations among Indian households. Firstly, we quantify the heterogeneity and model the persistent bias in expectations by employing an asymmetric loss function. Further, we examine the demographic factors that contributes to the systemic heterogeneity among the respondents of the Inflation Expectations Survey of Households (IESH) conducted by the Reserve Bank of India (RBI).

Figure 1: Inflation and Expectations in India



Source: RBI Handbook of Statistics on Indian Economy

This study makes a significant contribution to the existing literature by offering novel insights into the persistent forecast errors in Indian household inflation expectations. It employs an asymmetric loss function to explain the bias in expectations, which is a novel approach in the Indian literature. The study utilizes microdata and panel data to explore systemic heterogeneity and demographic determinants of expectations. Additionally, the study performs a matching exercise to explore the asymmetry in expectations due to education and income.

The rest of the paper is structured as the following. Section 2 provides an overview of the existing research on heterogeneity in inflation expectations, focusing on the Indian context.

Section 3 describes the data used in our analysis. The subsequent section details the modeling of the systemic bias in expectations. Section 5 empirically estimates demographic determinants of expectations formation. Finally, the paper summarizes and concludes in Section 6.

2. Literature Review

The inflation experience that shapes expectations formation among a heterogeneous population varies significantly, especially in a developing country like India, where the population is much more diverse compared to developed countries. Literature misses out on the intricacies of the heterogeneity. Unit level data (micro data) on inflation expectations is generally used to analyse the heterogeneity. Nonetheless, majority of the studies used aggregate data in analysing inflation expectations.

Souleles (2004) examine the usage of aggregate in inflation expectations analysis. The author suggests that the summarization methods using the central tendency measures disregard the complexities of information available in the expectations survey. He also argues that the excessive aggregation can lead to spurious regression. Moreover, he underscores the importance of microdata for examining the rationality of respondents and their reactions to macroeconomic shocks. Subsequently, numerous studies have employed microdata and panel data to address the heterogeneity of inflation expectations among various entities, including households (Reid et al., 2021; Ueno & Namba, 2014), consumers (Anderson et al., 2010), and firms (Bartiloro et al., 2019).

Anderson et al. (2010) explains how the heterogeneity among respondents is largely ignored in the literature. However, recent empirical studies have demonstrated substantial heterogeneity in inflation expectations, revealing that certain individuals possess more accurate expectations than others. Bachmann et al. (2015) and Coibion & Gorodnichenko (2015) assert the lack of consensus on how households form inflation expectations, they also point out the

challenges associated with empirically measuring the extent of heterogeneity in inflation expectations. There are various factors that can contribute to the heterogeneity of expectations, such as informational frictions, personal experiences, and demographic characteristics.

A stream of literature examined the heterogeneity in inflation expectations, focusing on the factors that contribute to the differences in expectations among individuals or groups (Armantier et al., 2016a; Bruine de Bruin et al., 2010; Bryan & Venkatu, 2001). Furthermore, studies has established that inflation expectations are significantly influenced by an individual's socioeconomic status (Ben-David et al., 2018). Bryan & Venkatu (2001) and Pfajfar & Santoro (2010), have largely found that gender, age, race, education, and income play major roles in developing heterogeneity. However, theoretical models that tackle the process of expectation formation frequently highlight the significance of informational frictions and heterogeneity in shaping inflation expectations.

Bryan & Venkatu (2001) find different demographic groups perceive expectations differently and that perception plays a major role in the consistent reservation of certain bias in expectations among some categories of the sample in the survey. For example, unmarried, middle-aged and men have lower expectations throughout the surveys compared to their counterparts. This indicate that the price of the baskets of corresponding groups are not much varying over time. This, in effect, keep the perception about the price being constant for a period of time unless there is a bigger shift in the overall prices.

Studies have shown that lower-income and education groups tend to have higher inflation expectations compared to higher-income and education groups (Fritzer & Rumler, 2015). Souleles (2004) finds that the higher income group and the older people have higher positive forecast errors, while the negative error is prominent for divorcees and minorities. Additionally, female, older, and single individuals tend to have higher inflation expectations

compared to their counterparts (Bruine de Bruin et al., 2010). On the other hand, better-educated and high-income individuals have lower expectations (Bryan & Venkatu, 2001). Explaining such asymmetries, Armantier et al. (2016b) argue that females, lower income, and less educated individuals tend to possess lower numeracy and financial literacy and are more likely to provide higher and more volatile inflation expectations.

The macroeconomic expectations are highly influenced by the socioeconomic status (SES) of individuals (Angelico & Di Giacomo, 2019; Ben-David et al., 2018). Moreover, the correlation between demographic characteristics and forecast error was found to be systematic (Malmendier & Nagel, 2016; Souleles, 2004). It is advocated that this systematic relationship is due to the difference in life experiences, which in effect, also provides systematic forecast errors. In order to unveil this systematic relationship, Angelico & Di Giacomo (2019) test the influence of past shopping experiences and the knowledge of the respondents with regard to inflation on the formation of their expectations. The test is executed using a model built on psychological foundations with a special focus on each SESs. The authors also checked whether past experiences led to more accurate forecasts or systematic errors. The study finds that the memory formed through recurrent shopping contributes more towards memory formation and thus becomes a stronger base for forecasting. Interestingly, the model demonstrates that such formed memories led to predictable errors in individuals' forecasting exercises, rather than reducing the forecast error. Angelico & Di Giacomo (2019) found that poor households have higher inflation expectations than rich households, which may be due to the recall of different shopping experiences and information about aggregate inflation.

One of the demographic factors that have been found to be relevant for understanding heterogeneity in inflation expectations is age. Diamond et al. (2019) found a direct and positive relationship between age and expectations, with older individuals having higher expectations, which may be due to the fact that younger people in Japan have never experienced inflation in

their lifetimes and, therefore, may expect lower inflation or deflation. It is to be noted that Japan has experienced prolonged deflation since 1995. Similar to the Japanese case, Malmendier & Nagel (2016) and Reid et al. (2021) found that that younger individuals generally exhibit lower inflation expectations compared to older individuals that could be attributed to younger individuals having less experience with inflation and being more susceptible to the influence of recent inflation trends. Ueno & Namba (2014) found an inverted U-shaped relationship between age and inflation expectations, such that middle-aged individuals had higher expectations, possibly because they are more concerned about future developments and retirement planning.

Education is another demographic factor that plays a relevant role in understanding heterogeneity in inflation expectations. Certain studies have shown that individuals with higher levels of education tend to have lower inflation expectations compared to those with lower levels of education (Bruine de Bruin et al., 2010; Reid et al., 2021). This could be attributed to individuals with higher education possessing greater financial literacy, enabling them to better comprehend the factors influencing inflation.

Some studies have revealed that individuals with higher incomes typically exhibit lower inflation expectations compared to those with lower incomes (Bruine de Bruin et al., 2010). This disparity can be partially attributed to differences in expectation formation and financial literacy. Individuals with lower incomes may prioritize their ability to cover future expenses and the prices of everyday goods and services, rather than focusing on macroeconomic indicators such as the national inflation rate. Reid et al. (2021) conducted an investigation using various regression techniques on a dataset of 12,000 data points from 2006-2012 to explore the impact of gender, education, race, income, and age on twelve-month ahead

inflation expectations. They found an inverse relationship between education and income with inflation expectations. This could be because individuals with higher incomes tend to have more significant financial stakes and, therefore, may be more cautious and informed about inflation expectations.

The occupation was also found relevant for understanding heterogeneity in inflation expectations. Some studies have found that individuals in certain occupations, such as managers and professionals, tend to have lower inflation expectations than those in other occupations, such as blue-collar workers and service sector workers (Blanchflower & MacCoille, 2009). This may be because individuals in certain occupations tend to have greater access to information and are more likely to be aware of the factors that influence inflation.

Additionally, several studies have found that inflation expectations are positively correlated with past inflation (McDonald, 2003). However, people react to current inflation differently while forming inflation expectations. Kamada (2013) conducted research using data from the Survey of Life Consciousness and found that individuals are more concerned about inflationary periods than deflationary periods. During periods of high inflation, the correlation between expected and realized inflation is higher, while during periods of low inflation, this correlation is lower. This observation might be due to households' risk-averse nature and their inclination to avoid negative outcomes for themselves, as suggested by Hori & Kawagoe (2013). A. Cavallo et al. (2017) also argued that regions with higher inflation, such as Argentina, have stronger information about past inflation, while in the US, where inflation is lower, agents are less attentive to price changes and have lower rates of updating information. Ueno & Namba (2014) employed an asymmetric loss function to model the cost of forecast error and found that underestimating inflation has a lower cost than overestimating it in Japan.

At the same time, these beliefs with regard to the inflationary and deflationary periods are also subjected to demographic heterogeneity. Ueno & Namba (2014) found that socially disadvantaged individuals placed more emphasis on market price movements or shopping experiences, while the socially advantaged focused more on overall price movements or CPI inflation. Additionally, they found lower-income groups had stickier expectations and higher forecast errors.

According to Madeira & Zafar (2015), their study reveals significant demographic heterogeneity in inflation expectations. Individuals differ in the importance they place on inflation experience and the speed at which they update their information. Specifically, women, ethnic minorities, and less educated individuals tend to give more weight to inflation experience and update their beliefs more slowly. On the other hand, men, non-Hispanic whites, and more educated individuals tend to assign less weight to life experience inflation and update their beliefs more rapidly.

In addition to demographic characteristics, other factors that have been found to influence heterogeneity in inflation expectations include the availability and use of information, cognitive skills, and the impact of past experiences. Bruine de Bruin et al. (2010) studied the effect of financial literacy correlated with the demographic factors in the heterogeneity of survey expectations in the US. They argued that female, lower income, single, and less educated individuals tend to report higher expectations as they possess lower financial literacy. Furthermore, Armantier, Nelson, et al. (2016a) found that individuals with higher financial literacy and numeracy skills are more likely to have more accurate inflation expectations. These findings highlight the importance of various factors in shaping inflation expectations and the need to consider a range of determinants for a comprehensive understanding of heterogeneity.

Heterogeneity in expectations has also been linked to differences in access to information and the ability to process it in the context of life decisions faced by agents (Ueno & Namba, 2014). Demographic variables often play a key role in explaining these socioeconomic differences. Meeks & Monti (2019) examined the distribution of inflation expectations and found that 80% of the total variation in US inflation expectations was explained by disagreement or the cross-sectional dispersion of forecasts. They also found a significant statistical association between the distribution of beliefs about future inflation and actual inflation, such that lagged inflation variables become insignificant once inflation expectations are incorporated into the Philips curve equation, indicating that previous inflation data is already captured by inflation forecasts. Coibion, Georgarakos, et al. (2020) explored how individual expectations are formed and highlighted the importance of economic agents' capacity or limitations in processing information about inflation.

Further research addressing socioeconomic factors in inflation expectations includes studies on learning and updating (Evans & Honkapohja, 2001; Pfajfar & Santoro, 2010) and models of expectations (Carroll, 2003; Xu et al., 2016).

In the Indian context, Goyal & Parab (2019) find that there is heterogeneity across various categories of households, which influences the formation of inflation expectations. They also argue that households' expectations do not exhibit overreactions when compared to the forecasts of the RBI and professional forecasters. The study concludes that households' expectations are adaptive and backward-looking. Similarly, Sharma & Bicchal (2018) report similar results, noting that survey respondents do not form expectations rationally, regardless of the reference measures of inflation used (CPIIW or WPI). A panel data analysis of Indian cities conducted by Saakshi & Sahu (2019) reveals that cities with higher economic activity

and a higher cost of living tend to have higher inflation expectations. Additionally, the study finds that disagreement in inflation expectations across cities increases when the output gap or rate of inflation rises. This suggests that information friction plays a crucial role in explaining the disparities in inflation expectations among different cities.

In a pooled cross-sectional analysis of demographic categories, Das et al. (2019) found that women, homemakers, older individuals, and city dwellers from Tier 2 and 3 cities tend to have higher inflation expectations compared to their counterparts. Moreover, these same cohorts exhibit a faster speed of adjustment when new information is released by central banks. This suggests that communication from central banks plays a significant role in influencing how households form their inflation expectations.

3. Data

The variable of primary concern is the 12 months ahead inflation expectations collected from the IESH conducted by RBI. The data is collected quarterly from September 2008 to March 2020. We have also used Consumer Confidence Survey (CCS) data published by the RBI from June 2015 to March 2020. This study uses dummy variables for all demographic variables, such as gender, age, employment, and city. We we have calculated the forecast error $\pi_{t,t-q}^{fe}$ as the difference between the realized inflation at time *t* and expectations for time *t* forecasted at *t* – *q*. The equation is given by $\pi_{t,t-q}^{fe} = \pi_{t,t-q}^{e} - \pi_t$. A positive value denotes overestimating expectations, and a negative value denotes underestimating.

3.1. IESH Data

The RBI has been conducting the IESH survey since 2005. The way the survey is conducted has undergone numerous adjustments. Until 2016, the survey was carried out quarterly; after that, it was done bimonthly. In order to keep the regularity of data, we stick to 4 quarters – March, June, September, and December – of every year. After 2015, it was

collected at 6-time points in the year.[1] The data includes a sample of about 5,000 households from 19 Indian cities. There are 2,19,008 observations in the microdata that is formatted as pooled cross-section data. We also use it as a panel data, with the city serving as its panel variable.

The IESH consists of a questionnaire that is divided into four sections. The first two sections collect demographic information about the respondent, including age, gender, employment, and city of residence. The third section asks respondents for their views on inflation expectations over the next three months and one year, with responses classified into five categories: (i) "Decline in Prices", (ii) "No change in Prices", (iii) "Prices change less than the previous year", (iv) "Price changes are same as the previous year" and (v) "Prices change more than the previous year". These responses are collected for overall inflation and specific categories such as food, non-food items, household durables, services, and housing prices. This provides us with the qualitative data for analysis. Finally, the survey collects quantitative responses on households' expectations of inflation for four quarters ahead ($\pi^e_{t,t+4}$), one quarter ahead ($\pi^e_{t,t+1}$), as well as their perceptions of the current level of inflation (π^p_t).

It also gathers information on the demographic categorization from where we attempt to understand the determinants of the heterogeneity of the inflation expectations in the survey of households. They are gender, age, employment, and city of residence. It is also to be noted that the survey is purposive random sampling in which the frequency of respondents from each category has been more or less fixed. The average share of each cohort is displayed in the following Table 1.

[1] In case the data is not released in the above said time, we stick to the closest data release time which comes after the four months mentioned.

Table 1: Sampling Cohorts

Category	% Share	Category	% Share
Gender		**City**	
Female	42.83	Ahmedabad	5.54
Male	57.17	Bangalore	6.17
Age		Bhopal	4.69
Up to 25 years	16.67	Chennai	9.88
25 to 30 years	15.97	Delhi	11.57
30 to 35 years	14.05	Guwahati	4.63
35 to 40 years	13.83	Hyderabad	5.84
40 to 45 years	10.16	Jaipur	4.79
45 to 50 years	8.6	Kolkata	10.44
50 to 55 years	5.91	Lucknow	5.04
55 to 60 years	5.23	Mumbai	11.32
60 years and above	9.58	Patna	4.74
Employment		Nagpur	3.15
Financial Sector	8.36	Thiruvananthapuram	2.57
Other Employees	16.75	Bhubaneswar	2.79
Self-employed	20.06	Chandigarh	1.69
Housewife	29.81	Ranchi	1.86
Retired Persons	8.58	Kolhapur	1.49
Daily Workers	9.62	Raipur	1.78
Other Category	6.81	**Total Observation**	**2,19,008**

This study focuses on 12 cities continuously included in the survey since 2008. The cities are again categorized in two ways for analysis; (i) based on their geographic locality as North, East, West, and South; and (ii) their level of economic activity as Tier -1, Tier -2, and Tier - 3. The East panel includes Guwahati, Kolkata, and Patna; the West panel includes Ahmedabad, Jaipur, and Mumbai; The North panel includes Bhopal, Delhi, and Lucknow; The South panel consists of Bangalore, Chennai, and Hyderabad. Further, for the second classification, Tier-1 cities identified for the study are Ahmedabad, Mumbai, Chennai, Delhi, Kolkata, Bangalore, and Hyderabad. We consider other cities – Bhopal, Guwahati, Jaipur, Lucknow, and Patna –Tier-2 and Tier-3.

3.2. CCS data

The RBI conducts the Consumer Confidence Survey (CCS) to obtain current perceptions and one-year-ahead expectations on the general economic situation, employment scenario, overall price situation, and own income and spending across 19 major cities. It has been conducted bimonthly since 2016, quarterly before that. However, the survey is limited to collecting qualitative responses wherein the respondents are asked to select their expectations from the given three options – (i) "will go up", (ii) "will remain unchanged", and (iii) "will go down".

It is to be noted that both IESH and CCS classify the respondents according to their gender, age, employment, and city of residence. What makes the CCS survey different from IESH is that it also records the respondents' income, educational qualification, number of family members, and the number of earning members in the family. These variables are also important for the analysis of heterogeneity of inflation expectations.

In this study, we made an attempt to combine the IESH and CCS data sets through a matching exercise. We generated average inflation expectations of the respondents in the IESH survey for each cohort separately and assigned those values to the respondents in the matching cohorts in the CCS data. By doing this, the CCS data is enriched with quantitative data on inflation expectations, leading to more analysis, especially regarding the influence of demographic variables in the formation of inflation expectations in India. This kind of exercise is novel in the context of India. In order to make this matching exercise credible, we take up some empirical exercises in section 4.5.1 using the new data and confirms its legitimacy.[2]

[2] However, it is not clear from the data sources whether the data for both IESH and CCS are collected from the same households or not, which keeps the issues of double counting the households unclear.

Making use of such data, we could deduce the effect of education and income on Indian household expectations.

3.3. Summary statistics

We attempt to look into the descriptive statistics of inflation expectations and forecast error for each demographic variable. A few inferences stand out from Table 2. The male cohort has lower expectations compared to the female. However, the difference is meagre. On the contrary, the average perception was higher for males. Among the employment categories, employees in the *financial sector* are expected to have lower expectations as they have more access to the data on changes in prices. The lowest average expectation is of the *other category*, and the highest value is of the *retired persons*. It is believed that the higher expectations from retired persons are because they have experienced higher inflation for a long period in their life. This is also evident in the age category analysis. Average expectations are found to be increasing with an increase in age.

City has brought in considerable differences in the average perception and expectations. The statistics displayed here show no specific pattern that the cities follow in forming expectations. However, the highest average expectation was held by Jaipur City of Rajasthan state. The average perception of Bangalore city was the lowest, although with high variance. Patna City reported the lowest variability of all.

In general, the average Non-IT expectations are higher than the perception and expectations in the IT period. On average, there is a 2-3% drop in expectations since IT. It is valid for all demographic groups except for cities like Kolkata, Guwahati, and Chennai. Bangalore is also noted for the highest drop in expectations since the adoption of IT among the cities.

As noted before, inflation expectations are higher than the actual inflation. This leads to an overestimation of inflation and, thus, an upward bias. Forecast error is measured as the difference between the expectations and the realized inflation. Table 3 reports the forecast error by different demographic groups in the household survey.

Interestingly, the forecast error in the non-IT period was much lower than the post-IT period, by almost 2-3%. This is due to the fact that there was a decline in the realized inflation following IT, whereas the decline in the expectations that followed was much lower. All the demographic groups, such as gender, employment, and age groups, display a considerable increase in forecast error. The male has lesser forecast error than the female cohorts. Financial sector employees display the lowest forecast error among the employment categories, except for the 12 months ahead expectations. There is an increase in upward bias with an increase in age. From among the cities, forecast error in all cities except Bangalore has displayed higher errors post-IT. Similar is the case of Mumbai and Jaipur for the 12 months ahead average bias.

Table 2: Inflation Expectations of Demographic Groups before and after IT

	Perception			***1 quarter expectations***			***4 quarters expectations***		
	Mean			Mean			Mean		
	Full sample	**Non-IT**	**IT**	**All**	**Non-IT**	**IT**	**All**	**Non-IT**	**IT**
Overall									
	9.59	10.57	8.23	10.07	10.93	8.86	10.62	11.64	9.18
Gender									
Male	9.63	10.5	8.29	10.05	10.83	8.85	10.59	11.57	9.09
Female	9.55	10.68	8.16	10.09	11.08	8.87	10.64	11.75	9.29
Employment									
Financial Sector	9.46	10.21	7.91	9.82	10.51	8.4	10.48	11.19	9.02
Other Employees	9.47	10.4	8.22	9.91	10.71	8.85	10.44	11.46	9.06
Self-employed	9.64	10.55	8.31	10.04	10.88	8.81	10.55	11.62	8.97
Housewife	9.64	10.75	8.19	10.2	11.18	8.9	10.75	11.86	9.29
Retired Persons	9.94	10.73	8.64	10.34	11.02	9.21	10.91	11.67	9.65
Daily Workers	9.72	10.85	8.34	10.24	11.23	9.04	10.78	11.94	9.37
Other Category	9.09	10.2	7.9	9.66	10.63	8.63	10.24	11.42	8.97
Age									
Up to 25 years	9.18	10.37	7.63	9.77	10.84	8.35	10.39	11.56	8.87
25 to 30 years	9.33	10.38	7.94	9.84	10.8	8.6	10.43	11.5	9.03
30 to 35 years	9.53	10.5	8.15	10.01	10.87	8.78	10.57	11.58	9.13
35 to 40 years	9.65	10.57	8.33	10.13	10.94	8.96	10.67	11.65	9.25
40 to 45 years	9.73	10.64	8.38	10.18	10.98	9.01	10.7	11.73	9.19
45 to 50 years	9.79	10.73	8.49	10.2	11.03	9.03	10.71	11.75	9.25
50 to 55 years	9.95	10.77	8.76	10.32	11	9.32	10.77	11.69	9.41
55 to 60 years	9.91	10.73	8.74	10.32	10.99	9.36	10.78	11.71	9.46
60 years and above	10.05	10.9	8.81	10.42	11.15	9.35	10.96	11.85	9.65
City									
Ahmedabad	9.93	10.04	9.78	10.99	11.15	10.76	11.75	12.52	10.72
Bangalore	9.28	12.57	6.07	9.81	12.78	6.9	10.4	13.35	7.51
Bhopal	8.29	8.74	7.33	9.38	9.91	8.24	10.29	11.13	8.47
Chennai	9.41	9.66	8.94	10.09	10.15	9.97	10.4	10	11.17
Delhi	8.87	9.78	7.79	9.41	10.33	8.31	9.75	11.16	8.05
Guwahati	10.31	10.16	10.66	10.3	10.43	9.99	10.91	11.23	10.17
Hyderabad	9.63	10.47	8.53	10.28	11.04	9.28	11.03	11.67	10.19
Jaipur	11.12	12.73	8.02	11.35	12.84	8.48	12.05	13.77	8.73
Kolkata	9.54	9.39	9.77	9.72	9.24	10.44	10.26	9.9	10.82
Lucknow	9.92	11.08	7.66	10.35	11.5	8.1	10.99	12.17	8.69
Mumbai	10.62	12.15	8.52	10.69	11.9	9.03	10.91	12.7	8.45
Patna	9.61	10.57	7.34	10.39	11.42	7.95	11.2	12.31	8.54

Table 3: Forecast Errors of Demographic Groups before and after IT

	Perception			***1 quarter expectations***			***4 quarters expectations***		
	Mean			Mean			Mean		
	Full Sample	**Non-IT**	**IT**	**Full Sample**	**Non-IT**	**IT**	**Full Sample**	**Non-IT**	**IT**
Overall									
	2.5	1.38	4.07	3.01	1.87	4.61	3.76	3.1	4.68
Gender									
Male	2.37	1.23	4.13	2.83	1.69	4.6	3.61	2.95	4.62
Female	2.67	1.6	4	3.25	2.14	4.62	3.97	3.33	4.75
Employment									
Financial Sector	1.94	1.1	3.68	2.41	1.53	4.25	3.54	2.73	5.23
Other Employees	2.4	1.13	4.09	2.87	1.57	4.61	3.51	2.83	4.43
Self-employed	2.47	1.33	4.14	2.91	1.79	4.55	3.67	3.1	4.49
Housewife	2.63	1.57	4.02	3.21	2.13	4.63	3.93	3.33	4.72
Retired Persons	2.68	1.62	4.42	3.14	2.04	4.94	4.02	3.15	5.46
Daily Workers	2.89	1.8	4.22	3.45	2.32	4.82	4.09	3.5	4.8
Other Category	2.19	0.74	3.76	2.77	1.3	4.35	3.38	2.68	4.14
Age									
Up to 25 years	2.26	1.33	3.48	2.9	1.95	4.15	3.74	3.26	4.38
25 to 30 years	2.31	1.18	3.8	2.88	1.73	4.37	3.64	2.97	4.53
30 to 35 years	2.41	1.3	3.99	2.93	1.79	4.53	3.67	2.99	4.62
35 to 40 years	2.47	1.29	4.17	2.97	1.77	4.7	3.68	2.96	4.73
40 to 45 years	2.52	1.36	4.23	3.02	1.83	4.76	3.74	3.13	4.64
45 to 50 years	2.65	1.45	4.32	3.08	1.9	4.75	3.8	3.15	4.71
50 to 55 years	2.72	1.44	4.59	3.14	1.83	5.06	3.78	3.05	4.85
55 to 60 years	2.8	1.56	4.55	3.24	1.95	5.07	3.92	3.16	4.99
60 years and above	2.94	1.82	4.6	3.35	2.21	5.03	4.14	3.36	5.28
City									
Ahmedabad	2.66	0.45	5.67	3.73	1.68	6.5	4.58	3.53	5.98
Bangalore	2.37	2.79	1.97	2.84	3.11	2.58	3.29	4.17	2.43
Bhopal	0.44	-0.79	3.11	1.61	0.51	4.02	2.87	2.23	4.28
Chennai	1.69	0.12	4.74	2.44	0.75	5.73	3.05	1.09	6.85
Delhi	1.84	0.31	3.68	2.36	0.98	4.01	2.68	2.24	3.21
Guwahati	2.48	0.79	6.48	2.56	1.18	5.84	3.52	2.42	6.14
Hyderabad	2.51	1.04	4.43	3.16	1.74	5.01	3.93	2.85	5.34
Jaipur	3.37	3.12	3.87	3.66	3.33	4.3	4.6	4.72	4.36
Kolkata	2.19	-0.09	5.63	2.39	-0.11	6.17	3.06	0.98	6.2
Lucknow	2.23	1.6	3.46	2.74	2.17	3.85	3.71	3.36	4.39
Mumbai	3.41	2.71	4.38	3.48	2.59	4.72	3.78	3.85	3.68
Patna	1.73	1.16	3.1	2.61	2.13	3.75	3.83	3.51	4.58

4. The Persistent Forecast Error

We have already graphically shown that there exists a consistent positive bias in $\pi^{e}_{t,t+4}$ with respect to the π_t, which is otherwise defined as the forecast error. The bias on average is 2.50, 3.01, and 3.76 for inflation perception, one quarter ahead inflation expectations, and four quarters ahead inflation expectations, respectively; see, Table 4. Despite a decline in the actual inflation post-2014, $\pi^{e}_{t,t+4}$ does not decrease to the same extent as the CPI; see, Figure 1.

Table 4: Descriptive Statistics

	Mean	**SD**
$\boldsymbol{\pi^{p}_{t}}$	9.59	4.36
$\boldsymbol{\pi^{e}_{t,t+1}}$	10.07	4.50
$\boldsymbol{\pi^{e}_{t,t+4}}$	10.62	4.80
$\boldsymbol{\pi_{t}}$	7.09	3.46
$\boldsymbol{\pi^{fep}_{t}}$	2.50	4.96
$\boldsymbol{\pi^{fe}_{t,t+1}}$	3.01	5.23
$\boldsymbol{\pi^{fe}_{t,t+4}}$	3.76	5.72

4.1. Measurement of dispersion of inflation expectations

This skewed pattern of overestimating expectations may be due to a higher frequency of extreme values. In order to evaluate this heterogeneity, we evaluate the distribution of expectations and estimate dispersion. Furthermore, we assess the impact of the adoption of IT on the dispersion of inflation expectations controlling for the level of inflation and its variability.

As we mentioned before, along with the quantitative responses of the households, they also select one from the given options of response categories defined as “Decline in Prices”, “No change in Prices”, “Prices change less than the previous year”, “Price changes are same as the previous year”, and “Prices change more than the previous year”. Using this, we estimate the Lacy (2006) measure as the baseline measure to calculate the extent of the dispersion of the

responses among the five choices. Lacy (2006) measure records the d^2 index of ordinal variation (IOV) and is defined as:

$$\text{Lacy Measure } = \sum_{i=1}^{K-1} F^i(1 - F^i) \quad (1)$$

where K is the number of categories of responses. In our case, K=5. F^i is the cumulative response share in category i. e.g. $F^2 = s^1 + s^2$ wherein s^1 is the share of 1st response against overall responses. The Lacy measure takes a value of 0 if the responses are uniform. It will approach 1 when the responses are scattered across the response categories.

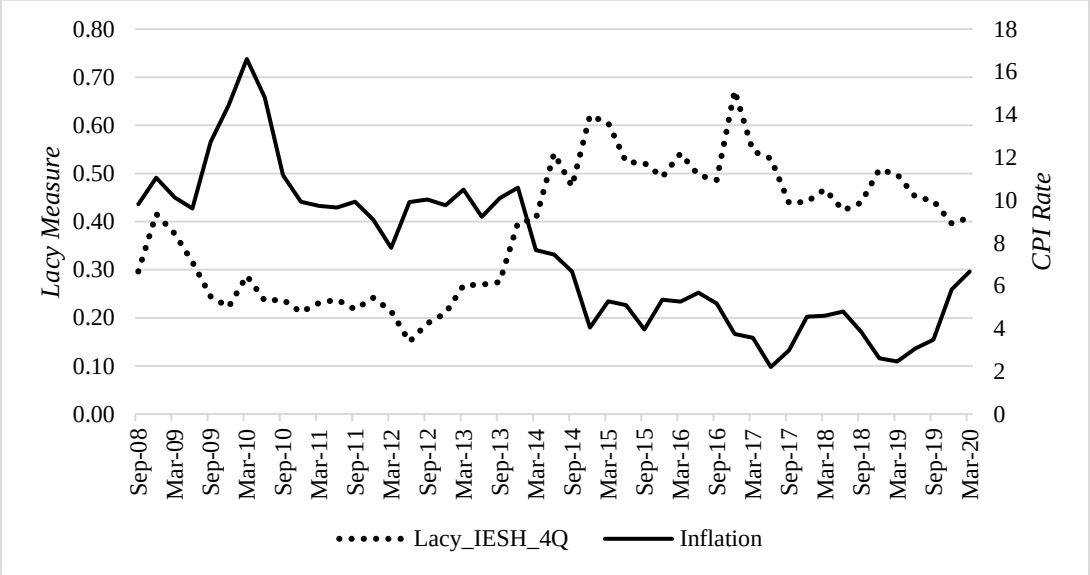
4.2. Aggregate statistics

Figure 2 displays the Lacy (2006) measure for the four quarters ahead household expectations (Lacy_IESH_4Q) against the realized inflation. For the sake of demonstration, we demonstrate the inflation acceleration period as between March 2009 to June 2010, and deceleration period as September 2012 to June 2016.[3] It suggests that the Lacy measure took an upturn after June 2012 and continued to hover around 0.5-0.7, reaching its maximum (0.8) in December 2016. It is also to be noted that the intersection of the Lacy measure and the CPI in March 2014 is the *glide path announcement* period. Interestingly the interplay between the CPI and Lacy (2006) measure is such that the heterogeneity increased with a decline in the realized inflation and vice versa. This also suggests that the responses of the survey respondents are less discrete in the higher inflation period and more discrete in the lower inflation period. This suggests a convergence of opinions during periods of increasing inflation. Similar pattern is visible in Ueno & Namba (2014) wherein they study expectations of the Japanese households. They also find that the responses are not uniform in the inflation deceleration

[3] Acceleration and decoration of inflation is solely based on the growth of inflation. It doesn't depict whether inflation is in the range of inflation targeting or not.

period. An increase in inflation induces lesser changes in heterogeneity than a decrease in inflation.

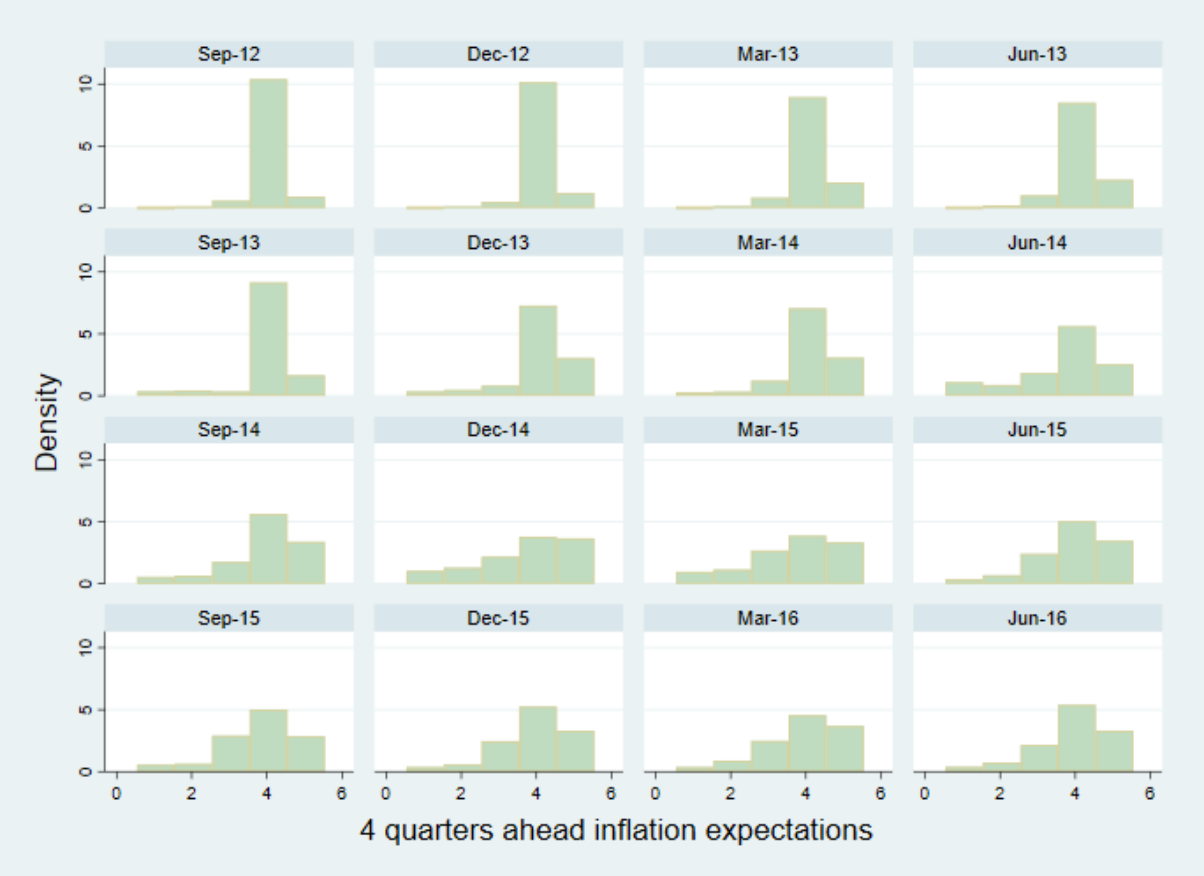
Figure 2: Heterogeneity in Household Inflation Expectations



***Sources*:** RBI and author's calculation

Figure 3 displays the distribution of qualitative responses for 12-month ahead inflation expectations from September 2012 to June 2016, which represents the transition period from higher to lower inflation. The distribution shows a high concentration on one choice initially, but gradually becomes more discrete as inflation decreases. Additionally, the distribution shifts slightly left over this period. In contrast, Figure 4, representing the inflation acceleration period in 2009-10, shows a slow rightward shift and less discrete responses. This indicates that households respond faster to inflation deceleration, resulting in a diversified opinion about future inflation. Conversely, their responses are slower during inflationary periods, leading to a less discrete response pool accumulating towards the right. The Figures 3 and 4 affirms what has been learned from the Lacy (2006) analysis that the responses become more discrete in the inflation deceleration period.

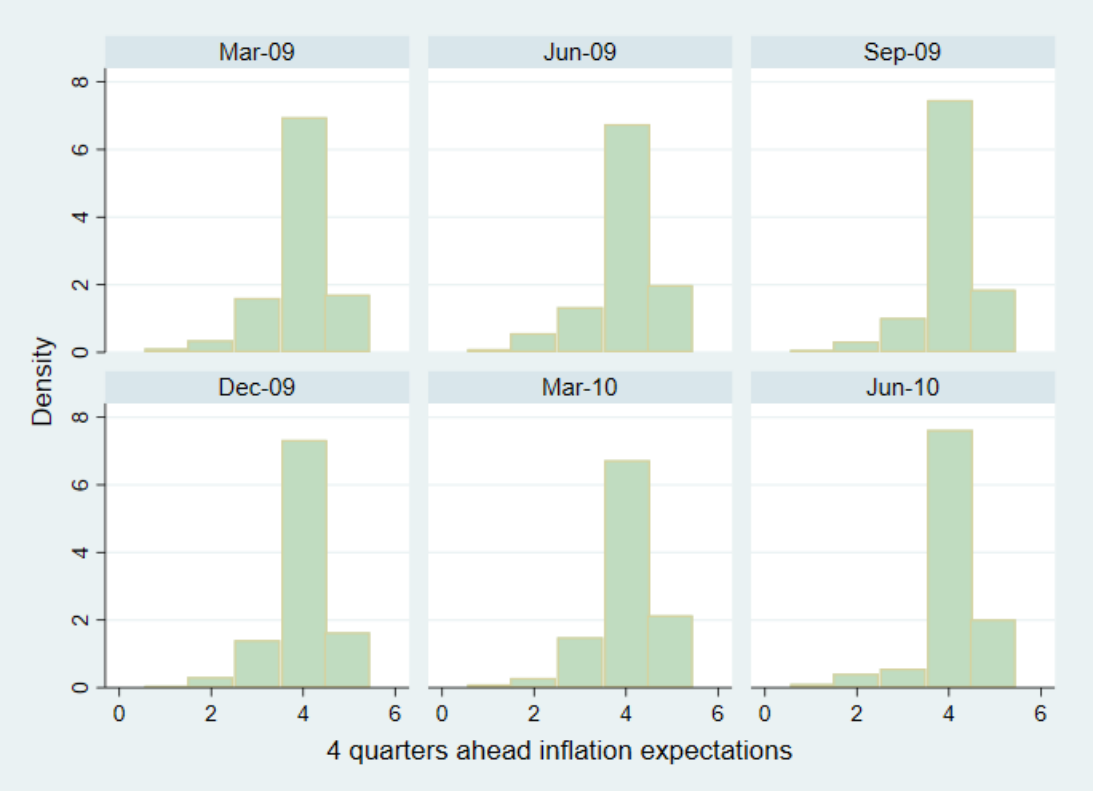
Figure 3: Distribution of expected inflation (deceleration period)



Source: Authors calculation from the IESH data

Note: The numbers along the x-axis denote qualitative choices provided to the respondents

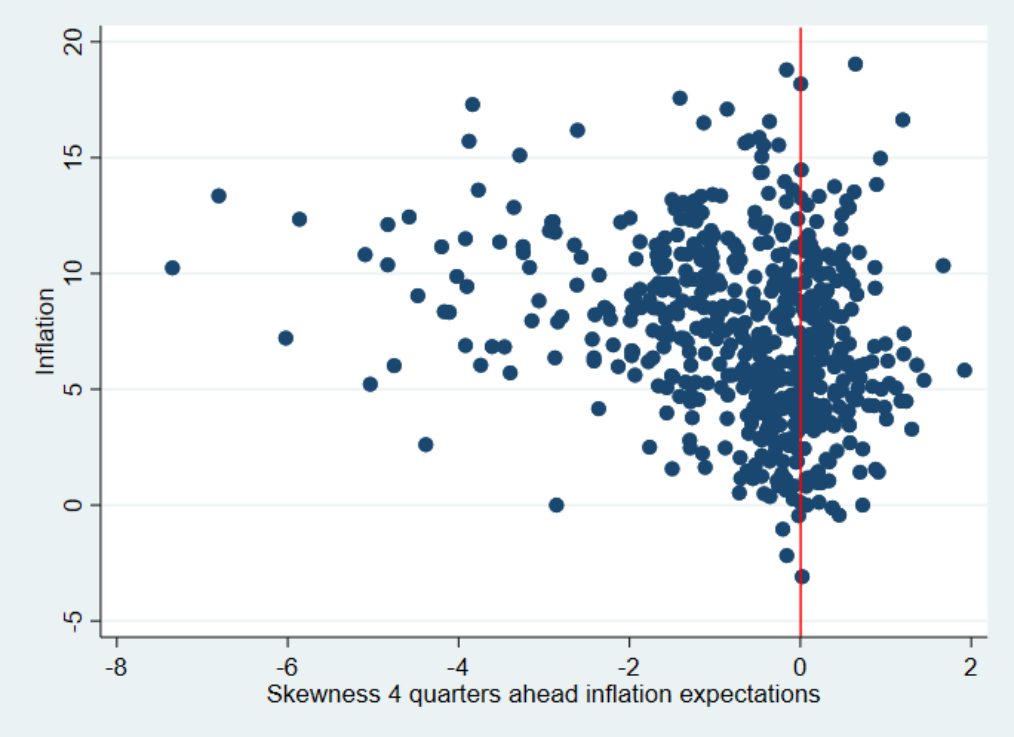
Figure 4: Distribution of expected inflation (acceleration period)



Source: Authors calculation from the IESH data

To further examine the extent of strain in the distribution, we utilize the measure of skewness. Skewness is calculated based on the third moment about the mean of the responses and provides a general way to assess distortion in a distribution.[4] A positive skewness value indicates that the distribution of expectations is skewed to the right, while a negative skewness value indicates a skew to the left. A skewness value of zero suggests a symmetrical distribution.

Figure 5: Inflation rate and skewness in expectations



Source: Authors calculation from the IESH data

Figure 5 plots skewness four quarters ahead inflation expectations against the realized inflation. It displays how skewness behaves with the movement of inflation. In higher inflation, the skewness is dispersed in the negative region or distorted to the left. However, when inflation is near zero, skewness is more distributed to the right compared to the left. The skewness is

[4] Skewness is the third moment about mean. S^{th} moment of a series with n observations can be defined as $(x_1^s + x_2^s + x_3^s + \cdots + x_n^s)$/n or alternatively $[\sum_{i=1}^{n} x_i^s]/n$. S^{th} moment about mean is defined as $m_s = [\sum_{i=1}^{s}(x_i - m)^s]/n$ where m is the mean of the series.

assembled near the zero, be it higher inflation or lower. This may indicate the limited distribution of distortion.

4.3. Category-wise statistics

We have noted that the responses are positively biased and dispersed. We further examine the heterogeneity across different demographic groups using Lacy (2006) measure. Figure 6 shows minor differences in inflation expectations heterogeneity within the demographic categories of gender, age, and employment See panels (a), (b), and (c) of Figure 6. However, the cities display significant disagreement. The extent of disagreement among the cities is also evident from Table 5. The test for equality of mean suggests that except for the city, all others accept the null hypothesis of no difference between the mean of two or more groups. For the city, significant heterogeneity in the forecasting of inflation is found.

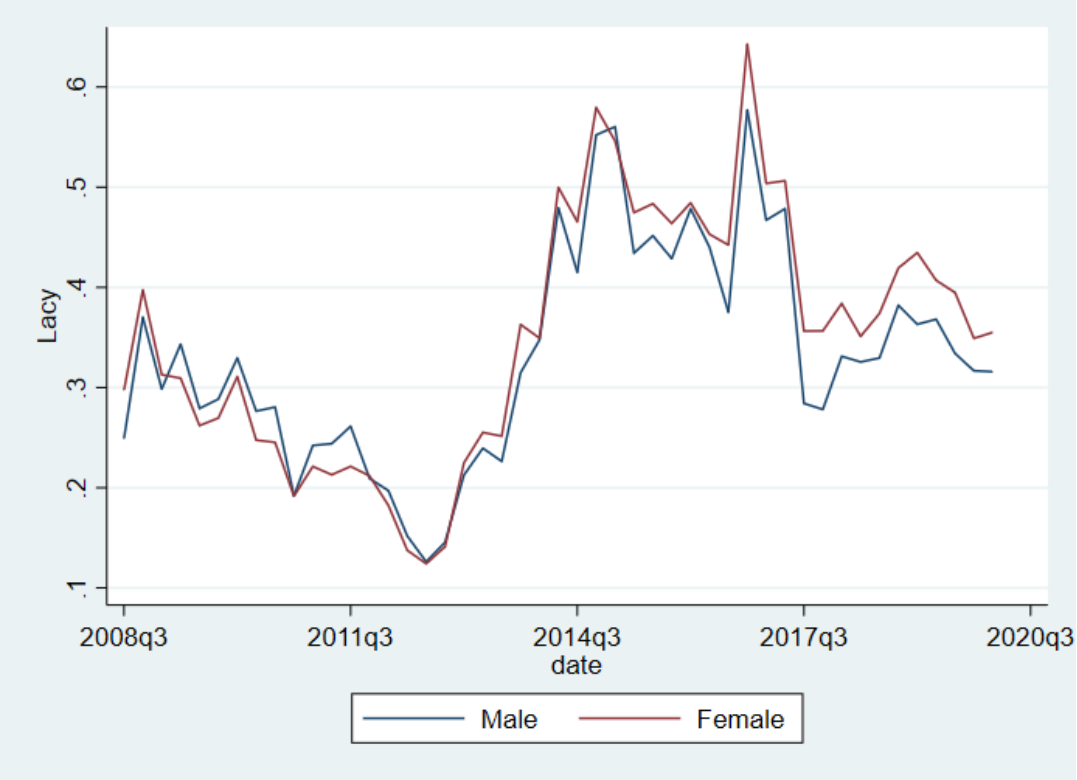
***City Heterogeneity*:** We categorize cities into four zones based on their geographic locality. East, West, North, and South. Zoning the cities into four geographical classifications does make sense as they display some patterns of heterogeneity among themselves. Panel (d) of Figure 6 shows that all the cities in the North zone seem to have followed the same path throughout the period. Table 5 suggests that expectations formed in the North region are not much different across the cities, while cities in other regions form expectations differently. Cities in the South Zone seem to have followed a pattern of heterogeneity after June 2013. However, they have displayed considerable non-cohesion before that. Similarly does West and East.

Table 5: Tests of Equality of Means

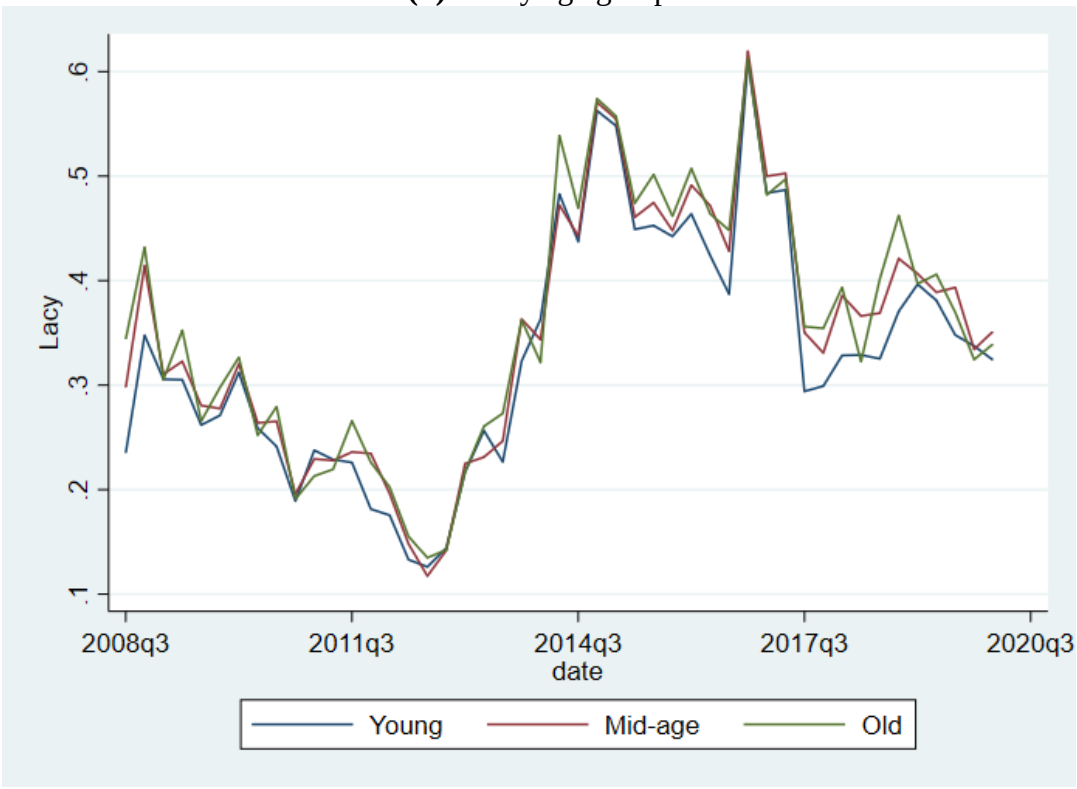
Method		Value	Prob.
	Gender		
t-test		0.77	0.44
	Age		
Anova F-test		0.66	0.73
	Employment		
Anova F-test		0.66	0.69
	City		
Anova F-test	Overall	8.27	0.00
	East	15.45	0.00
	West	6.43	0.00
	North	0.66	0.52
	South	15.86	0.00
	Tier-1	13.00	0.00
	Tier-2&3	4.25	0.00

Figure 6: Inflation Expectations Heterogeneity across Demographic Groups in India

(a) by gender



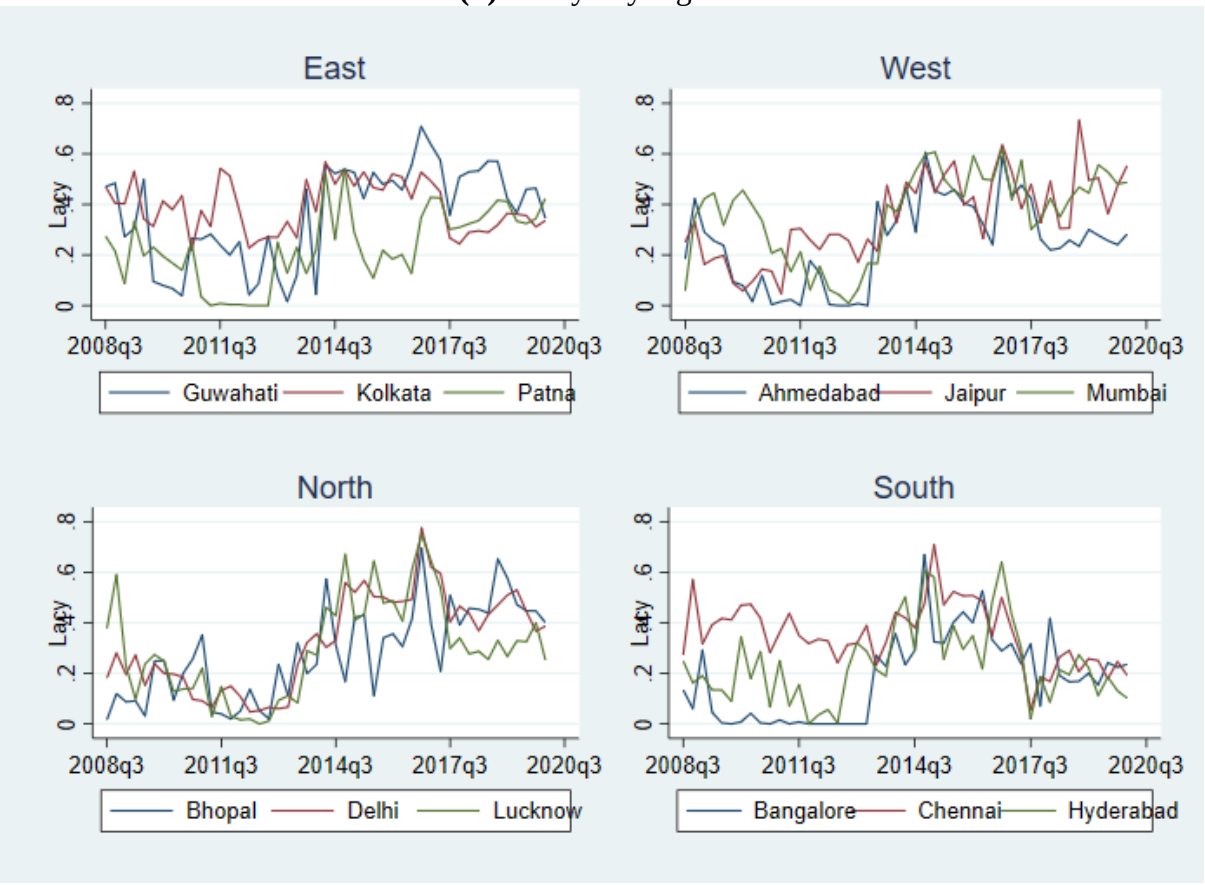
(b) by age group



(c) by occupation



(d) by city regions



4.4. Asymmetric loss function

We have discussed the upward bias in the expectations, which suggests the expectations formed by the households in India, on average, are higher than the realized expectations. We also found that the city is the most heterogeneous demographic characteristic in the formation of inflation expectations in India. We use the microdata for a panel data set, with city as the panel variable.

In an attempt to explain the structural bias, Capistrán & Timmermann (2009) uses the linex loss function proposed by Varian (1975) to formulate an asymmetric loss function.[5] We

[5] The Asymmetric Loss Function (ALF) model is a monetary policy framework that is used to analyze the trade-offs that policymakers face when setting interest rates, with a special reference to the costs of high inflation than the costs of low inflation. In other words, the ALF model assumes that policymakers have an asymmetric loss function, in which they incur greater losses from high inflation than they do from low inflation.

assume the loss is higher with a higher positive and negative bias. The equation for such a model, as depicted by Ueno & Namba (2014) is given as:

$$L\left(\pi_{t,t+12}^{fe}, \emptyset\right) = 1/\emptyset^2[\exp\left(\emptyset\pi_{t,t+12}^{fe}\right) - \emptyset\pi_{t,t+12}^{fe} - 1] \quad (2)$$

wherein, $\pi_{t,t+12}^{fe}$ is the forecast error of inflation expectations with respect to the realized CPI inflation, $\emptyset$ is the measure of the extent of asymmetry. The $\emptyset$ can take positive or negative values. A positive value of $\emptyset$ indicates that an overestimation is more severe than an underestimation, and a negative value of $\emptyset$ represents the opposite. The loss function becomes symmetric when $\emptyset$ approaches zero.

Next, we find an optimal forecast model wherein the loss function is minimal. We make three assumptions: (1) the parameter of asymmetry $\emptyset$ is identical for all households, (2) household expectations are rational, and (3) information sets for all households are identical. When the inflation rate follows a normal distribution with mean $\mu_{t,t+12}$ and variance $\sigma_{t,t+12}^2$, the optimal forecast can be described as:

$$\pi_{t,t+12}^{e*} = \mu_{t,t+12} + \frac{\emptyset}{2}\sigma_{t,t+12}^2 \quad (3)$$

If we relax the assumptions, then it is expected to have different levels of asymmetry for each city denoted as $\emptyset_i$ wherein *i* denotes the individual city. Furthermore, we expect a 'departure' from the optimal forecast for every city, say by a margin of $\pi_{b,i}$.

$$\pi_{t,t+12,i}^{e} = \mu_{t,t+12} + \frac{\emptyset_i}{2}\sigma_{t,t+12}^2 + \pi_{b,i} \quad (4)$$

The crucial factor in this analysis is to estimate $\emptyset_i$. In doing so, we assume the following. Let the inflation rate at time *t*+12 be π_{t+12} and information set at the time *t* be ρ_t, then the expected forecast error for period *t*+12 is:

$$E(|\pi_{t+12} - \pi^{e}_{t,t+12,i}|\rho_t) = -\pi_{b,i} \ -\frac{\emptyset_i}{2}\sigma^2_{t,t+12} \quad (5)$$

This proposition indicates that the loss function will not be zero even if the departure, $\pi_{b,i} = 0$. Solving this equation will reach us to calculate $\emptyset_i$. If we assume $\pi_{b,i} = 0$, we can calculate the asymmetry parameter as:

$$\emptyset_i = -2\sum \frac{\pi^{fe}_{t,t+12,i}}{\sigma^2_{t,t+12}} \quad (6)$$

where $\pi^{fe}_{t,t+12,i}$ is the forecast error defined as the difference between the average forecast of the city *i* at time *t* for *t*+12 and the realized city-wise CPI inflation at time *t*+12.

Figure 7: Estimated Conditional Variance

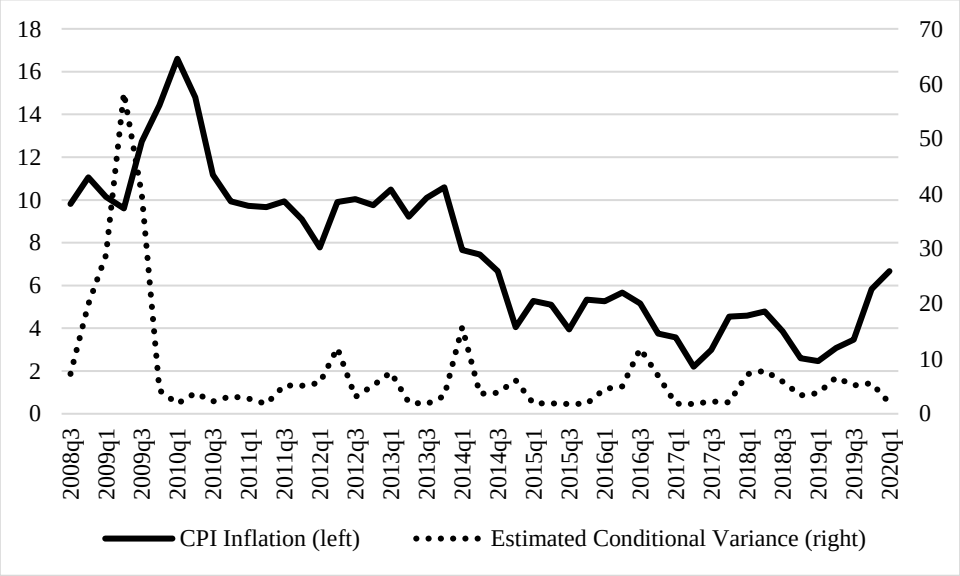
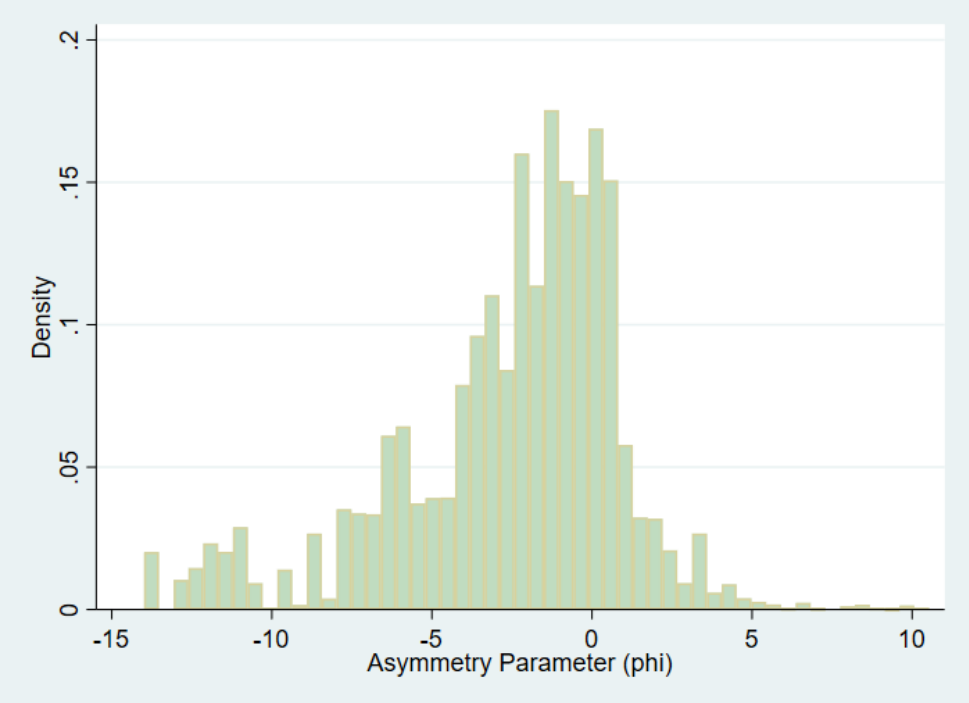


Figure 8 displays the distribution of asymmetry parameter $\emptyset_i$.estimated using equation (6).[6] It has a thicker tail towards the left-hand side, indicating most households possess negative, $\emptyset_i$. This finding, in contrast with Ueno & Namba (2014), indicates that Indian households' loss from *overestimating* the inflation rate is greater than *underestimating*

[6] The calculation of $\sigma^2_{t,t+12}$ is explained in detail in Appendix 4A.

inflation. Hence, for this reason, most respondents quote higher inflation even when the inflation is declining.

Figure 8: Distribution of Estimated Asymmetry Parameter ($\pi_{b,i} = 0$)



If we relax the assumption of $\pi_{b,i} = 0$, we can calculate the asymmetry parameter using the following regression model:

$$\pi^{fe}_{t,t+12,i} = C_{0,i} + C_{1,i}\sigma^2_{t,t+12} + \varepsilon_{t+12,i} \quad (7)$$

wherein $C_{0,i}$, $C_{1,i}$ are the parameters, and $\varepsilon_{t+12,i}$ the error term.

The estimates of $\emptyset_i$ is derived from the coefficient $C_{1,i}$. The histogram of the estimated asymmetry parameter is presented in Figure 9. Once again, the majority of the households report negative $\emptyset_i$.

We take the cross-section of household expectations data to obtain the quantile distribution of $\emptyset_i$; See Table 6. Based on the results, we plot the loss level using equation (2) in Figure 10. As can be observed, the loss function is symmetric when $\emptyset_i = 0$. The loss level

is 3 for a forecast error of -2 when the $\emptyset_i = -0.64$, which comes under the first quantile. For a similar forecast error, the loss level is more than double for the second quantile. It is much higher for the third quantile.[7] However, the positive values of $\emptyset_i$ brings in proportionate losses or even less. Hence, we can say that the loss of Indian households from underestimating inflation is higher than overestimating inflation.

Figure 9: Distribution of Estimated Asymmetry Parameter ($\pi_{b,i} \neq 0$)

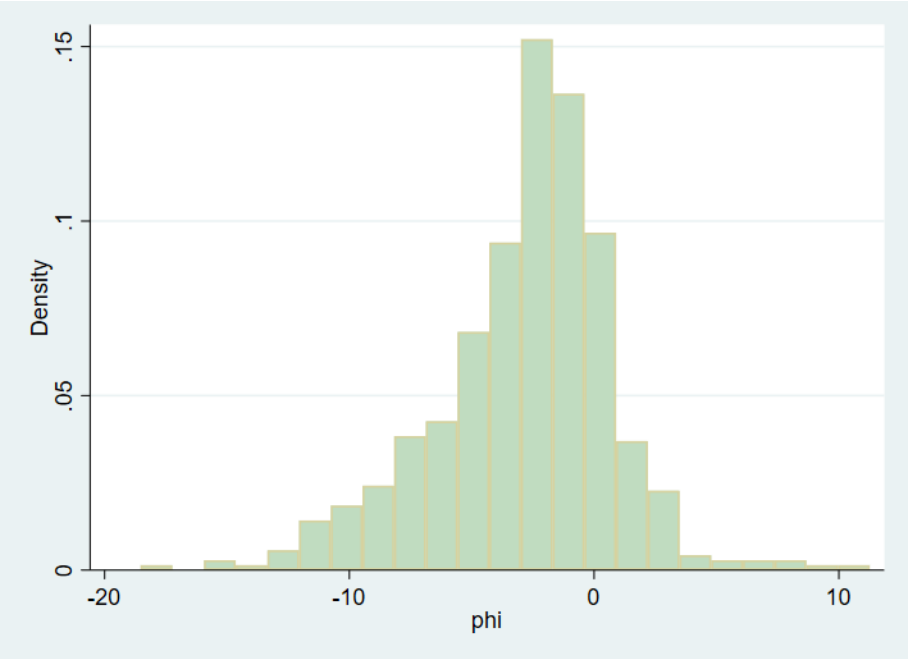
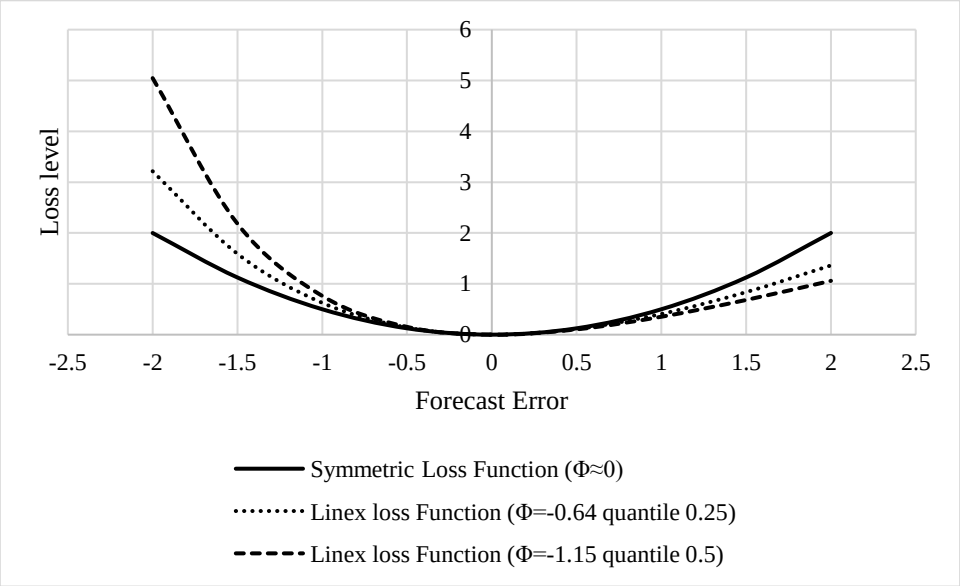


Table 6: Summary Statistics of the Distribution of Φ

	Obs	Mean	Std. Dev.	Min	Max
Quantile 1	54,896	-0.64	0.25	-1.46	-0.45
Quantile 2	54,778	-1.15	0.57	-2.96	-0.45
Quantile 3	54,657	-1.83	1.55	-9.97	-0.45
Quantile 4	54,582	-3.32	4.06	-14.59	-0.45
Total	219,008	-1.73	2.41	-14.59	-0.45

[7] For the ease of depiction of loss level, we have only displayed the estimate for 2 quantiles here. Graph with the third quantile estimate is given in the Appendix A - Figure A.1

Figure 10: Loss Level and Forecast Error



Based on these findings, we investigate the relationship between demographic variables and household inflation expectations.

5. Demographic Determinants of Expectations

In this section, we find the demographic determinants of household expectations using two data sets, IESH and CCS. We explore the factors such as gender, age, employment, and city of residence using the IESH data and the effect of education and income using the CCS. The 12 months ahead household inflation expectations in the IESH and CCS are termed IESH12 and CCS12, respectively.

Firstly, in order to find the demographic determinants of heterogeneous expectations, we regress IESH12 over dummies of demographic variables. The pooled cross-section data is used for the regression. The results can be seen in Table 7, where we perform separate regressions for each demographic characteristic (models 1 to 3) and the model (4) includes additional control variables such as city and quarter dummies. These dummy variables control for regional disagreements and seasonal factors.

Table 7: Demographic determinants of inflation expectations

	(1)	(2)	(3)	(4)
Gender				
Female	-	-	-	-
Male	-0.05*			-0.15***
	(0.02)			(0.03)
Age				
Up to 25 years	-	-	-	-
25 to 30 years		0.04		-0.01
		(0.04)		(0.03)
30 to 35 years		0.17***		0.06
		(0.04)		(0.04)
35 to 40 years		0.27***		0.13***
		(0.04)		(0.04)
40 to 45 years		0.31***		0.15***
		(0.04)		(0.04)
45 to 50 years		0.31***		0.17***
		(0.04)		(0.04)
50 to 55 years		0.37***		0.23***
		(0.05)		(0.05)
55 to 60 years		0.39***		0.30***
		(0.05)		(0.05)
60 years and above		0.56***		0.46***
		(0.04)		(0.05)
Employment				
Financial Sector	-	-	-	-
Other Employees			-0.05	0.28***
			(0.04)	(0.04)
Self-employed			0.07	0.29***
			(0.04)	(0.04)
Housewife			0.27***	0.44***
			(0.04)	(0.04)
Retired Persons			0.43***	0.26***
			(0.05)	(0.06)
Daily Workers			0.30***	0.66***
			(0.05)	(0.04)
Other Category			-0.24***	0.30***
			(0.05)	(0.05)
City dummies	-	-	-	Yes
Quarter dummies	-	-	-	Yes
Constant	10.64***	10.39***	10.48***	13.19***
N	218913	218913	218913	218913
R^2	0	0.001	0.001	0.184

Note: *, ** and *** represent significance at 10%, 5% and 1%, respectively.
Robust standard errors are in the paranthesis.

The results suggest that male has lower expectations than female; see, model (1) in Table 7. Age and expectations share a positive linear relationship within which an increase in age results in higher expectations. In general, older individuals anticipate higher inflation rates than younger people; See model (2). Results of model (3) suggest that people generally hold higher expectations in comparison with the respondents from the financial sector. The only exception is "other category workers". We controls for city variations and quarter variations in model 4. Expectations are insignificant for the younger age groups, 25 to 35 years old. The rest of the demographic dummies are significant. Model (4) supports results in model (2). It also indicates that every category of employment holds higher expectations compared to the financial sector employees.

5.1. Effect of income and education on expectations

Apart from analyzing age, gender, employment, and city, this data set allows us to explore the effect of income and education levels on the expectations formation. As mentioned before, we make use of the new IESH-CCS matched data. Table 8 suggest that expectations increase with an increase in income; see, model (1). Model (3) which controls for gender, age, city, and employment, shows higher significant coefficients for income.

At the same time, education displays an inverse U shape relationship with expectations. It suggests that compared to an illiterate person, expectations increase with an increase in education level up to 12^{th} grade. Further, higher studies are negatively correlated with expectations. A graduate and post-graduate possess lesser expectations than an illiterate. Further, regressions with more variables are also estimated, which resulted in similar output.

Table 8: Impact of Income and Education on Inflation expectations

	(1)	(2)	(3)
Income			
1 lakh or less (Base)	–	–	–
1 to 3 lakhs	0.03***		0.03***
	(0.01)		(0.01)
3 to 5 lakhs	0.05***		0.10***
	(0.02)		(0.01)
5 lakh or more	0.16***		0.22***
	(0.03)		(0.02)
Education			
Illiterate (Base)	–	–	–
Below 5th Std		0.01	0.03*
		(0.01)	(0.01)
5th to 10th Std		0.43***	0.48***
		(0.01)	(0.01)
10th to 12th Std		0.89***	0.92***
		(0.01)	(0.01)
12th Std		0.85***	0.92***
		(0.01)	(0.01)
Graduate		-0.09***	0.04**
		(0.01)	(0.01)
Post Graduate		-0.07***	0.03
		(0.01)	(0.02)
Dummies			
Gender Dummies			Yes
Age Dummies			yes
Employment Dummies			yes
City Dummies			yes
Quarter Dummies			
Constant	9.73***	9.12***	8.62***
N	54525	54525	54525
R^2	0.0009	0.1509	0.1853

Note: *, ** and *** represent significance at 10%, 5% and 1%, respectively. Robust standard errors are in the paranthesis.

A caveat here is to make sure the matching exercise is legible. For that purpose and to confirm the robustness of our analysis, we test the relationship of gender and age with the IESH results. Column 2 and 3 of the Table B.1 reveals that the male has comparatively lesser expectations compared to female with an exact coefficient of -0.05, and expectations increase

with increasing age. These results confirm with the IESH result tabulated in Table 7 and hence proves the credibility of the matching exercise; see Appendix B.

6. Summary and Conclusions

This study explores the asymmetry and heterogeneity in households' inflation expectations. It explores IESH data to observe a systemic positive forecast error in the inflation expectations among Indian households. Making use of the asymmetric loss function the study found that households incur larger losses for underestimating inflation than overestimating it with an exponential margin. The loss function thus explains the persistent positive bias in household inflation expectations.

The study finds that the expectations are significantly heterogeneous. This heterogeneity depends on the demographic characteristics of the survey respondents and other macroeconomic variables, especially the realized inflation. When the Lacy (2006) measure (as the index of ordinal variation) is plotted against inflation, it indicates a higher dispersion in households' responses during low inflation periods compared to high inflation periods. This suggests that people tend to reach a consensus on inflation forecasts when inflation is high, whereas they have differing opinions during periods of low inflation. Moreover, it is observed that people respond more slowly to inflation deceleration compared to inflation acceleration. Another measure of dispersion, skewness in inflation expectations, shows significant dispersion in the negative region during high inflation periods and approaches zero during low inflation periods.

Using the Lacy (2006) measure, the study found that the responses do not vary much amongst the demographic characteristics such as gender, age, and employment; instead, they vary between cities of residence. The dispersion is found to have had positive changes due to

the adoption of IT in 2016, indicating that people have different opinions regarding future expectations post-IT.

Further, the study also found that the female cohort has higher expectations than males. Expectations were linearly correlated with age, wherein the expectations were found to increase with an increase in age. Among various employment categories, retired individuals tend to have the highest inflation expectations, while employees in the financial sector have the lowest expectations. Income shows a positive relationship with expectations. Higher income people seem more apprehensive about future inflation than the poorer ones. Concerning the education factor, graduates and post-graduates have the lowest expectations compared to illiterates. However, people that acquired education up to 12^{th} grade have a higher forecast than the illiterates, which displays a non-linear relationship between expectations and education.

Overall, the study found a consistent positive bias in the households' inflation forecast because of the fear of higher loss that they may incur due to underestimating inflation compared to overestimation. Realized inflation and dispersion of expectations are found to have an inverse relationship. IT positively affects the dispersion of expectations and thus indicates unanchored expectations. Demographic determinants of expectations such as gender, age, employment, city, income, and education are significant. However, age and income have a linear relationship, while others are non-linear. The study concludes that heterogeneity in expectations is a concern that requires serious attention from policymakers.

To address heterogeneity in inflation expectations, policymakers can improve the transparency and predictability of monetary policy, increase the credibility of central banks, and reduce uncertainty about future inflation. These actions can help to anchor expectations around their target and promote economic stability.

Appendix A

Estimation of conditional variance:

In order to derive the estimated value of conditional variance $\sigma^2_{t,t+12}$ at period t + 12, given the information set at t, we estimate a generalized autoregressive conditional heteroskedasticity (GARCH) model as below. The GARCH model by (Bollerslev, 1986) is a generalized version of the autoregressive conditional heteroskedasticity (ARCH) model by (Engle, 1982).

$$\pi_{t+12} = \beta_0 + \beta_1 \pi_t + \beta_2 \pi_{t-1} + \varepsilon_{t+12}$$

$$\varepsilon_{t+12} \sim N(0, \sigma^2_{t,t+12})$$

$$\sigma^2_{t,t+12} = \gamma_0 + \gamma_1 \varepsilon^2_t + \gamma_2 \sigma^2_{t,t+12}$$

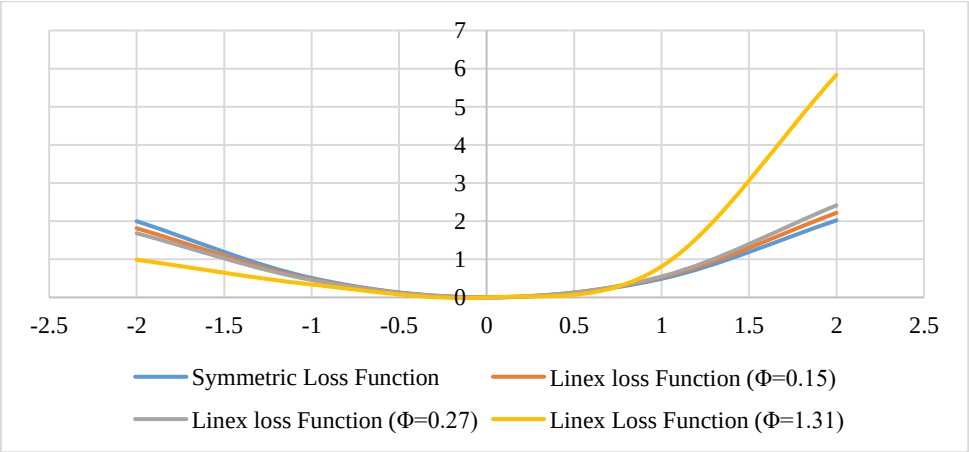
where $\beta 0$, $\beta 1$, $\beta 2$, and $\gamma 0$, $\gamma 1$, $\gamma 2$ are parameters, and εt+12 is an error term. The estimation result with the general CPI is summarized in Table A.1.

Table A.1: Estimates of GARCH model

Dependent variable: CPI

	Coefficient	**Std. Error**	**z-Statistic**
$\boldsymbol{\beta_0}$	0.58	0.36	1.61
$\boldsymbol{\beta_1}$	1.02***	0.04	24.20
$\boldsymbol{\beta_2}$	-0.12	0.09	-1.33
Variance Equation			
$\boldsymbol{\gamma_0}$	0.06	0.08	0.71
$\boldsymbol{\gamma_1}$	-0.19	0.15	-1.25
$\boldsymbol{\gamma_2}$	1.16***	0.18	6.46
R-squared	0.86		
Log likelihood	-69.58		

Figure A.1: Loss Level and Forecast Error - Extended



Appendix B

Table B.1: Impact of Income and Education on Inflation expectations

	(1)	(2)	(3)	(4)	(5)
Female (Base)	–	–	–	–	–
Male	-0.05***			-0.07***	0
22 to 29 years (Base)	–	–	–	–	–
30 to 39 years		0.25***		0.21***	0.20***
40 to 59 years		0.33***		0.31***	0.31***
60 years & above		0.49***		0.45***	0.45***
1 lakh or less (Base)	–	–	–	–	–
1 to 3 lakhs				0.03***	0
3 to 5 lakhs				0.10***	-0.01***
5 lakh or more				0.22***	0
Illiterate (Base)	–	–	–	–	–
Below 5th Std				0.03	0.01
5th to 10th Std				0.48***	0.02***
10th to 12th Std				0.92***	0.02***
12th Std				0.92***	0.01*
Graduate				0.04	0.02***
Post Graduate				0.03	0.01
Other Employment (Base)	–	–	–	–	–
Self Employed			0.48***	0.04	0
Home Maker			0.24***	-0.05***	0
Retired Person			0.18***	-0.03*	-0.01
Daily Worker			0.19***	-0.06***	0
City Dummies				yes	yes
Quarter Dummies					yes
Constant	9.78***	9.52***	9.55***	8.62***	9.45***
R^2	0	0.03	0.01	0.19	0.96
N	54525	54525	54525	54525	54525

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