Indian Inflation Expectations: An Analysis Based on 271,000 Households, 2008-2022

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Abstract: We analyze household inflation expectations data from the Reserve Bank of India's Household Inflation Expectations Survey. We analyze both the qualitative and quantitative data from the survey and fit a four-parameter generalized beta distribution to study the household disagreement. Our paper reports four major findings. First, household inflation perceptions in India are higher than observed inflation - and higher inflation perceptions are significant in explaining persistently higher future inflation expectations in India. Second, Household characteristics can explain up to 20 per cent of the nowcast errors in inflation perceptions. Third, the cross-sectional variation in prices of essential items such as food and fuel affect expectations disproportionately. Large regional heterogeneity in prices has a substantial effect on household disagreement. Four, we find that households are better at forecasting the directional change in inflation. Based on our findings, we propose a filtering mechanism that relies on households that have an unbiased perception data. Using these observations, we can substantially reduce the bias in aggregate popular price expectations.

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Introduction:

The pandemic has reversed the great inflation moderation since 1990s across advanced and emerging economies. Initially, professional forecasters, economists and central bankers attributed the unanticipated surge in inflation to supply chain disruptions. But sustained months of inflation above the inflation target has amplified concerns regarding elevated inflation expectations. This has reignited interest in understanding Household Surveys and the formation of popular price expectations.

The importance of expectations can be gauged by the recent statement by Federal Reserve chair Jerome Powell (2021):

"An episode of one-time price increases as the economy re-opens is not the same thing as, and is not likely to lead to, persistently higher year-over-year inflation."

He further added –

If inflation were to… *"persistently and materially above 2% in a manner that threatened to move longer-term inflation expectations materially above 2% we would use our tools to bring inflation expectations down to mandate consistent levels."* – Jerome Powell (29th April 2021)

Expectations matter for monetary and fiscal policymakers as future expectations play a role in influencing the decision of the consumers. Higher household inflation expectations influence inter-temporal consumption (and savings) choices for consumers, while firms' inflation expectations and general macroeconomic expectations guide their decision regarding wage offers, employment and pricing of their goods or services. Therefore, expectations matter, and most central bankers pay inordinate attention towards them.

These expectations have long been measured through surveys for households and firms across many advanced economies. Several such surveys have been analyzed by authors over the last few decades. While some study survey design (e.g., Bruine de Bruin *et al.* (2012)), many other researchers focus on the expectation formation process and the information content of household expectations (e.g., Pfajfar and Santoro (2010)).

Abundant evidence indicates that these expectations are unlikely to be fully rational and unbiased. Instead, certain irregularities are often found in the dynamics and dispersion of household expectations.[1] For instance, household inflation expectations are higher than inflation realization across several countries such as US, Japan and Sweden. Bruine de Bruin et. al. (2011), D'Acunto, Malmendier and Weber (2021) find that the upward bias is higher for women than for men. D'Acunto et. al. (2019) observes a higher bias for agents with lower cognitive abilities while Das, Kuhnen and Nagel (2020) explain cross sectional variation in expectations using formal education and income levels.

In addition, Niu & Harvey (2023) demonstrate through a series of experiments the household expectations formation process. By conducting the experiment during periods of low & stable, high & volatile and high & stable inflation, they find that the expectation formation process adapts to the level of inflation.

[1] Recent studies include Bruine de Bruin *et al.* (2011), Dräger and Lamla (2012), Easaw *et al.* (2013), Hayo and Neumeler (2018), Weber et. al. (2022) among others.

Individual inflation expectations are driven by inflation experience by households and therefore, perception about present inflation plays a role in formation of future inflation expectations. Jonung (1982) documented this for Sweden and recently, Weber et. al. (2022) used US data and reported a similar finding. Weber et. al. (2022) further add that much of disagreement about future inflation expectations could potentially be explained through the disagreement regarding inflation perceptions.

Mankiw, Reis and Wolfers (2003) used US data on household expectations and professional forecasters to explain the disagreement regarding inflation. They make the following three observations:

1. There is disagreement about inflation expectations between households ("naïve") and expert populations.
2. The level of disagreement among households are greater than that between experts.
3. While the level of disagreement varies between households and professional forecasters, they both display a similar time-series pattern.

They further find that the amount of disagreement varies over time and use the sticky-information model to explain the expectations formation process of households.

Biased inflation expectations and high degree of disagreement among households have resulted in many to conclude that standard macroeconomic assumptions of rational expectations are not well-founded and such models are of limited policy relevance. Coibion and Gorodnichenko (2015) propose a test the full-information rational expectations hypothesis. Their test has an added advantage as it help identify whether the rejection of the hypothesis is due to the presence of information rigidities. Further, Coibion *et al.* (2018) review several surveys around the world and discuss how they may be utilized by central banks.

While biases in household expectations are hardly a new discovery, most of the studies on survey expectations are focused on developed countries like the U.S., while only a few look at data from developing economies, e.g., Abbas *et al.* (2014). Unlike their well-developed peers, emerging market economies often experience volatile and levitating inflation. Many emerging markets have their own surveys, but the responses are gathered from populations that are less literate than those in the advanced economies. As a result, expectations of households in developing economies tend to exhibit more irregularities, which are often not well examined.

We address this issue by documenting the apparent irregularities in the household inflation expectations of a major developing economy – India, where the Reserve Bank of India (RBI) monitors the expectations using the Inflation Expectations Survey of Households (IESH). The importance of the IESH data for policymakers can be gauged by the statement made by RBI's former Governor, Raghuram Rajan while announcing his first policy rate cut on 15 January 2015:

"Households' inflation expectations have adapted, and both near-term and longer-term inflation expectations have eased to single digits. These developments have provided headroom for a shift in the monetary policy stance."

However, for several years, the IESH has been heavily criticized by economists and policy makers because the results are apparently disconnected from the official data. We look at both the qualitative and quantitative data contained in the household-level survey data which have not been adequately studied previously. Using this data, we show that the observed misalignment between the actual and the expected inflation rates is not merely the result of irrationalities in the expectation formation process. Rather, the survey results contain valuable information about economic realities, that, when well understood by policymakers, could potentially make the central bank's strategies more effective. In addition, we take a close look at the qualitative data contained in the survey.

More specifically, we begin with an examination of the dynamics of aggregated quantitative data on perceptions and expectations. Consistent with what reported in scholarly journals and popular press, we find notable pessimism in these simple aggregates. Aggregated inflation perceptions and expectations are substantially higher than the actual inflation realization. We explain this using various socio-economic variables.

However, much of this variation can be attributed to significant variation in prices across various cities in India. Regulations restricting trade between various states combined with different domestic taxes on fuel perhaps add to the variation in prices. This variation in prices is an important feature in explaining the disagreement among households regarding inflation perceptions. We then document the properties of the expectation formation process using both household-level data and aggregate data. In particular, we quantify the sensitivity of household inflation expectations to price changes of a selected set of commodities that households frequently purchase.

Our analyses show that the observed irregularities in household inflation expectations reflect, at least in part, India's economic realities. We find that inflation perceptions tend to play a major role in determining future inflation expectations. Household demographics help explain some of the inflation perception and bias in perceptions. For example, older workers in non-financial industries tend to be more pessimistic than younger workers and those in the financial industry. In addition, we find that, compared with the weights of certain commodities, (such as wheat, rice, and onion) in a typical household's consumption basket, the changes in these products' prices have disproportionally large impact on household expectations.[2] Such excess sensitivity may well be rationally motivated given that these prices were the main driving forces behind recent inflationary episodes in India.[3]

Our results also suggest that, while households do follow news on inflation and adapt their expectations to actual inflation rate, there may be a significant and regime-dependent inertia in the process. Households seem to react quickly to sudden surges in inflation that results in persistently high rate of price increases. In addition, we attempt to quantify the role played by prior beliefs and information on disagreement about inflation. However, they remain cautious and lower their expectations slowly when the actual rate declines. In addition, we find that qualitative data in the form of balance statistic is useful for policymakers.

[2] As discussed in Coibion *et al.* (2018), researchers made similar observations when studying the effect of gasoline prices on U.S. households' expectations.
[3] See Holtemöller and Mallick (2016) for a recent discussion on India's exposure to global commodity price shocks, in particular, food price shocks.

Overall, our results highlight the usefulness of the survey and the resulting measures of household inflation expectations. In particular, we argue that the observed biases in the levels of inflation expectation do not render it useless. Quite to the contrary, lots of information revealing the underlying structural factors in India's economic realities can be inferred from the dynamics of and the heterogeneities in the survey results. Proper interpretation and understanding of these signals are key to making the survey useful in guiding monetary policies and central bank communication strategies.

The rest of the paper is organized as follows: Section 2 introduces the survey and our data set. In Section 3, we provide a comprehensive comparison of quantitative inflation perceptions and expectations with associated actual values. We then fit a generalized four parameter beta distribution. In section five we look at the qualitative responses from the survey and construct the balance statistic. Section six concludes.

Section II: Background and Data:

The Reserve Bank of India (RBI) introduced the IESH in September 2005. Since its inception, the primary purpose of this quarterly survey has been to collect information regarding regional heterogeneities of inflation expectations of urban households. The initial two rounds of the survey covered 2,000 households, 500 each from four major metropolitan areas, New Delhi, Chennai, Kolkata, and Mumbai, representing four geographical zones (North, South, East, and West). Starting from its third round, the IESH was extended to cover eight additional cities. With 250 households from each of the newly added cities, the total sample size reached 4,000. Each geographical zone was represented by three cities: Delhi, Jaipur, and Lucknow in the north; Chennai, Bangalore, and Hyderabad in the south; Kolkata, Guwahati, and Patna in the east; and Mumbai, Ahmedabad, and Bhopal in the west. In round 30 (2012Q4), four more cities were added viz., Kolhapur, Nagpur, Thiruvananthapuram and Bhubaneswar. A sample of 250 households is selected from each of the added cities, bringing the total sample size to 5,000.

Initially, the survey asked for only qualitative responses on three-month- and one-year-ahead expectations on the prices of food products and housing, in addition to prices in general. Subsequent expansions of the survey included questions on the prices of non-food products and services. As an addition to the set of questions soliciting qualitative responses, a new set of questions soliciting quantitative responses was also added. Survey respondents are only asked to provide quantitative responses on the overall inflation rate, not on the price levels of different categories of products and services. Starting from the 9th round of the survey (2007Q3), quantitative data on perceptions are collected in addition to three-month- and one-year-ahead expectations. This new set of questions is independent from the ones soliciting qualitative responses. In this paper, we focus on the quantitative data since they are the basis for the headline inflation expectations measure that the RBI releases regularly.[4]

Till June 2018 quota sampling was used and the survey design was primarily purposive. Households are sampled to give adequate representation of different geographical areas, with a

[4] We analyze the qualitative data in search of a potentially better measure of household expectations and the associated uncertainty in a different paper, see Das *et al.* (2018).

prescribed mix of gender, age, and employment status of the heads of the households. However, since September 2018, a two-stage probability sample design was introduced. For the first stage, pooling booths are selected by a systematic random sampling while for the second stage 15 households are selected.

The survey respondents are broadly categorized based on their primary occupation. The categories are financial sector employees, other employees, self-employed, homemakers, retired persons, daily workers, and others. Only adults who are at least 18 years old are included in the sample. The target male to female ratio is 3:2. The target composition of occupations is given in Table 1. A change of the target composition occurred in September 2008, where the quota of homemakers was increased from 15% to 30%. These targets do not have obvious statistical basis and are not precisely achieved in every round of the survey.[5]

Table 1: Target Quota in the Sample (Percentage)

Categories of respondents	Survey Rounds	
	Before Sept 2008	From Sept 2008
Financial sector employees	10	10
Other employees	20	15
Self-employed	20	20
Housewives	15	30
Retired persons	10	10
Daily workers	10	10
Others	15	5

Source: Reserve Bank of India (2010)

Due to the significant changes that were implemented after the inception of the survey in 2005, we do not use the data before 2008Q3, at which point the survey was considered stabilized. Our data set ends in 2022Q2. In addition, for each of the 16 cities covered in the survey, we have data on the corresponding city-wise CPI-IW (industrial workers) inflation rates till August of 2020. We also have data on the all India CPI-IW inflation rate, as well as CPI inflation for specific groups of goods and services. In addition, we have prices of common articles of food consumption till February 2020 by each individual city. Data on food prices and city-wise CPI-IW for some months during the pandemic is not available. However, we do have the corresponding national CPI-IW inflation.

The adoption of inflation targeting made the Consumer Price Index Inflation (CPI-Combined) the target instrument and gave the Monetary Policy Committee an explicit mandate of keeping CPI inflation at 4 per cent (+/-2 per cent). Therefore, we supplement our dataset with the CPI-Rural, CPI-Urban and CPI-Combined at the country level since 2011.

We begin by looking at aggregate inflation perceptions and contemptuous realized inflation. Figure 1 highlights the persistent bias in household inflation expectations compared to CPI Inflation for Industrial Workers. The bias becomes more pronounced when we include the survey responses for greater than 16 per cent. While inflation expectations have come down with a

[5] See Reserve Bank of India (2010) for additional details on the survey's design and structure.

reduction in the inflation numbers however, inflation has declined faster than expectations and this decline in expectations predates the formal adoption of inflation targeting.

Figure 1: Inflation Perceptions and CPI Inflation (Industrial Workers)

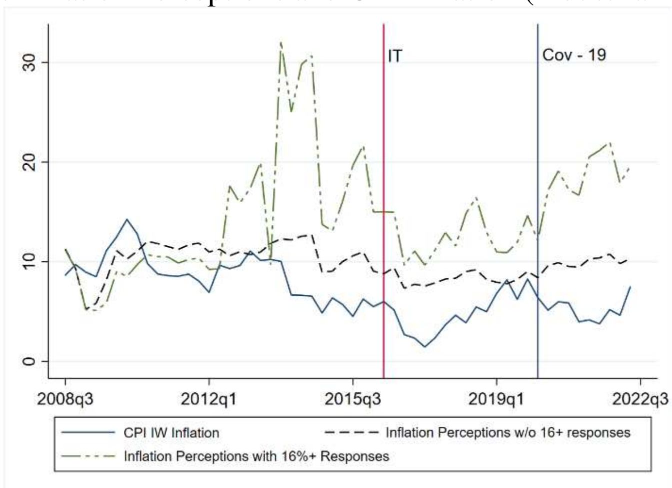
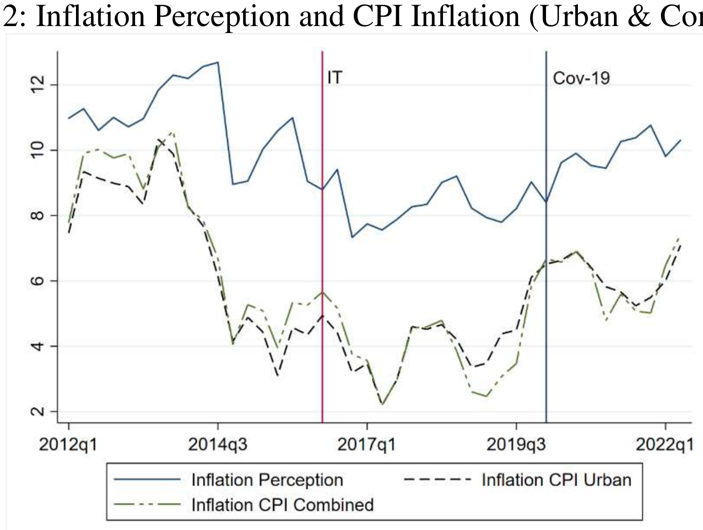


Figure 2 looks at aggregate household inflation perceptions as reported by households as against the actual CPI Inflation for Urban and Combined.[6] Figure 3 look at sub-categories of CPI inflation such as food and clothing while figure 4 looks at fuel and housing inflation. Three immediate conclusions follow. First, there is similarity between inflation perceptions and one year ahead inflation expectations. Second, there is significant amount of positive bias in both perceptions and expectations for most quarters. Third, perceptions and expectations do not seem to respond instantaneously to changes in inflation rates.

Figure 2: Inflation Perception and CPI Inflation (Urban & Combined)



[6] Combined refers to CPI Inflation in both rural and urban areas.

Figure 3: Food and Clothes Inflation

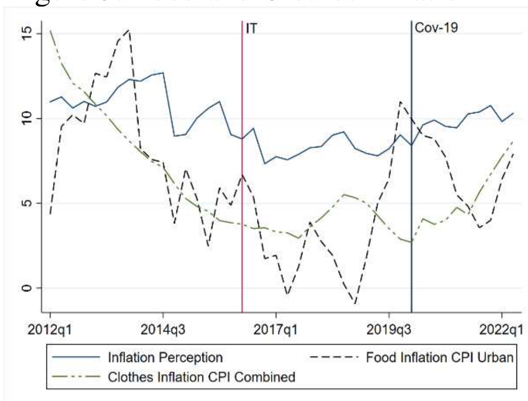
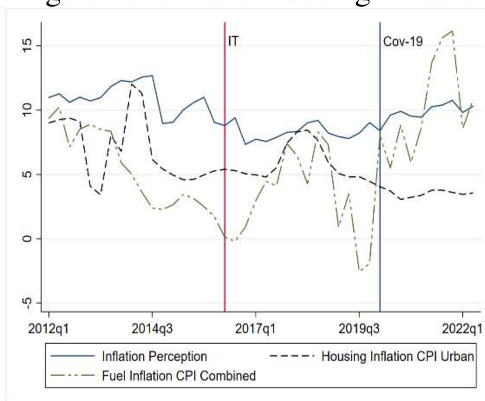


Figure 4: Fuel and Housing Inflation



In Table 2, we provide the means and standard deviation for inflation perception and urban CPI inflation for various periods. Low and stable inflation has resulted in both moderation of inflation perceptions and a reduction in volatility. However, the positive bias in perceptions increased during periods of sharp decline in inflation rates.[7]

Table 2: Mean and Standard Deviation of Inflation and Perception

	Mean		Standard Deviation	
Period	Inflation Perception	CPI Urban Inflation	Inflation Perception	CPI Urban Inflation
2007Q4 – 2011Q4	10.17	9.93*	4.26	1.88*
2012Q1 – 2014Q1	11.21	9.04	0.58	0.88
2014Q1 – 2016Q1	10.88	5.41	1.50	1.80
2016Q1 – 2018Q1	8.25	3.76	0.75	0.95
2018Q1 – 2020Q1	8.47	4.40	0.54	0.84
2020Q1 – 2022Q2	9.84	6.17	0.66	0.62
2012Q1 – 2016Q2	10.93	7.06	1.17	2.36
2016Q2 – 2020Q1	8.32	4.07	0.64	0.95
2020Q1 – 2022Q2	9.84	6.17	0.66	0.62

*CPI-IW Data used as CPI – Urban is available only from 2012 onwards

It is worth noting that biases alone should not be causes for not trusting the data. While the amount of overestimation in the aggregate expectations seems significant, it is by no means unique to India. In a recent study, Abbas *et al.* (2014) find in Pakistan data that “inflation expectations are systematically exaggerated, and this biasedness is entrenched for low-income, less educated,

[7] A recent study by Conrad et al (2022) used German data and found that the information channels used by households to informs play an important role in determining the level of inflation perceptions and expectations while the individual experience plays an important role in their expectations of future changes.

female and younger respondents." Campelo *et al.* (2015) reviewed similar household surveys for six individual countries and the Euro area as a whole and found upward bias in household expectations everywhere.[8] Bordalo et al (2020) used data from Blue Chip Survey and the Survey of Professional Forecasters and observed overreaction by individual forecasters to inflation while the consensus forecast under-reacts to the same.

Figures A1 and A2 in appendix show the distribution of responses by each category for both inflation perceptions and expectations by different quarters. For some quarters, the distribution of responses appears to be multi-modal consistent with the discussion in Mankiw, Reis and Wolfers (2003). The multiple modes in the Indian data appear to be due to the cross-sectional variation in responses.

Section III: Inflation Perception, Expectations and Nowcast Errors

We look at the cross-sectional distribution of the responses in each group in each city separately for perceptions and inflation expectations. Table 3 summarizes the responses by clubbing them into two broad categories (greater than and less than 16 per cent inflation). The percentages are calculated with all the responses in each group as a total. In the absence of cross-sectional variation in responses, the proportion of respondents giving "greater than 16 per cent" response will not vary for individual cities. Table 3 shows that respondents living in Bangalore, Jaipur and Mumbai give a disproportionally high number of "greater than 16 per cent" than others. Similarly, respondents living in Bhopal, Chennai, Delhi, Hyderabad and Patna give a disproportionally low number of such responses. The cross-sectional variation offers an additional dimension to the analysis of household subjective inflation perceptions (and expectations) in India.

Table 3: Household Inflation Perception and Expectations in India

City	Perception				1-Year Inflation Expectation			
	<16%		>=16%		<16%		>=16%	
	N	%	N	%	N	%	N	%
Ahmedabad	13,560	6.3	2,685	5.4	11,593	5.9	4,271	6.6
Bangalore	15,433	7.1	5,128	10.4	13,911	7.1	5,971	9.3
Bhopal	11,131	5.1	1,043	2.1	9,963	5.1	1,763	2.7
Bhubaneswar	6,321	2.9	945	1.9	5,670	2.9	1,384	2.2
Chennai	22,556	10.4	3,445	7.0	20,201	10.3	5,237	8.2
Delhi	30,296	14.0	4,981	10.1	27,433	14.0	6,889	10.7
Guwahati	8,815	4.1	2,536	5.1	8,325	4.3	2,750	4.3
Hyderabad	14,054	6.5	3,298	6.7	12,518	6.4	4,572	7.1
Jaipur	9,354	4.3	3,521	7.1	8,077	4.1	4,371	6.8
Kolhapur	1,934	0.9	1,539	3.1	1,631	0.8	1,676	2.6
Kolkata	24,386	11.3	5,770	11.7	22,277	11.4	6,710	10.4
Lucknow	10,571	4.9	2,482	5.0	9,706	5.0	3,216	5.0
Mumbai	24,879	11.5	8,215	16.6	23,010	11.8	9,817	15.3

[8] For example, from 2003 to 2009, actual inflation in the Euro area was 2.1% while household expectations are as high as 6.5%. For the complete table of results for all the countries, see their Table 5.

Nagpur	7,054	3.3	1,690	3.4	6,405	3.3	2,281	3.6
Patna	10,488	4.8	979	2.0	9,794	5.0	1,558	2.4
Trivandrum	5,847	2.7	1,193	2.4	4,892	2.5	1,782	2.8
Total	216,679	100	49,450	100	195,406	100	64,248	100

Source: Data from various survey rounds, IESH during the 2008Q3-2020Q2 period, Reserve Bank of India.

The importance of inflation perception can be gauged from the fact that it serves as an important part of the information set for the household. Therefore, a higher inflation perception by households would imply a higher forecast for future inflation. Recent studies by Weber, Gorodnichenko & Coibion (2022) show that individuals with a higher inflation perception tend to have higher future inflation expectations based on surveys in the US. In table 4 and 5 we replicate the Weber, Gorodnichenko & Coibion (2022) specification for various demographic groups using the data from Indian surveys.

Table 4: Inflation Expectations and Inflation Perceptions

	One Year Ahead Inflation Expectations					
	All	Female	Male	Less than 45 years	40-60 years	Above 60 years
Inflation Perception	0.89***	0.88***	0.90***	0.89***	0.90***	0.90***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	2.26***	2.47***	2.09***	2.93***	2.19***	2.12***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.03)
R-Square	0.78	0.77	0.80	0.78	0.80	0.81
N	260241	110809	149432	184453	52035	23753

* p<0.05, ** p<0.01, *** p<0.001

Huber Regressions with one year ahead inflation expectations as the dependent variable.

Our results using Indian data are similar to their findings for household surveys in the US. Inclusion of inflation perception in the estimation equation reduces the coefficient of contemporaneous inflation. Therefore, inflation perception may play a greater role in determining future household inflation expectations than the aggregate inflation rate. Moreover, across demographic groups we find a similar coefficient on the inflation perception variable. The coefficient using Indian surveys are higher than that reported by Weber, Gorodnichenko & Coibion (2022) which suggests existing inflation perception plays a more important part in the information set of Indian households.

Table 5: Inflation Expectations and Inflation Perceptions

	One Year Ahead Inflation Expectations	
Inflation Perception	0.90***	
	(0.00)	
Inflation	0.02***	0.18***
	(0.00)	(0.00)
Constant	2.06***	9.60***
	(0.01)	(0.02)

R-Square	0.80	0.02
N	220155	220157

* p<0.05, ** p<0.01, *** p<0.001

Huber Regressions with one year ahead inflation expectations as the dependent variable.

The importance of inflation perceptions in determining inflation expectations have been understated for developing countries. Evidence from India shows they serve as an important determinant of future inflation expectations. Household characteristics might be able to explain part of the high inflation perception. We look at nowcast errors defined as follows

$$Nowcast\ Error_{it} = Inflation_{\ jt} - Household\ Inflation\ Perception_{it}$$

Where $Inflation_{\ jt}$ is inflation in city j at time t.
$Household\ Inflation\ Perception_{it}$ is household i's inflation perception at time t.

We find that common attributes shared by households might be able to explain some part of the forecast errors as recorded from the surveys. In these models, the dependent variable is the "nowcast error" of the households. The independent variables include a set of dummies for survey round (i.e., quarter), city, age group, gender, and employment category. In order to reveal the importance of each of these characteristics, we estimate fix models. A set of dummy variables are representing city in model 1, age group in model 2, gender in model 3, or employment category in model 4. Model 5 contains all the variables used in models 1 to 4 simultaneously. Table 6 reports the estimation results.

Overall, up to 20% of the discrepancies between perceptions and the actual inflation rate can be explained by household characteristics reported in the survey, as we can see from the adjusted R-squared of model 5. All else equal, older people in non-financial industries tend to have more pessimistic views, that is, their perceptions and expectations tend to be higher than the actual rate. This is consistent with similar findings by Bruine de Bruin et al (2010) who looked at the expectations data of US households and found demographic factors as key drivers of disagreement in inflation expectations. In particular, they too observed older and people in non-financial industries had a higher inflation expectation.

In addition, consistent with what we reported earlier, there are significant differences between households in different cities: Residents in Kolhapur, Jaipur, Mumbai & Bangalore are among the most pessimistic ones, while those in Bhopal, Bhubaneswar, Chennai, and Delhi are the most optimistic ones. Bruine de Bruin et al (2010) point at different respondents depending on their demography might have different concerns that could drive differences in inflation expectations. The data from India seems to support this point.

In order to make sure that these results are not merely driven by the large number of respondents giving extremely high responses, we also conducted this same exercise but only using data before 2009Q3 and after 2015Q4. That is, we use the quarters at the two ends of our sample. The conclusions are largely the same as those based on the full sample. However, employment category and age are no longer significant in our models estimated using this subsample. This is an important change, since it highlights the fact that different population segments react to aggregate shocks differently.

Table 6: Nowcast Errors and Individual Characteristics

Variable Group	Variable Name	1	2	3	4	5
City	Bangalore	-0.189**				-0.258***
	Bhopal	2.582***				2.462***
	Bhubaneswar	0.760***				1.790***
	Chennai	0.931***				0.887***
	Delhi	1.772***				1.726***
	Guwahati	0.480***				0.439***
	Hyderabad	0.086				-0.057
	Jaipur	-0.649***				-0.743***
	Kolhapur	-0.758***				0.055
	Kolkata	0.122*				0.139**
	Lucknow	1.738***				1.671***
	Mumbai	-0.328***				-0.421***
	Nagpur	0.945***				1.920***
	Patna	1.801***				1.723***
	Thiruvananthapuram	1.500***				2.700***
Age Group	25 to 30 years		-0.133***			-0.110**
	30 to 35 years		-0.242***			-0.257***
	35 to 40 years		-0.328***			-0.370***
	40 to 45 years		-0.416***			-0.493***
	45 to 50 years		-0.461***			-0.506***
	50 to 55 years		-0.578***			-0.701***
	55 to 60 years		-0.627***			-0.716***
	60 years and above		-0.800***			-0.950***
Gender	Female			-0.213***		-0.101***
Employment Category	Daily Workers				-0.522***	-0.440***
	Homemaker				-0.693***	-0.192***
	Housewife				-0.237***	-0.263***
	Other Category				0.296***	-0.015
	Other Employees				-0.215***	-0.235***
	Retired Persons				-0.635***	-0.036
	Self Employed				-0.224***	-0.210***

Constant	-3.584***	-2.598***	-2.835***	-2.651***	-3.342***
N	226577	226577	226577	226577	226577
R-Square	0.031	0.002	0.00	0.002	0.231

* p<0.05, ** p<0.01, *** p<0.001

Lin and Ye (2009) and Brito and Bystedt (2010) conclude that the effect of inflation targeting is highly heterogeneous. These authors treated the population in a country as a whole, and therefore did not discuss potential heterogeneity across population segments within an economy.

Our results here suggest that this overlooked aspect may explain some of the observed heterogeneous effect. In addition, we add two dummies to consider the effect of the transition to inflation targeting regime in India and the impact of COVID – 19 pandemic on nowcast errors.

Further, we look at the role played by prices of high frequency consumption items by households in the perceptions and expectations formation process. That is, we want to examine the hypothesis that do households give disproportionally large weights to the inflation rates of some commodities. (This could be due to the frequency or the value of purchases) In other words, do households attach higher weights to some commodities than their weights in the official consumption bundle?

From India's Labor Bureau, we collected data on all-India inflation rate of fuel, as well as that of vegetables and fruits. We also obtained city-specific inflation rates of rice, wheat atta, dal, groundnut oil, goat meat, fish, milk, onion, sugar, and kerosene for all the cities in our sample. To check if these inflation rates have disproportional effect on household perceptions and expectations, we look at whether after controlling for observed household characteristics, the addition of the inflation rates of these goods and services leads to a significant improvement in the model's explanatory power. More specifically, we estimate four progressively more comprehensive models.

The dependent variables of all four models are the same – households' quantitative inflation perceptions. The independent variables in the baseline model, Model 1, include a constant and four lags of the actual inflation rate. Model 2 extends the baseline with dummy variables for the age group, employment category, and gender of the respondents. Extending Model 2, Model 3 also includes four lags of the actual inflation rates on fuel, as well as vegetables and fruits. Model 4 adds to the independent variables in Model 3 two lags of the inflation rates on rice, wheat, dal, oil, goat meat, fish, milk, onion, sugar, and kerosene. This exercise is conducted separately for perceptions and expectations. We estimate the model separately for each city, in addition to using data from all the cities together.

The results from inflation perceptions are reported in Table 7, which lists the $\bar{R}^2$ of each of the four models for each city and all cities as a whole. These results support our hypothesis strongly: Using only the lagged official overall inflation rates (as in Model 1), we are only able to explain a small proportion of the variations in individuals' inflation perceptions. Adding individual characteristics to the model (as in Model 2) results in increased explanatory power, although the increase is rather mild.

Once we allow the inflation rates of fuel, vegetables, and fruits to influence household perceptions differently than other goods and services (as in Model 3), we observe increased explanatory powers across the board. The increases are often significant (e.g., in the case of Bangalore, Chennai, Guwahati, and Lucknow), even though the added variables are not city specific. With the addition of city-level inflation rates of frequently purchased food items such as wheat and rice (as in Model 4), the models are able to account for a large proportion of variations in household inflation perceptions. Overall, for all India as a whole, the baseline model's $\bar{R}$^2 is only about 5%, while that of the most comprehensive of the four models is 18%. However, for cities such as Bangalore, Model 4 explains close to 62% of the variation in household inflation perceptions while for Jaipur it explains 42%. This is not surprising given the evidence on households paying special attention to items that are more frequently purchased (De Fiore, (2022), D'Acunto et al (2019)).

Table 7: Effect of Inflation Rates of Selected Commodities.

	Adjusted R-Squared			
	Model 1	Model 2	Model 3	Model 4
10 Cities	0.0520	0.0606	0.0870	0.1890
Ahmedabad	0.0196	0.0236	0.0605	0.2196
Bangalore	0.3198	0.3306	0.5452	0.6217
Bhopal	0.0236	0.0338	0.1081	0.2139
Chennai	0.0094	0.0122	0.1894	0.2707
Delhi	0.0487	0.0618	0.1452	0.2356
Guwahati	0.0184	0.0408	0.1490	0.2937
Hyderabad	0.1232	0.1411	0.2123	0.2502
Jaipur	0.1711	0.1990	0.3598	0.4214
Lucknow	0.0269	0.0491	0.1970	0.3571
Mumbai	0.1961	0.2094	0.2870	0.3686

One could certainly argue that these results are driven by the irrationalities in household behaviour. However, individuals may also pay more attention to particular prices due to a number of other factors, including the frequency and volume of consumption. Moreover, existing restrictions on inter-state movement of agricultural produce creates friction thereby adding to the overall cross-sectional variation in price realization. Therefore, these cross-sectional variations combined with high inter-temporal variation in prices appear to play a key role in adding to the variation in subjective price perceptions and expectations.

In addition, the CPI-IW measure with a base year of 2001 is computed with weighting diagrams derived from the results of the Working-Class Family Income and Expenditure Surveys conducted during 1999-2000. If the consumption bundle of households today is significantly different than what used to compute the index, one would expect to see households attaching disproportional weights to certain commodities. Nonetheless, the fact that the inflation rates of a few selected commodities have much additional explanatory power beyond the overall inflation rate should prompt monetary authority to pay more attention to the cross-sectional heterogeneity in household consumption patterns.

Section IV: Estimating Household Expectations and Disagreement

Our results so far clearly establish that household expectations are not totally detached from economic reality, although the average of the individuals' expectations often significantly exceeds the official inflation rate. In this subsection, we propose that, rather than aggregating individual survey responses by simply taking the mean or median, we fit them to a generalized beta distribution.[9] Then, both measures of central tendency and dispersion can be easily obtained from the fitted distributions. This approach has previously been successfully applied to professional forecasts.[10]

Assuming that households' perceptions/expectations have a unimodal distribution that belongs to the generalized beta family, we can estimate the parameters of the distribution by minimizing the sum of the squared distances between each point on the empirical distribution and that of the beta distribution. Specifically, we estimate the parameters a, b, l, and u so as to minimize

$$\sum_{i=1}^{17}[\mathrm{Beta}(s_i, a, b, l, u) - F(s_i)]^2, \tag{1}$$

where s_i is the upper end of response interval i[11] and $F(s_i)$ is the share of responses in intervals 1 to i. The CDF of the beta distribution, $\mathrm{Beta}(\cdot)$, is given by

$$\mathrm{Beta}(s_i, a, b, l, u) = \begin{cases} 0 & \text{if } s_i \leq l, \\ \dfrac{1}{B(a,b)} \displaystyle\int_l^{s_i} \frac{(x-l)^{a-1}(u-x)^{b-1}}{(u-l)^{a+b-1}} \mathrm{d}x & \text{if } l < s_i \leq u, \\ 1 & \text{if } s_i > u, \end{cases} \tag{2}$$

where $B(a,b) = [\Gamma(a)\Gamma(b)]/[\Gamma(a+b)]$ is the beta function and $\Gamma(\cdot)$ is the gamma function. This distribution generalizes the support of a standard beta distribution from $(0,1)$ to (l, u). To ensure that the distribution is unimodal, we constrain both a and b so that they are greater than unity. The lower end of the support, l, is constrained to be 0. The upper end of the support, u, is constrained to be 70%.[12] This estimation is carried out separately for each quarter, using the survey responses from all the cities. We report the parameters for each individual survey in Tables 91 and 9b.

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[9] In a separate paper, we looked into an alternative aggregate measure based on the qualitative responses rather than the quantitative responses. See Das *et al.* (2018) for more detailed discussions.

[10] See Engelberg *et al.* (2009) and Lahiri and Wang (2014).

[11] As stated in Section 2, the response intervals are <1%, 1% to 2%, …, 15% to 16%, >16%.

[12] The lower bound of l, as long as it is less than zero, has no effect on the estimation results. However, the upper bound of u does affect the results somewhat – as the bound is relaxed, the estimate of u increases as well, due to the large number of responses in the >16% interval. We considered several choices from 17% to 500% and decided to use 70% based on the same guiding principles discussed in Curtin (1996).

Figure 5: Comparing Mean and Median of Empirical and Fitted Beta Distribution

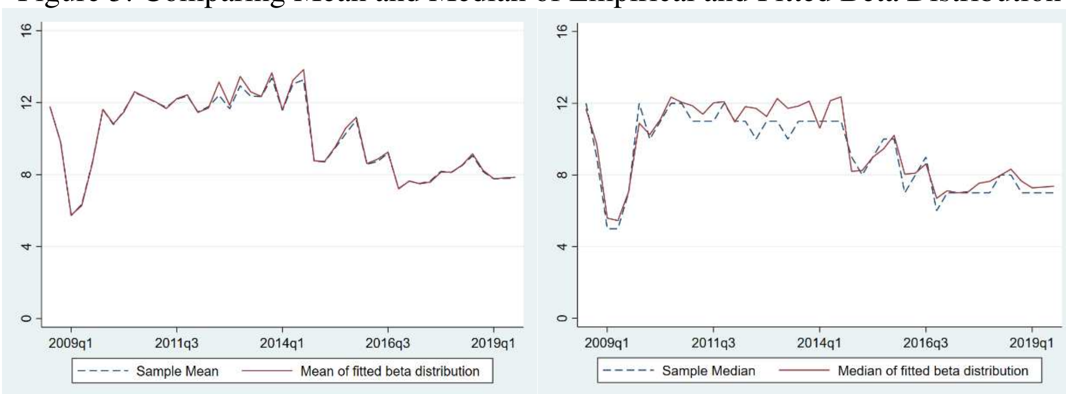


Figure 5 compares the mean (right plot) and median (left plot) of the fitted beta distributions. Unsurprisingly, since the empirical distributions are censored at the >16% response interval, there is a notable underestimation in the sample mean, which is calculated based on the assumption that all the responses in as interval are at exactly the midpoint of the interval. This is particularly obvious from 2013 to 2014, where around half of the responses are in the >16% interval. On the other hand, in late 2008 to early 2009, when few respondents had perceptions higher than 16%, the sample mean and that of the fitted beta distributions are almost identical.

Given the abundance of outliers in the IESH data, the median may be a more suitable measure than the mean. The RBI has been reporting the sample median in its data releases. The sample median is calculated based on the assumption that the responses in an interval are uniformly distributed. This assumption is obviously relaxed when a beta distribution is fitted to the data, which makes the median of the fitted beta distribution a more desirable measure. Comparing the two, we note that both exhibit similar dynamics.

Figure 6: Measuring Disagreement of Inflation Perceptions

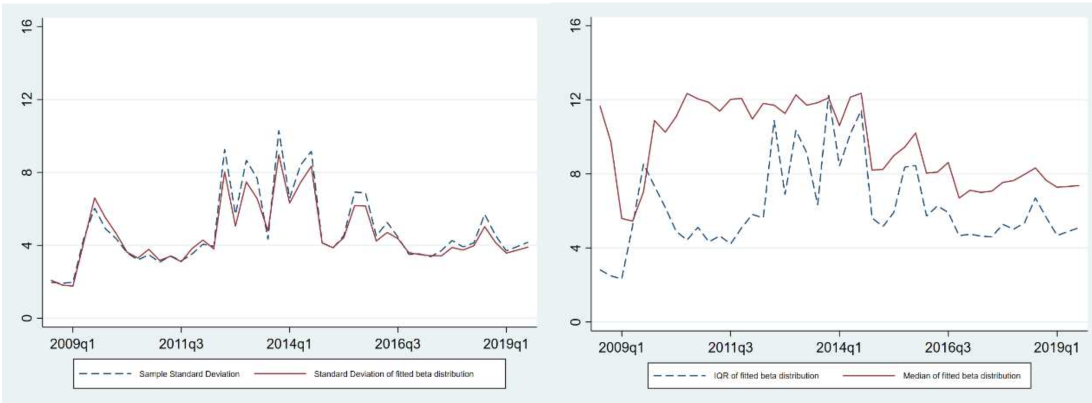


Figure 6 shows the measures of disagreement. The right plot compares the sample standard deviation and that of the fitted beta distributions. While the two series are largely synchronous, the standard deviations of the beta distribution are lower than their sample counterparts. For the same reason that the median is preferred to the mean as a measure of central tendency of this data, the interquartile range is preferred to standard deviation as a measure of disagreement among survey respondents. The solid line in the bottom plot shows the interquartile range calculated from the fitted beta distributions.

When examined against the median, the IQR shows some interesting patterns: In general, when households report higher inflation perceptions, they tend to disagree more. In late 2008 for example, when the median increased sharply, so did the IQR. The same can be said about the episodes around late 2013 and the period from 2017 to late 2018, albeit in the latter period, perceptions increased at a slower pace. Two significant declines in IQR happened in early 2010 and late 2014. In the first case, the median stabilized after a sharp increase. In the second case, the median also declined significantly. These observations suggest an asymmetric relationship between the two, which could help us further understand the expectation formation process.

Table 8a: Beta Distribution Parameters

Sample	year	alpha	beta	l	u
Truncated	2008q3	27.5	136.2	0.0	70.0
Truncated	2008q4	24.5	150.2	0.0	70.0
Truncated	2009q1	9.5	106.6	0.0	70.0
Truncated	2009q2	2.0	19.6	0.0	70.0
Truncated	2009q3	1.4	10.2	0.0	70.0
Truncated	2009q4	3.6	18.2	0.0	70.0
Truncated	2010q1	4.6	25.4	0.0	70.0
Truncated	2010q2	8.4	42.5	0.0	70.0
Truncated	2010q3	11.6	53.2	0.0	70.0
Truncated	2010q4	8.5	39.9	0.0	70.0
Truncated	2011q1	11.8	57.0	0.0	70.0
Truncated	2011q2	9.7	48.3	0.0	70.0
Truncated	2011q3	12.5	59.5	0.0	70.0

Truncated	2011q4	8.4	39.0	0.0	70.0
Truncated	2012q1	6.0	30.7	0.0	70.0
Truncated	2012q2	7.0	34.8	0.0	70.0
Full Sample	2012q3	2.0	8.8	0.0	70.0
Full Sample	2012q4	4.3	21.4	0.0	70.0
Full Sample	2013q1	2.5	10.4	0.0	70.0
Full Sample	2013q2	2.8	12.7	0.0	70.0
Truncated	2013q3	5.4	25.3	0.0	70.0
Full Sample	2013q4	1.6	6.5	0.0	70.0
Full Sample	2014q1	2.6	12.9	0.0	70.0
Full Sample	2014q2	2.3	9.7	0.0	70.0
Full Sample	2014q3	2.0	8.4	0.0	70.0
Full Sample	2014q4	3.8	26.8	0.0	70.0
Full Sample	2015q1	4.4	30.7	0.0	70.0
Full Sample	2015q2	4.0	25.6	0.0	70.0
Full Sample	2015q3	2.3	13.3	0.0	70.0

Table 8b: Beta Distribution Parameters

Sample	year	alpha	beta	l	u
Full Sample	2015q4	2.7	14.2	0.0	70.0
Full Sample	2016q1	3.5	25.0	0.0	70.0
Full Sample	2016q2	3.0	20.6	0.0	70.0
Full Sample	2016q3	3.9	25.8	0.0	70.0
Full Sample	2016q4	3.5	30.6	0.0	70.0
Full Sample	2017q1	4.1	3.6	0.0	70.0
Full Sample	2017q2	4.2	35.0	0.0	70.0
Full Sample	2017q3	4.3	34.9	0.0	70.0
Full Sample	2017q4	3.8	28.4	0.0	70.0
Full Sample	2018q1	4.1	31.0	0.0	70.0
Full Sample	2018q2	3.9	27.9	0.0	70.0
Full Sample	2018q3	2.8	18.6	0.0	70.0
Full Sample	2018q4	3.5	26.1	0.0	70.0
Full Sample	2019q1	4.2	33.3	0.0	70.0
Full Sample	2019q2	3.6	28.4	0.0	70.0
Full Sample	2019q3	3.8	30.1	0.0	70.0
Full Sample	2019q4	3.5	24.7	0.0	70.0

Borrowing from Lahiri and Sheng (2010) we attempt to use a Bayesian learning model to identify the relative importance of different pathways through which households disagree. The two sources of disagreement in their model are due to differences in prior beliefs and differences in the interpretation of new public information.

We use the non-linear least squares to estimate the parameters $\sigma^2_{\lambda|th}$ and $\sigma^2_{\mu|th}$ using the relationship derived between disagreements in two consecutive rounds of fixed target forecasting by Lahiri and Sheng (2008):

$$\sigma^2_{F|th} = \sigma^2_{F|th+1}\left(\sigma^2_{\lambda|th} + \lambda^2_{th}\right) + \sigma^2_{\mu|th}\left[\sigma^2_{\lambda|th} + (1-\lambda_{th})^2\right] + \sigma^2_{\lambda|th}\left[\frac{\Delta F_{th}}{(1-\lambda_{th})^2}\right]^2$$

Where, $\Delta F_{th} = F_{th} - F_{th+1}$

For our data:

F_{th} is Inflation Perception

F_{th+1} is lagged one year ahead inflation expectations

In addition, based on our computations we substitute the value for λ_{th} as $\lambda_{th} = 0.72$.

The $\sigma^2_{\lambda|th}$ is the differences in weight attached to prior beliefs and $\sigma^2_{\mu|th}$ is the differences attached to interpretation of public signals. Table 10 presents the results of the model.

Table 9: Disagreement and prior beliefs

	$\boldsymbol{\sigma^2_{F\|th}}$
$\boldsymbol{\sigma^2_{\lambda\|th}}$	0.37***
	(0.02)
$\boldsymbol{\sigma^2_{\mu\|th}}$	0.00
	(0.00)
R-Square	0.99

* p<0.05, ** p<0.01, *** p<0.001

Table 9 shows that disagreements about prior beliefs play a dominant role in generating overall disagreement regarding inflation expectations. The results presented here are robust to the assumed value of λ_{th}. These results indicate stickiness in expectations that help partly explain the muted decline in expectations even as inflation declined substantially between 2013 and 2018.[13]

V: Signal Extraction

The cross-sectional variation of the price expectations are of information value, however, the bias in the aggregate inflation expectations poses as a challenge to the use of this data for the purpose of formulating monetary policy. More so during times of heightened uncertainty where inflation expectations play a prominent role in guiding policymakers. This opens the question of

[13] Goyal and Parab (2021) used a Carroll (2003) specification and modify it to explain inflation expectations. They found that the speed of adjustments of households to news was higher in India than compared to developing economies. This could partly be driven by the large decline in inflation which reduced from 12% to less than 4% between 2013 and 2018. However, the adjustment in expectations was only partly complete as illustrate earlier given the persistent positively biased expectations.

how best to use the data from the survey. We view this signal extraction problem as one that requires to look at both the qualitative and quantitative aspects of the survey.

Das, Lahiri and Zhao (2019) explored the qualitative aspects of the survey by quantifying the reported qualitative responses. Borrowing from their framework, we construct the balance statistic for 3 months ahead and one year ahead inflation expectations. Balance statistic is defined as the difference between the proportion of households who believe prices will increase at a higher rate in future or at the same rate (acceleration in inflation) as against people who think prices would either fall (deflation), remain unchanged or increase at a slower pace (disinflation)**.**

We are interested in exploring whether changes in balance statistic contain any information about likely movements in future inflation rates. Figure 7 shows the balance statistic for 3 months ahead inflation expectations along with the CPI – IW inflation while figure 8 shows the balance statistic for one year ahead inflation expectations. Two immediate conclusions follow. First, the balance statistic does contain valuable information regarding the direction of movement in inflation rates thereby indicating that the qualitative assessments of households are broadly correct. Second, households are better equipped at forecasting inflation at 3 months horizon than compared to one year (12 months).

These findings suggests that even when households are unable to predict the level of contemporaneous or future inflation, they are able to predict the direction of changes in inflation. This is useful for policymakers who are interested in tracking inflation expectations. The directional information contained in these surveys can potentially help better inform policymakers about household expectations for future price movements and may compliment the use of professional forecaster surveys.

Figure 7: Balance Statistic (One Year Ahead Inflation Expectations) and Inflation

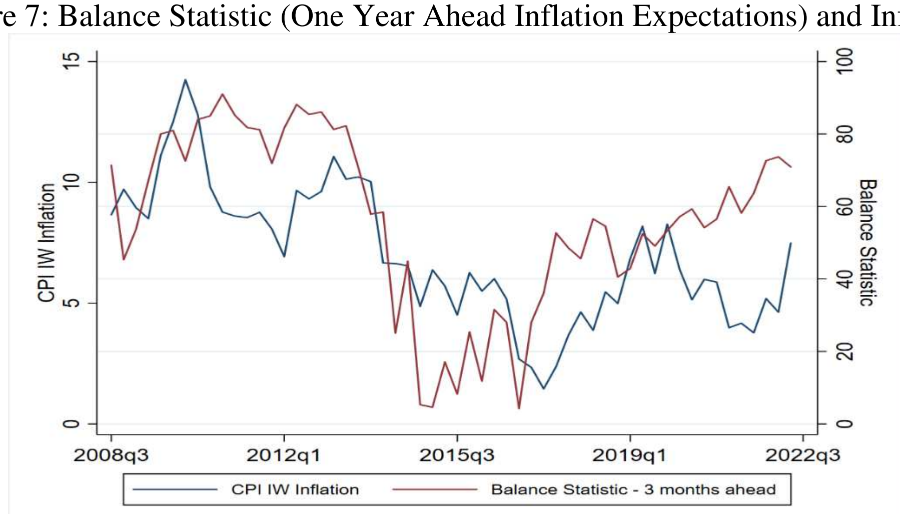
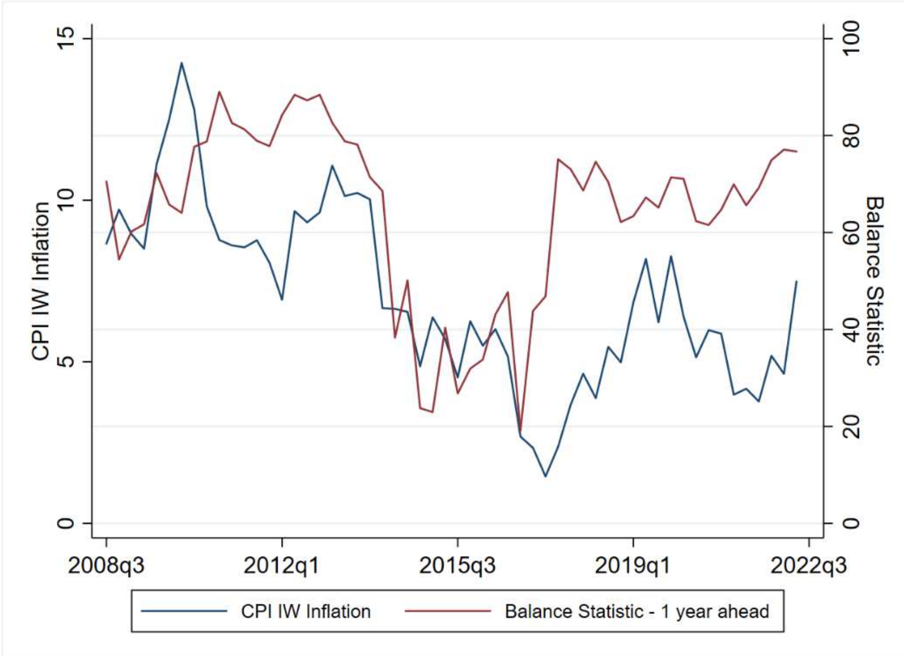


Figure 8: Balance Statistic (One Year Ahead Inflation Expectations) and Inflation



In addition to the balance statistic, we look at both the qualitative data and the quantitative data to explore further whether households are able to gauge the directional changes in actual inflation better than predicting the level of inflation. Table 10 provides the results for both the qualitative and quantitative data. Hit rate is measured as the percentage times when the direction of the change in inflation expectations matches with the direction of the change in inflation rate. That is, they both have the same sign. False alarm is when the direction of change in inflation expectations and the direction of change in inflation rate have opposite signs. We undertake this for both, contemporaneous inflation expectations defined as inflation perceptions and for one year ahead inflation expectations. The change is measured over one quarter – that is, between two survey rounds.

Table 10: Qualitative Data – Hit Rate and False Alarm

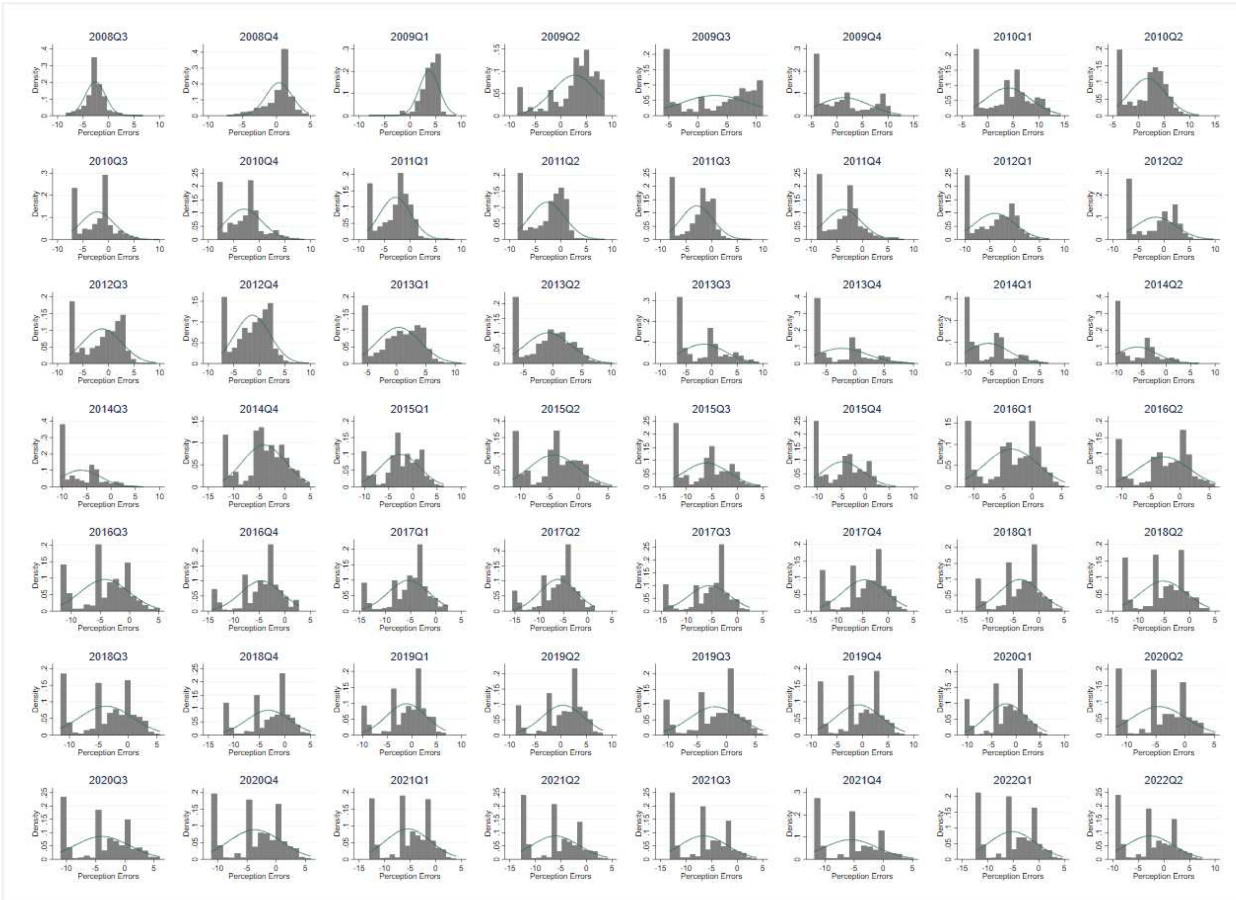
	Hit Rate	False Alarm
Qualitative Data		
Full Sample: 2008Q3 – 2022Q2		
Inflation Perceptions	41.41	58.59
One year ahead inflation expectations	45.17	54.83
Non-Inflation Targeting		
Inflation Perceptions	38.27	61.73
One year ahead inflation expectations	40.54	59.46
Inflation Targeting		
Inflation Perceptions	45.14	54.86
One year ahead inflation expectations	50.70	49.30
Pre-Covid Quarters		
Inflation Perceptions	42.01	57.99
One year ahead inflation expectations	49.87	50.13
Covid Quarters		

Inflation Perceptions	38.88	61.12
One year ahead inflation expectations	25.55	74.45
Quantitative Data		
Full Sample: 2008Q3 – 2022Q2		
Inflation Perceptions	60.71	39.29
One year ahead inflation expectations	55.36	44.64
Non-Inflation Targeting		
Inflation Perceptions	58.06	41.94
One year ahead inflation expectations	54.84	45.16
Inflation Targeting		
Inflation Perceptions	64.00	36.00
One year ahead inflation expectations	56.00	44.00
Pre-Covid Quarters		
Inflation Perceptions	56.52	43.48
One year ahead inflation expectations	52.17	47.83
Covid Quarters		
Inflation Perceptions	80.00	20.00
One year ahead inflation expectations	70.00	30.00

Table 10 shows that the quantitative data performs better than the qualitative data in terms of gauging the direction of inflation change. In particular, households are more accurate in predicting acceleration in inflation rather than deceleration in inflation.

In figure 9 we plot the distribution of perception errors for different rounds of the survey. The results are similar to the plot of inflation perceptions and inflation expectations for given rounds of the survey.

Figure 9: Distribution of Perception Errors (Defined as Inflation – Inflation Perception)



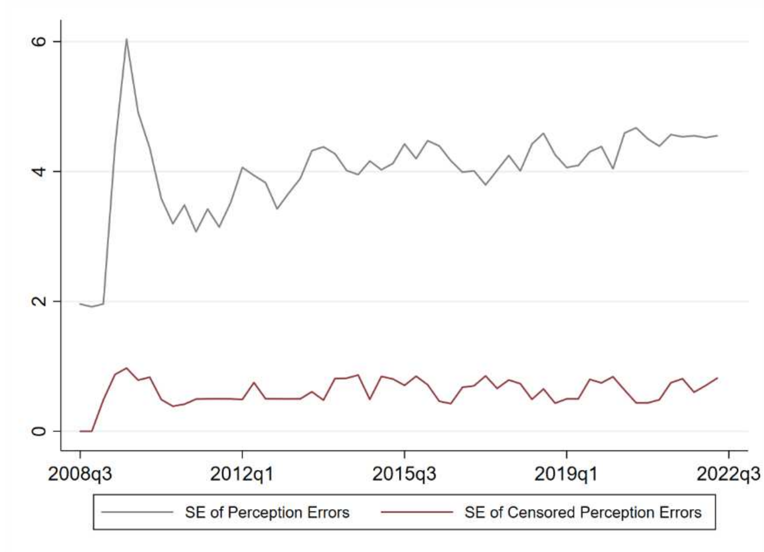
We propose a filtering algorithm that makes use of the inflation perception data. We use only those observations that satisfy:

– 0.30 st dev of perception errors <= perception errors <= 0.30 st dev of perception errors

The objective is to retain only those observations that are within 0.30 standard deviation of perception errors centered around 0. These households are more informed and must pay greater attention towards inflation leading to a lower bias in inflation perceptions. Consequently, their future inflation expectations might also have a relatively lower bias.

The censoring of data using the proposed algorithm leaves us with households that have a more informed view of the current inflation levels. In figure 10, we look at the standard errors for perception errors both the censored and the uncensored data. It is instructive to note that both the censored and uncensored standard errors for perception errors display a similar dynamic over time however, the censored standard error is substantially lower than the uncensored standard error. Therefore, the censored data does contain similar dynamics over time as the uncensored data even as it has a lower disagreement regarding existing inflation rate.

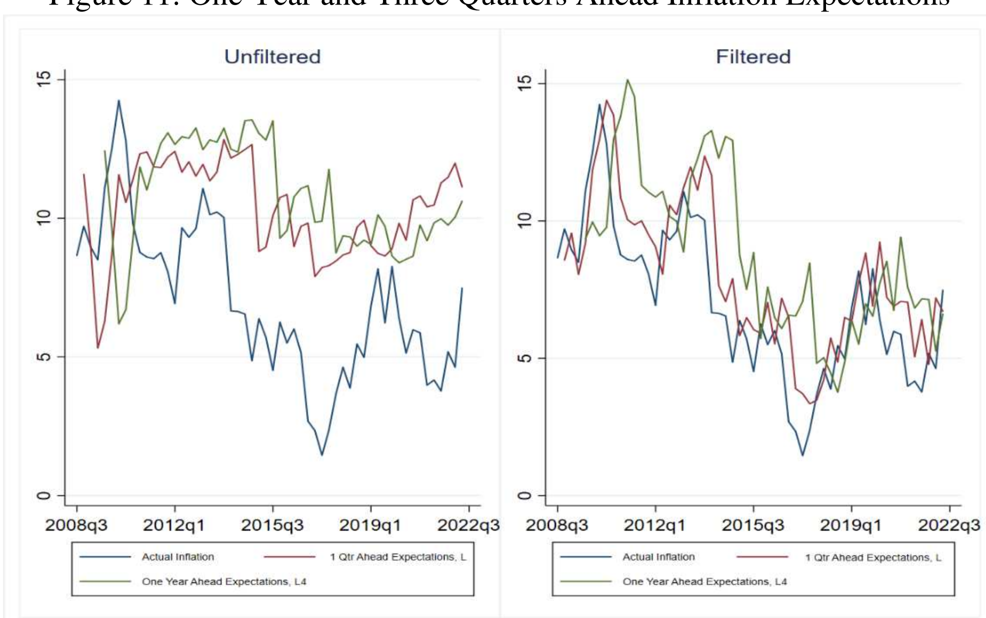
Figure 10: Standard Error in Perception Errors for censored and overall sample



We now turn to the censored and uncensored estimates for one year and three months ahead inflation expectations in figure 11. Figure 11 contains the four-quarter lagged one year ahead inflation expectations, one quarter lagged 3 months ahead inflation expectations for both the filtered (censored) and unfiltered (uncensored) data.

As expected, the one quarter ahead inflation expectations computed using the filtering mechanism performs better compared to the one year ahead inflation expectations. However, the filtered expectations perform better than the simple aggregates computed from the uncensored dataset.

Figure 11: One Year and Three Quarters Ahead Inflation Expectations



The use of the filtering algorithm using inflation perception enables us to get more reliable forecasts for three months ahead inflation expectations relative to the one year ahead inflation expectations. These results are consistent with the estimates of the deep structural parameters outlined in section IV of the results where we found prior beliefs to have a predominant role in determining inflation expectations.[14]

Conclusion

In this paper, we examined both the quantitative and qualitative inflation perceptions and expectations reported in the Inflation Expectations Survey of Households from the Reserve Bank of India. Consistent with prior findings and evidence from other countries and regions around the world, we found significant and persistent pessimism in household perceptions and expectations. This pessimism is then identified to be the result of large number of unusually high ("> 16%") responses. Subsequent examinations of the data revealed that a large number of such responses came from residents in only a few cities. In terms of socio-demographic characteristics, we find that respondents who are older, female, not working or working in non-finance industries tend to be more pessimistic. We demonstrated that by simply discarding these extreme responses, one can obtain significantly less biased estimates of inflation perceptions and expectations.

In addition, we looked into the hypothesis that the inflation rates of frequently purchased commodities may affect household inflation perceptions and expectations in a way that is disproportional to the weights of these commodities in the official CPI consumption bundle. We found strong evidence supporting this hypothesis: In models of individuals' perceptions and expectations, after controlling for actual inflation rates and observed respondent characteristics, the addition of the inflation rate of a set of commodities doubles the explanatory power. We observed that households report to the survey based on their actual experiences while their numerical responses may, at the same time, be irrationally high.

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[14] Recently Muduli, Nadhanael & Pattanaik (2022) at the RBI attempted to adjust households biases for the median of one year ahead inflation expectations. They begin by determining the variables responsible of the inflation expectations bias and use the predicted bias to adjust for the one year ahead inflation expectations. Such an approach misses out on cross-sectional heterogeneity of prices that serve as an important driver of disagreement among households.

We thus proposed to use the median and interquartile range of a set of fitted beta distributions instead of the mean and the standard deviation of the raw data as aggregate measures of expectations and disagreement. In addition, we show the disproportionate role played by prior beliefs in explaining the disagreement. This is consistent with other evidence presented in the paper.

We also examined the qualitative responses contained in the data and obtained the balance statistic. The balance statistic provides a reliable measure of directional change in inflation rates and therefore should be of interest to policymakers. Using both the qualitative and quantitative data, we find that households are more accurate in nowcasting an acceleration in inflation rather than a deceleration. Further, we proposed filtering the data using the households that are better equipped at nowcasting inflation perception accurately to generate a more reliable measure of aggregate future inflation expectations.

Overall, our results suggest that the observed irregularities and pessimism in household inflation perceptions and expectations likely reflect structural features of the Indian economy. Therefore, rather than discounting household expectations due to their apparent irregularities, monetary policy makers should take advantage of this valuable information.

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Appendix:

Table A1: Distribution of Inflation Perceptions

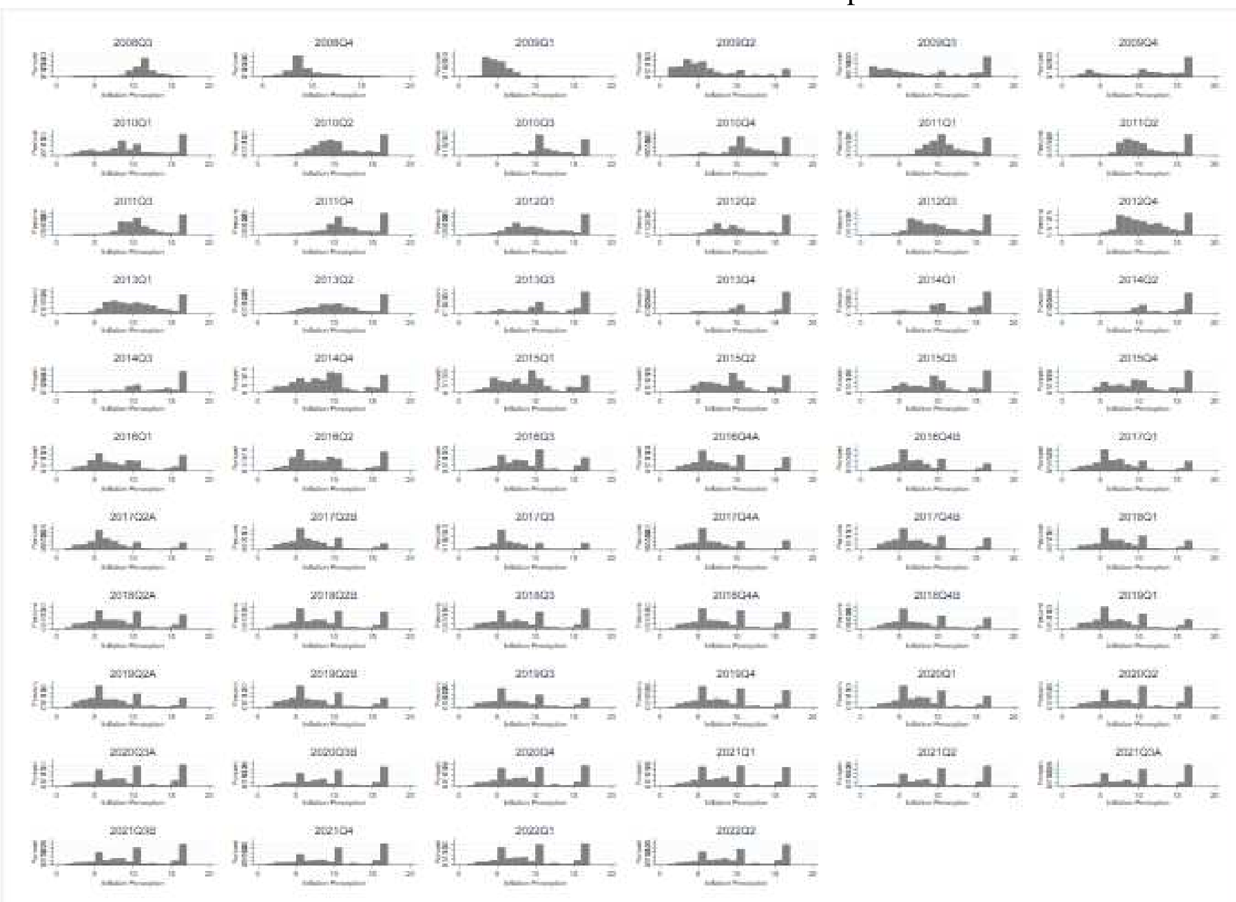

Table A2: Distribution of Inflation Expectations

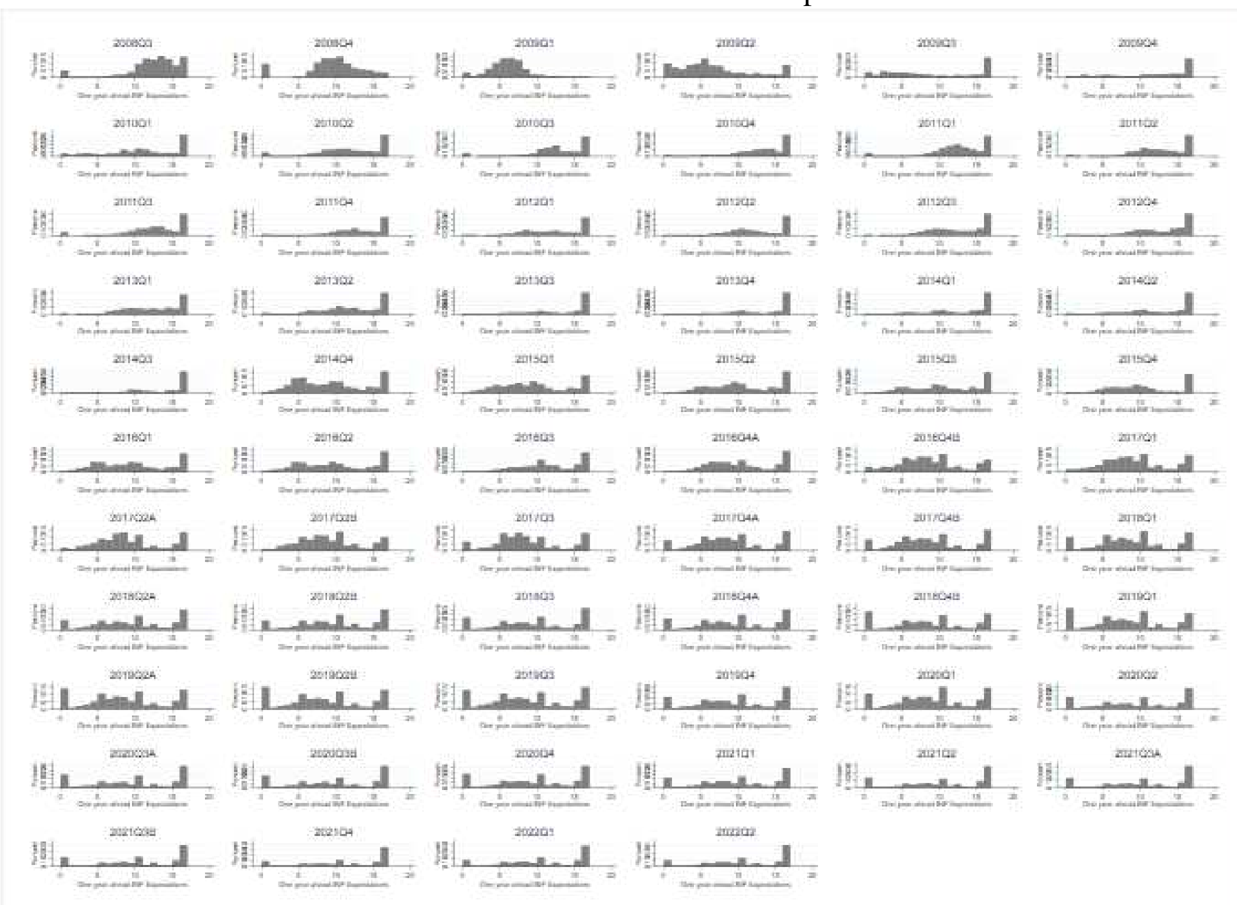

Figure A3: Inflation Perception and Inflation

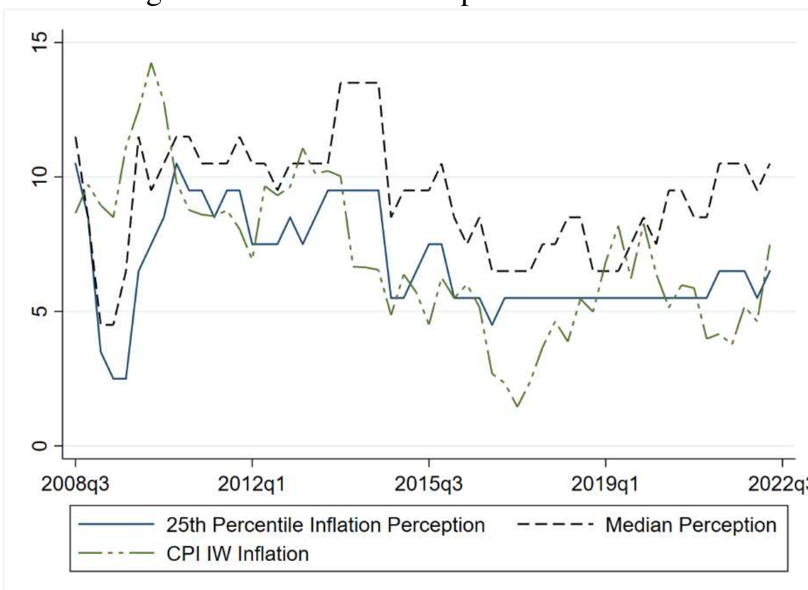

Figure A4: Inflation and Interquartile Range

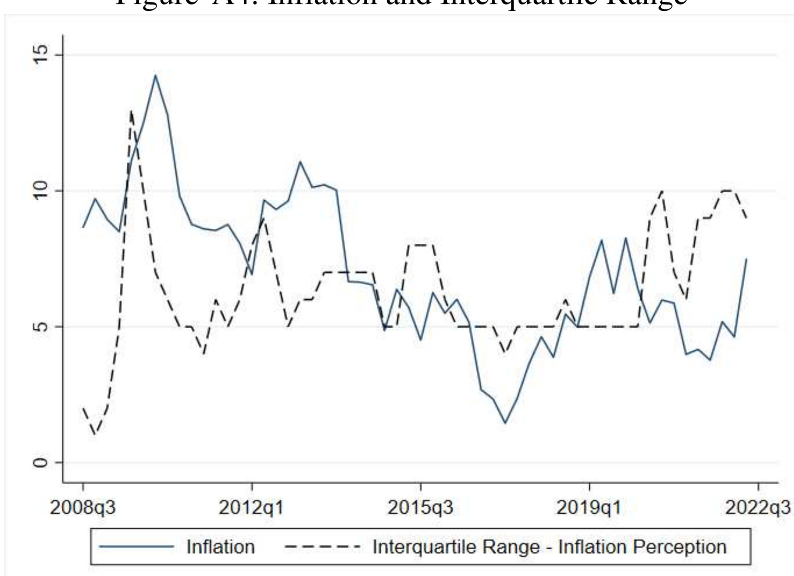

Table A1: Overall Sample and Censored Sample Size

Quarter	Sample	Censored Sample	CPI Inflation
2008q3	4,000	127	8.66
2008q4	4,000	645	9.71
2009q1	4,000	112	8.95
2009q2	4,000	357	8.50
2009q3	4,000	465	11.11
2009q4	3,989	695	12.50
2010q1	4,000	302	14.25
2010q2	4,000	305	12.80
2010q3	4,000	1,429	9.81
2010q4	4,000	563	8.77
2011q1	4,000	991	8.60
2011q2	4,000	1,217	8.54
2011q3	4,000	1,186	8.76
2011q4	4,000	358	8.06
2012q1	4,000	901	6.92
2012q2	4,000	1,158	9.66
2012q3	4,000	789	9.31
2012q4	5,000	1,037	9.62
2013q1	5,000	903	11.07
2013q2	4,960	1,059	10.13
2013q3	4,765	1,390	10.22
2013q4	4,907	1,201	10.03
2014q1	4,926	418	6.66
2014q2	4,931	439	6.64
2014q3	4,933	421	6.54
2014q4	5,000	806	4.86
2015q1	4,996	1,280	6.38
2015q2	4,994	1,132	5.71
2015q3	4,903	800	4.51
2015q4	4,825	1,065	6.26
2016q1	4,917	1,572	5.50

2016q2	4,616	1,155	6.01
2016q3	4,556	875	5.16
2016q4	4,454	580	2.69
2017q1	4,359	452	2.34
2017q2	4,078	276	1.45

Table A1: Overall Sample and Censored Sample Size

Quarter	Sample	Censored Sample	CPI Inflation
2017q3	4,355	434	2.37
2017q4	4,571	845	3.67
2018q1	4,537	1,419	4.63
2018q2	4,563	452	3.88
2018q3	5,467	1,565	5.46
2018q4	5,529	1,710	4.98
2019q1	5,532	943	6.84
2019q2	5,421	774	8.18
2019q3	5,516	1,999	6.22
2019q4	5,527	974	8.27
2020q1	5,615	2,155	6.40
2020q2	5,467	1,463	5.14
2020q3	5,368	1,079	5.98
2020q4	5,616	1,251	5.87
2021q1	5,756	513	3.98
2021q2	5,775	1,192	4.17
2021q3	5,787	499	3.77
2021q4	5,711	1,155	5.19
2022q1	5,734	1,391	4.63
2022q2	5,763	1,042	7.48

Table A2: CPI Inflation & Censored Inflation Perceptions

	CPI Inflation
Inflation Perception	0.943***
	(0.00)
Constant	0.291***
	(0.01)
N	51316

* p<0.05, ** p<0.01, *** p<0.001