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Keywords: Cross-Sectional Models; Disagreement**;** Inflation; Inflation expectations; Survey; Uncertainty

JEL classification: C21, C83, D84, E31

Insights from Indian households' qualitative inflation expectations

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Insights from Indian households' qualitative inflation expectations

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January 25, 2025

Abstract

Using the Reserve Bank of India's inflation expectations survey of households (IESH) covering the period 2008 to 2023, we analyze the qualitative inflation expectations (IE) of Indian households at the general and item-wise level. We determine whether they have any forward-looking properties and additionally study the pattern of uncertainties and disagreements associated with households' IE during various economic episodes in India. We find that the households have different opinions on the IE of different items, and they are influenced by various macroeconomic shocks. Additionally, their three-months-ahead overall IE are formed mainly based on their IE on food products, followed by cost of services and non-food products, while their one-year-ahead IE are formed mainly based on the IE of non-food products, followed by cost of services and food products. Moreover, the quantified three-months-ahead IE and one-year-ahead IE when fitted into the hybrid version of the New Keynesian Phillips Curve were found to be statistically significant in predicting inflation. Further, the respondents' demographic characteristics have an impact on their qualitative IE and the uncertainty that comes with it. Lastly, we discovered that the inflation shocks in either direction led to an increase in the disagreements on IE of households.

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Introduction

Policymakers across the globe track the inflation expectations (IE) of different agents regularly due to its vital role in determining inflation. IE of different agents like households, firms, and professional forecasters are therefore collected by the central banks through various surveys. In India, IE of households are captured in both quantitative and qualitative terms. Moreover, the qualitative IE are captured at the aggregate level and item-wise. The quantitative IE has been thoroughly investigated in the past, while the qualitative IE at the aggregate and item-wise levels are less explored. In this paper, we try to examine the properties of general and item-wise qualitative IE of Indian households' by quantifying them with different methods that use either aggregate or granular level data and check whether they have any forward-looking properties. In addition, we study the pattern of uncertainties and disagreements associated with households' IE during various economic episodes in India and the factors affecting them.

The literature has revealed that, in general, household quantitative IE are biased and not rational and may have less predictive power for forecasting inflation (Keane and Runkle,1990; Maddala et al. 1981; Gramlich,1983; Batchelor,1986; Souleles, 2004). The IE of Indian households are also not different from the global scenario, and studies have found that their inflation expectations are biased and not rational because they do not fully incorporate all available information (Shaw, 2019; Muduli et al., 2022; Singh et al., 2022). Furthermore, studies have shown that the formation of households' IE is not straightforward, and it may not be representative of CPI inflation because households give high weightage to changes in the prices of the items they purchase frequently and may not give proper weightage to each component in the CPI basket (D'Acunto et al.,2022), further biasing the quantitative IE. As this is a global phenomenon and many surveys only collect qualitative responses, researchers focused on the qualitative IE of households and developed various methods to quantify the qualitative IE, such as balance statistics, the Carlson-Parkin (CP) method, the hierarchical ordered probit (HOPIT) model, and so on. Furthermore, qualitative IE has fewer measurement errors than quantitative IE because it only records the direction of the price change, not the magnitude. As a result, this study focuses on qualitative IE.

Similarly, uncertainty plays a crucial role in the formation of IE since uncertain consumers have higher inflation perceptions and expectations. Reiche and Meyler (2022) found that in the Eurozone, the uncertainty caused by the pandemic had increased consumer IE. Moreover, they found that inflation uncertainty varies systematically across socio-demographic groups, and a negative economic outlook increases individual inflation uncertainty. As a result, it is critical to understand the uncertainties and disagreements associated with household IE. Currently, the researchers use the dispersion of the qualitative data, a measure of disagreement, as a proxy of uncertainty. However, the existing measures of disagreement, which use only the aggregate, prevent the separation of uncertainty and disagreement and assume that the latter is a reasonable proxy of the former. Boero et al. (2008) and Rich & Tracy (2010) argued that the measure of disagreement is not an adequate substitute for the measure of uncertainty, and it is better to measure uncertainty at the individual level if it is possible. To overcome this challenge, Zhao (2022) proposed a procedure to quantify the individual-level qualitative data that jointly estimates expectations, uncertainties, and disagreements for the US using a flexible HOPIT model. Although Das et al. (2019) quantified the qualitative IE of Indian households, the joint estimation of expectations, uncertainties, and disagreements is yet to be explored in the Indian context. Hence, we try to estimate the expectations, uncertainties, and disagreements jointly for the Indian households.

The paper contributes to the literature in three major ways. First, we try to quantify the aggregate and item-wise IE by using different methods like normal distribution (CP method) with constant and time-varying thresholds, student's t distribution with constant and time-varying thresholds, and an ordered probit model to jointly estimate expectations, uncertainties, and disagreements. The Reserve Bank of India conducts the IESH bimonthly, which collects both quantitative and qualitative IE. However, item-wise IE (Food products, Non-food products[2], Household durables[3], Housing[4] and Cost of services[5]) are available only at the qualitative level, and they have not been much explored in research. Das et al. (2019) for India, quantified qualitative general IE and found that they track the actual inflation rate better than pure quantitative expectations. In this context, we attempt to quantify qualitative

[2]'Non-food products' include clothing, medicine, footwear, petrol/diesel, vessel, soap and detergent, etc.

[3]'Household durables' include television, mobile phone, telephone, camera, washing machine, AC, furniture, computer/laptop, etc.

[4]'Housing' includes house rent, maintenance charge, residential price etc.

[5]'Cost of services' include bus fare, train fare, landline/ mobile phone bill, school fee, doctor fee, courier charge, cinema ticket cost, etc.

IE at the general level and also at the item-wise level, and this would be the first study to quantify item-wise qualitative IE of the Indian households. Moreover, the previous studies conducted in India were before the outbreak of the pandemic, and the results may be different now due to the uncertainties and high inflation situations that have emerged recently due to the pandemic and other geo-political tensions. Hence, it is critical to thoroughly investigate the uncertainties and disagreements of households and incorporate them into the model in order to obtain a more accurate estimate of IE. Though Das et al. (2019) attempted to quantify the qualitative IE by using the HOPIT model with varying thresholds and the disagreements, this may be the first study to quantify the qualitative IE at the individual level by jointly estimating the expectations, uncertainties, and disagreements.

The results show that households have high IE on food products and non-food products and they have low IE on household durables. Further, the three-months-ahead general IE are formed mainly based on households IE on food products, followed by IE on cost of services and non-food products. While forming a one-year-ahead IE, they mainly focus on IE of non-food products, followed by IE on cost of services and food products. In the past few years, it was observed that the one-year-ahead general IE are higher than the item-wise IE, which ascertains the fact that while forming general IE, without giving proper weightage to each component in the CPI basket, households overestimate the general IE. Hence, the information on item-wise IE will give more insights to the policymakers about households' actual IE.

Second, we verify the forward-looking properties of quantified IE by fitting them to the hybrid version of the New Keynesian Phillips Curve (NKPC). Since household inflation expectations are adaptive, in hybrid NKPC models, household inflation expectations effectively work more as a substitute for adaptive expectations (Pattanaik et al., 2020). In this context, we check the forward-looking properties of qualitative IE, which is quantified using different methods already discussed above and by fitting them to the hybrid NKPC framework. The results revealed that, both three-months-ahead and one-year-ahead, qualitative IE quantified by different methods turned out to be significant in predicting CPI-Combined and CPI-Urban. Further, the three-months-ahead IE has better predictive power than one-year-ahead IE.

Third, we measure the disagreements at the general level and item-wise level by using different methods to compare the uncertainties and disagreements of the Indian households

during various macroeconomic episodes, and this could be the first study to explore the disagreements at the item-wise level. The results show that disagreement among households was lower during the high inflation phase of 2008 to 2013 in the pre-inflation targeting period and comparatively higher during the low inflation phase of 2014 onwards in the post-inflation targeting period[6]. Further, the disagreement augmented again during the recent high inflation episode that happened in 2022–23 due to the geopolitical tensions. This corroborates the fact that the sharp inflation changes in either direction may lead to a rise in the disagreement of IE (Mankiw et al., 2003). Further, households expect higher inflation for food products and non-food products with lesser uncertainty and expect comparatively lower inflation for household durables with higher uncertainty. This may be because, in India, the prices of items in the food products and non-food products groups are highly volatile and exhibit high inflation frequently. Further, households in general focus on the price changes of the items that they purchase frequently, like food products and non-food products. In addition, they put a higher weight on price increase than price reduction while forming their IE (D'Acunto et al., 2022).

The rest of the paper is organized as follows: Section 2 examines the related literature. Section 3 describes the data, and Section 4 explains the methodology used in the study. The results are discussed in Section 5, and the concluding observations are presented in Section 6.

2. Literature Review

The primary aim of this paper is to study the behaviour of qualitative IE of Indian households. To do so, it is necessary to quantify the qualitative IE and study its pattern. Initially, the balance statistic was used to quantify the qualitative IE. Later, in 1975, Carlson and Parkin developed the Carlson-Parkin (CP) method, which is considered the foundation for quantification methods. However, the classical CP approach assumes normality of the latent distribution of point forecasts, which has been criticized by Dasgupta and Lahiri (1992), who have experimented with the scaled t distribution to accommodate the excess kurtosis regularly found in quantitative expectations. Over the period, modified versions of the CP method were developed by researchers across the globe by relaxing the various assumptions (Lahiri and Zhao, 2015; Ito and Kaihatsu, 2016). Researchers applied different methods like CP, logistic, etc. to quantify the qualitative data of various surveys in different

[6] Reserve Bank of India adopted inflation targeting during 2016.

countries (Das Gupta and Lahiri, 1992; Balcombe, 1996). Afterward, to address the drawback of the assumption of constant threshold values in the probability approach, Smith and McAleer (1995) and Mokinski et. al. (2015) tried out the probability approach which allows for time-varying thresholds. The probability and regression approaches were used to quantify qualitative IE (Rosenblatt-Wisch and Scheufele, 2015). Later, Lahiri and Zhao (2015) proposed a flexible hierarchical ordered probit (HOPIT) model for quantification that allows for controlling for the socio-economic characteristics of the survey respondents in addition to relaxing the assumptions embedded in the CP procedure regarding indifference thresholds and the disagreements associated with the IE. The same method was used with Indian households IE, and it was found that quantified estimates derived from the qualitative responses tracked the actual inflation rate better than the pure quantitative expectations (Das et al., 2019).

The literature shows that IE is also dependent on the uncertainty and the disagreement associated with the respondents (Reiche and Meyler, 2022). Mankiw et al. (2003) suggested that disagreement may be a key to macroeconomic dynamics, and disagreement about the future inflation path tends to rise when inflation changes sharply in either direction. Łyziak and Sheng (2018) explored the disagreements in consumer IE and found that households pay close attention to salient price changes. Chen et al. (2022) investigated the disagreement among the IE in the Euro Area and proved that disagreement about future inflation increases in response to news when the current inflation is high and declines when current inflation is low. Currently, the dispersion of the qualitative data, a measure of disagreement, is used as a proxy of uncertainty, and the research in this area argues that the measure of disagreement is not an adequate substitute for the measure of uncertainty, and it is better to measure uncertainty at the individual level if it is possible (Boero et al., 2008; Rich and Tracy, 2010). To address this issue, Zhao (2022) proposed a method that jointly estimates the expectations, uncertainties, and disagreements using a flexible HOPIT model and individual-level qualitative data using the Michigan Survey of US Consumers. They argued that as uncertainties and disagreements associated with the US household IE have a strong positive correlation, measures of disagreements may be used to proxy uncertainties. They also experienced direct links between expectations, uncertainties, and households' perceptions of economic conditions and the socio-demographic characteristics at the individual level. In India, households' quantitative IE depends on their inflation perceptions and their demographic characteristics (Goyal and Parab, 2019). Moreover, IE are heterogeneous across

cities due to information friction (Saakshi and Sahu, 2019). In our paper, we quantified the qualitative IE by using the CP method and the student's t method, both with constant and time-varying thresholds developed by Mokinski et al. (2015). We further try to quantify the qualitative IE using the ordered probit method, which jointly estimates the expectations, uncertainty, and disagreement for quantifying the qualitative IE and verifies the impact of socio-demographic characteristics of respondents on their IE and the uncertainty associated with them.

In our paper, we try to verify the forward-looking properties of the quantified qualitative IE by fitting them to the hybrid NKPC. Different schools of economic thought believe that IE can influence prices (Phelps, 1967; Friedman, 1968; Fuhrer and Moore, 1995; Goodfriend and King, 1997; Roberts, 1997). Paloviita (2008) compared the empirical performance of the New Classical, New Keynesian, and Hybrid specifications of the Phillips curve and found that in the case of European countries, the purely forward-looking NKPC is surpassed by the New Classical and Hybrid Phillips curves. Similarly, there is evidence that the hybrid NKPC fits selected Eurozone countries, the US and the UK (Henzel and Wollmershaeuser, 2006). The studies conducted in India also show that the IE of households are backward-looking and largely adaptive (Shaw, 2019; Muduli et al., 2022; Singh et al., 2022). Hence, Pattanaik et al. (2020) used hybrid versions of the NKPC proposed by Clarida et al. (1999) that consider expectation as a hybrid version, i.e., both backward and forward-looking, to test the effectiveness of the IE of households in India to predict inflation. The results show that IE have significant predictive power in explaining future inflation.

With regard to the measurement of disagreement, there are few commonly used approaches to measure the dispersion in the qualitative survey data. The first measure of the nominal or ordinal variation approach is an index of qualitative variation (IQV), suggested by Gibbs and Poston (1975). However, the IQV has been criticized by Blair and Lacy (2000) for wasting information by treating ordinal responses as nominal, and they developed a new measure, Blair and Lacy's (2000) measure of ordinal variation (BL). Another index that measures the distance of an observed distribution from the point of maximum concentration, like Blair and Lacy's (2000) measure of ordinal variation is Kvalseth's (1995) coefficient of ordinal variation (COV). Both measures range between 0 and 1, obtaining their minimum when all responses fall into a single category and their maximum when the distribution of responses is polarized, i.e., the share of individuals who responded inflation will increase and the share of

individuals who responded inflation will decline, is equal to 0.5. Later, Reardon (2009) developed an entropy-based measure of ordinal variation, and Bachmann et al. (2013) proposed another measure of disagreement (the BES method) in qualitative survey data. In addition to that, the probability methods, viz., the CP method with normal and the student's t distribution, both with constant and time-varying thresholds, also calculate the standard deviation, which is used as a measure of dispersion. We also study the pattern of disagreement on general IE and item-wise IE separately by using the different methods discussed above during various macroeconomic scenarios.

3. Data

The study has used the granular data of IESH from September 2008 to September 2023. The survey was conducted in every quarter till 2016 and started conducting bimonthly in the subsequent years. The survey collects both quantitative and qualitative data of three months ahead and one-year-ahead IE of households from major cities in India. The survey also collects item-wise IE in qualitative terms. The qualitative IE are collected in five response categories, namely, 'Price increase more than current rate', 'Price increase similar to current rate', 'Price increase less than current rate', 'No changes in prices', and 'Decline in prices'. As suggested by Das et al. (2019), these five categories are grouped into three categories, viz., "up", "down", and "no change". As the inflation in India was persistently high and a very few respondents have the opinion that prices will decline, we have classified "up" to contain all who expect inflation to rise. While "down" contains 'Price increase less than current rate', 'No changes in prices', and 'Decline in prices'. 'Price increase similar to current rate' is classified as "no change".

The data of IESH from September 2008 is analyzed, and a balance statistic is calculated. Moreover, the IE are available at the item level, viz., 'Food Products', 'Non-Food Products', 'Household Durables', 'Housing Prices', and 'Cost of Services' in qualitative terms only. The general qualitative IE was quantified by using the CP method and t-distribution, both with constant as well as time-varying thresholds. While the item-wise IE are quantified by using the CP method and the t-distribution, with constant thresholds. The general qualitative IE is also quantified using the ordered probit method, which jointly estimates the expectations,

uncertainty, and disagreements. The ordered probit model was applied to the granular data of 68 rounds of the survey with 3,64,960 responses.

4. Methodology

4.1 Probability approach

To begin with, the quantification of qualitative IE was carried out with the probability approach with constant thresholds proposed by Carlson and Parkin (1975) (CP method) which provides a measure of dispersion as well. This method assumes that the unobserved point forecast f_{it}, i=1,.,.,., N_t at the time 't' is independently and identically distributed normally with mean μ_t and variance σ_t. In addition to that, the thresholds are constant and symmetric around zero. i.e., $\zeta_{up} = \zeta_{down} = \zeta$. The mean and variance are calculated as follows:

$$\mu_t = \zeta \left[\frac{\{\Phi^{-1}(p_{d,t})+\Phi^{-1}(1-p_{u,t})\}}{\{\Phi^{-1}(p_{d,t})-\Phi^{-1}(1-p_{u,t})\}}\right] \qquad (1)$$

$$\sigma_t = \left[\frac{2\zeta}{\{\Phi^{-1}(1-p_{u,t})-\Phi^{-1}(p_{d,t})\}}\right] \qquad (2)$$

Φ is the cumulative distribution function of standard normal distribution, and $p_{u,t}$ and $p_{d,t}$ are the population probabilities of observing up and down responses, respectively. σ_t is the measure of disagreement, which is a scale-free measure as ζ is invariant. ζ is calculated using the method attempted by Carlson and Parkin (1975), as mentioned below.

$$\zeta = \frac{\sum_1^t I_t}{\sum_1^t \left[\frac{\{F_k^{-1}(p_{d,t})+F_k^{-1}(1-p_{u,t})\}}{\{F_k^{-1}(p_{d,t})-F_k^{-1}(1-p_{u,t})\}}\right]} \qquad (3),$$

where I_t is the actual inflation at time t.

To accommodate the excess kurtosis often found in quantitative expectation, Dasgupta and Lahiri (1992) experimented with the same with the scaled t distribution. Assuming constant thresholds that are symmetric around zero, the mean and standard deviation of the distribution of the unobserved point forecasts are given as,

$$\mu_t = \zeta \left[\frac{\{F_k^{-1}(p_{d,t})+F_k^{-1}(1-p_{u,t})\}}{\{F_k^{-1}(p_{d,t})-F_k^{-1}(1-p_{u,t})\}}\right] \qquad (4)$$

$$\sigma_t = \left[\frac{2\zeta\sqrt{\frac{k}{k-1}}}{\{F_k^{-1}(1-p_{u,t})-F_k^{-1}(p_{d,t})\}}\right] \qquad (5)$$

F_k is the CDF of a random variable with a t distribution having k degrees of freedom.

Later, Breitung and Schmeling (2013) and Lahiri and Zhao (2015) argued that the threshold may also vary over time and the CP method, which holds the assumption of a constant threshold, may underperform while quantifying qualitative IE. As experimented by Smith and McAleer (1995) and Mokinski et. al (2015), we extend the probability approach to allow for variation in thresholds over time. We assume that the threshold level ζ follows a random walk.

$$\zeta_t = \zeta_{t-1} + \varepsilon_t \qquad (6)$$

where ε_t is a Gaussian disturbance with a mean 0 and a variance σ_ε^2. With time-varying thresholds and normally distributed point forecasts, the mean and standard deviation of the latent distribution are

$$\mu_t = \zeta_t \left[\frac{\{\Phi^{-1}(p_{d,t})+\Phi^{-1}(1-p_{u,t})\}}{\{\Phi^{-1}(p_{d,t})-\Phi^{-1}(1-p_{u,t})\}}\right] \qquad (7)$$

$$\text{and } \sigma_t = \left[\frac{2\zeta_t}{\{\Phi^{-1}(1-p_{u,t})-\Phi^{-1}(p_{d,t})\}}\right] \qquad (8)$$

We estimate ζ_t, with the help of the following equation,

$$I_t = \zeta_t * S_t + \gamma_t \qquad (9)$$

where I_t is the proxy for the mean of the latent distribution and

$$S_t = \left[\frac{\{\Phi^{-1}(p_{d,t})+\Phi^{-1}(1-p_{u,t})\}}{\{\Phi^{-1}(p_{d,t})-\Phi^{-1}(1-p_{u,t})\}}\right] \qquad (10)$$

Equations (6) and (9) will specify the state space model, where I_t is the measurement variable and ζ_t is the state variable. This model is estimated by using the Kalman filter to obtain smoothed estimates of the time-varying thresholds (cf. Koopman, 1997). To get the disagreement measure, we impute the estimated thresholds and the shares of responses into equation (8). A valid proxy for the mean of the unobserved distribution I_t is calculated by using the realization of the target variable. By assuming survey respondents have perfect foresight, I_t is calculated as the average monthly inflation rate of the next 12 months (Atkeson and Ohanian, 2001, AO method). The second method is a random walk forecast where the one-year ahead IE will be the same as it has been over the last year (cf. Faust and Wright, 2013, FW method). For calculation of I_t, we have used CPI-U, CPI-C, and CPI Industrial Workers.

4.2 Ordered Probit Method

Next, to analyze the uncertainty and disagreement associated with the households IE, we jointly estimate the inflation expectations, disagreement, and uncertainty at the individual level as proposed by Zhao (2022) by using the ordered probit method with the pooled cross section data of IESH. The equations used for joint estimation are given below.

Let $y_{it}^{*} = y_{t}^{*} + K_{it}\beta + \xi_{it}$ *(11)*

Where y^{*}_{t} is the latent aggregate expectation, $K_{it}\beta$ captures the individual heterogeneity in the expectations and ξ_{it} is the heteroskedastic error term. We cannot directly observe, y_{it}^{*} and we can only observe the qualitative response.

$$y_{it} = \sum_{j=1}^{J}[j * I(\vartheta_{itj-1} < y_{it}^{*} \leq \vartheta_{itj})] \qquad (12)$$

Let ϑ_{itj} captures the cross-sectional heterogeneity in the thresholds. Let $f_{it}(.)$ be the latent density forecast of individual I with mean y_{it}^{*} and standard deviation σ_{it}, where σ_{it} varies over time and depends on individual specific factors $V_{it.}$ The two sets of individual characteristics, K_{it} and V_{it} may have elements in common. The aggregate density forecast, i.e. the average of individual densities,

$$f_{t}(y) \equiv n_{t}^{-1}\sum_{i=1}^{n_t} f_{it}(y) \qquad (13)$$

Where n_t is the number of individuals in the t^{th} round survey. Zhao (2022) had proposed the HOPIT model, which uses the panel data to jointly estimate inflation expectations, disagreement, and uncertainty. However, as IESH is conducted as repeated cross-sections, we have used an ordered probit model with a pooled cross-section to estimate y^{*}_{it} and σ_{it} by making use of the data on y_{it}, K_{it} and V_{it}, which maximizes the following likelihood function.

$$L = \sum_{t=1}^{T}\sum_{i=1}^{n_t}\left[I(y_{it}=1)\ ln\left\{\Phi\left(\frac{\vartheta_{t1} - y_{t}^{*} - K_{it}\beta}{\sigma_{it}}\right)\right\}\right] +$$
$$\sum_{t=1}^{T}\sum_{i=1}^{n_t}\left[I(y_{it}=2)\ ln\left\{\Phi\left(\frac{\vartheta_{t2} - y_{t}^{*} - K_{it}\beta}{\sigma_{it}}\right) - \Phi\left(\frac{\vartheta_{t1} - y_{t}^{*} - K_{it}\beta}{\sigma_{it}}\right)\right\}\right] +$$
$$\sum_{t=1}^{T}\sum_{i=1}^{n_t}\left[I(y_{it}=3) ln\left\{1 - \Phi\left(\frac{\vartheta_{t2} - y_{t}^{*} - K_{it}\beta}{\sigma_{it}}\right)\right\}\right] \qquad (14)$$

Where $\Phi(.)$ is the normal CDF and T is the total number of time periods in the data. The following specification is used to ensure ϑs are properly ordered and σ_{it} is positive, where $\vartheta_{tj} < \vartheta_{tj+1}\ \forall\ j \in \{1,2,3\}$ and $\vartheta_{t1}<0$.

$$\sigma_{it} = exp\ (\sigma_{t} + V_{it}\Upsilon_{3}) \qquad (15)$$

Next, we calculate individual and aggregate expectations, uncertainty, and disagreement of general IE. The aggregate expectation is the average of y_{it}^*s.

Disagreement among individuals can be measured using cross-sectional dispersion of y_{it}^*, $i.e.$,

$$D_t = [\, n_t^{-1} \sum_{i=1}^{n_t} (y_{it}^* - n_t^{-1} \sum_{i=1}^{n_t} y_{it}^*)^2]^{\frac{1}{2}} \qquad (16)$$

Individual uncertainty is defined as the dispersion of f_{it}, which is measured by using σ_{it}. As our model allows us to estimate individual uncertainty, the aggregate uncertainty is calculated as

$$U_t = [\, n_t^{-1} \sum_{i=1}^{n_t} \sigma_{it}^{*\,2}]^{\frac{1}{2}} \qquad (17)$$

4.3 Forward-looking properties of qualitative data by using the Phillips curve

Further, we check the forward-looking properties of the quantified qualitative inflation expectations by using the hybrid NKPC as proposed by Pattanaik et al. (2020) with and without supply-side shocks. (Equation 18 and 19). Crude oil prices are taken as the proxy for supply-side shock.

$$\pi_t = \Upsilon_1 \pi_{t-1} + \Upsilon_2 E_{t-1} \pi_t^e + \Upsilon_3\, Output\ Gap + \xi_t \qquad (18),$$

$$\pi_t = \Upsilon_1 \pi_{t-1} + \Upsilon_2 E_{t-1} \pi_t^e + \Upsilon_3\, Output\ Gap + \Upsilon_4\, Oil\ Price + \xi_t \qquad (19),$$

where π_t is the realized inflation at time t and $E_{t-1}\pi_t^e$ is the inflation expectation for the time t at time t-1, and the output gap is measured as the deviations of quarterly GDP from HP filter-based trend GDP.

4.4 Measures of dispersion

Finally, we study the disagreement on households' IE by using various methods. The first measure of dispersion is the index of qualitative variation (IQV) proposed by Gibbs and Poston (1975). The index of qualitative variation is calculated as follows:

$$IQV = \frac{J}{J-1} \left(1 - \sum_{i=1}^{j} p_i^2\right) \qquad (20)$$

Where J is the number of categories and p_i is the proportion of respondents in each category. However, Blair and Lacy (2000) criticized IQV for treating ordinal responses as nominal and introduced Blair and Lacy's (2000) measure of ordinal variation, 1- l^2, where l^2 is the normalized measure of the concentration of ordinal data and calculated as,

$$l^2 = \frac{\sum_{i=1}^{j-1}(F_i - \frac{1}{2})^2}{[\frac{j-1}{4}]} \qquad (21)$$

Where F_i is the cumulative response share of the category, i.e., $F_1 = p_1$, $F_2 = p_1 + p_2$. Another measure, namely, Kvalseth's (1995) coefficient of ordinal variation (COV) = 1- l. Apart from IQV, we have calculated Blair and Lacy's (2000) measure of ordinal variation and Kvalseth's (1995) coefficient of ordinal variation (COV) to measure the disagreements among households. Reardon's (2009) entropy-based measure of ordinal variation also measuring the dispersion by using a different distance formula based on aggregate data as mentioned below.

$$\gamma = \frac{\sum_{i=1}^{j-1}\left[F_i log_2\left(\frac{1}{F_i}\right) + (1-F_i) log_2\left(\frac{1}{1-F_i}\right)\right]}{(j-1)} \qquad (22)$$

Finally, we used the BES method, proposed by Bachmann et al. (2013) which measures the dispersion as the standard deviation of coded responses based on the formula given below.

$$BES = \sqrt{p_1 + p_3 - (p_1 - p_3)^2} \qquad (23)$$

All these five measures are scale-dependent and always lie between 0 and 1. Higher values indicate higher levels of dispersion, and lower values indicate lower levels of dispersion. Besides these five methods, we use the standard deviations derived from the probability approach and ordered probit method to study the disagreement on IE of households.

5. Analytical Results

5.1 Quantification of Qualitative IEs

Figures 1 and 2 capture the means of the quantified three-months-ahead and one-year-ahead qualitative general and item-wise IE calculated based on the CP method[7] with a constant threshold. After quantification, it was observed that the one-year-ahead IE are higher than the three-months-ahead IE both item-wise and general. The same is in the case for the quantitative IE. i.e., the median of one-year-ahead IE is higher than the median of three-months-ahead IE. The reduction in the CPI-C during 2014 as a part of inflation targeting had been captured by the qualitative IE too. The sharp fall is witnessed for the quantified three-months-ahead and one-year-ahead IE at general and item-wise levels during 2014. As we have observed in the other methods, the reduction in the mean of quantified IE by using the

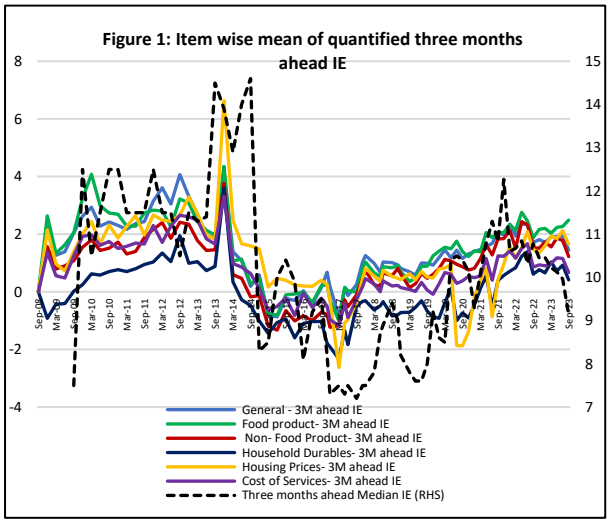
[7] The three-months-ahead and one-year-ahead IE were quantified by using the Carlson-Parkin Method and students' t distribution with constant thresholds both at the aggregate and item-wise level. The pattern of the means of the quantified IE are similar for both CP method and the t distribution. Hence, only the mean of the CP method is plotted in the paper.

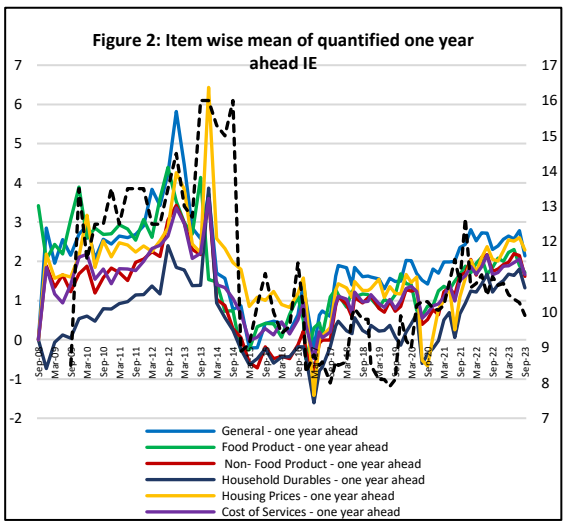
C-P method with time-varying thresholds and the ordered probit method was also observed during 2014 (Figures A2 and A3 in the Appendix). However, the mean value of the quantified IE calculated by using the C-P method with time-varying thresholds and the ordered probit method is highly volatile and impacted by the CPI changes[8]. The thresholds derived by the MSY method are portrayed in Figure A1 in the Appendix. It was noticed that the threshold values have also displayed a downward trend over the period along with the reduction in the actual inflation level.

On analyzing the three-months-ahead IE which is displayed in Figure 1, it was observed that during the past few years, respondents possess high three-months-ahead inflation expectations for food products, which is followed by non-food products. Their overall three-months-ahead IE is lower than their IE on food products but higher than other items. In general, households expect lower three months ahead inflation for household durables and services as compared to other items (Figure 1). On exploring one-year-ahead IE, it was found that the general one-year-ahead IE is higher than the item-wise IE. As in the case of three-months-ahead IE, household durables and cost of services recorded lower IE as compared to other items (Figure 2). Though households have comparatively high IE on housing, three months ahead IE and one year ahead IE on housing had fallen significantly during the period of the demonetization and the outbreak of COVID-19 and rose in the subsequent period. The correlation of item-wise IE with overall IE revealed that the three-months-ahead general IE is formed mainly based on their IE on food products followed by non-food products, and cost of services (Table A1 in the annexure). While households mainly focus on their IE on non-food products followed by the cost of services, and food products while forming one-year-ahead IE. It may also be noted that the non-food products contain fuel, for which households are highly sensitive.

It is evident from the results that households have distinct IE on different items, and their overall IE are mainly formed based on IE of food products, non-food products, and cost of services. Further, the individual item IE experiences varying effects from different macroeconomic shocks. Hence, the information on item-wise IE of households may provide more insights to the policymakers about households' actual IE.

[8] The quantification of qualitative IE by using the C-P method with time-varying thresholds and the ordered probit method incorporate information on CPI. Hence, by construction, the quantified IE by using these methods will fluctuate with actual inflation.





5.2 The factors affecting expectations and uncertainty

The results of the ordered probit model for one year ahead IE are displayed in Table 1 and that of three months ahead IE are portrayed in Table A2 in the Appendix. It can be observed that the three-months-ahead IE has a significant impact on forming one-year-ahead IE. The regression results reveal that the respondents who expect higher inflation in the next three months tend to expect higher inflation one year ahead too and vice versa (Table 1). Similarly, individuals below 40 years have higher inflation expectations compared to other groups, and female respondents' IE are higher than that of male respondents. The respondents who are in the daily wage category have higher IE than the respondents in other employment categories. Zhao (2021) has also experienced younger respondents, females, and those with lower levels of income and education typically have higher inflation expectations than their counterparts. The city and time have also had a significant impact in forming the IE of households. Over the period, the IE of households has come down gradually. It was observed that IE has come down significantly from 2014 onwards. The reduction in the CPI-C during 2014 as a part of inflation targeting had been captured by the qualitative IE too.

While focusing on the uncertainty part, it was revealed that the demographic factors influencing IE affect inflation uncertainty too. The respondents below 60 years are more uncertain than the other group which is consistent with Zhao (2021). Similarly, female respondents are more uncertain than male respondents, which is consistent with the findings of Binder (2017). The daily wage workers have high IE and are more certain about their

belief as compared to the respondents in other occupation categories. The uncertainty is impacted by the city also.

Table 1: Estimated coefficients of the Ordered Probit Model of one-year-ahead IE

	Students t - FW method		Students t - AO method		Normal - FW method		Normal - AO method	
Variable	Expectation equation	Uncertainty equation	Expectation equation	Uncertainty equation	Expectation equation	Uncertainty equation	Expectation equation	Uncertainty equation
Three months ahead IE								
Will increase	1.73***		1.62***		1.82***		1.76***	
Remain the same	Base		Base		Base		Base	
Will decrease	-0.88***		-0.83***		-0.92***		-0.89***	
Age								
Below 40	0.15***	0.085***	0.14***	0.08***	0.15***	0.08***	0.15***	0.08***
40 to 60	0.03*	0.05***	0.03***	0.05***	0.03*	0.05***	0.03*	0.05***
Above 60	Base	Base	Base	Base	Base	Base	Base	Base
Gender								
Male	-0.10***	-0.02***	-0.09***	-0.01**	-0.11***	-0.02***	-0.10***	-0.02***
Female	Base	Base	Base	Base	Base	Base	Base	Base
Occupation								
Daily wages	Base	Base	Base	Base	Base	Base	Base	Base
Financial sector	-0.04*	0.03**	-0.02	0.06***	-0.04**	0.02	-0.03	0.05***
Housewife	-0.09***	0.01	-0.07***	0.06***	-0.11***	-0.01	-0.08***	0.04***
Other category	0.04	0.04***	0.04*	0.06***	0.03	0.03**	0.04	0.05***
Other employees	-0.02	0.01	-0.01	0.04***	-0.02	-0.00	-0.01	0.02***
Retired persons	0.01	0.02*	0.02	0.06***	0.00	0.01	0.01	0.04***
Self employed	-0.06***	-0.01	-0.04***	0.02**	-0.06***	-0.02**	-0.05***	0.01
City	✔	✔	✔	✔	✔	✔	✔	✔
Time	✔	✔	✔	✔	✔	✔	✔	✔
Threshold levels								
Cut 1	-1.27		-1.25		-1.31		-1.33	
Cut 2	0.08		0.01		0.11		0.04	

Note: Coefficients of the city and time dummies are omitted. Each column represents each equation.

* (p<0.05),**(p<0.01),***(p<0.001)

5.3 Forward-looking properties of quantified qualitative IE

After quantification of the qualitative data, we verify the forward-looking properties of quantified three-months-ahead IE and one-year-ahead IE by fitting them into hybrid NKPC. We verify the forward-looking properties with CPI-IW, CPI-Urban, and CPI-combined by

using the IESH data from December 2013 to September 2023[9]. The Phillips curve was fitted with the three-months-ahead and one-year-ahead IE quantified with various methods like the CP and students' t distribution with constant and time-varying thresholds, ordered probit model with normal distribution, and t distribution. The ordered probit model is calculated with time-varying thresholds (both with AO and FW methods).

The results of the Phillips curve without oil prices for three-months-ahead IE are displayed in Table A3 in the Appendix, and those with oil prices are displayed in Table 2. The results of the Phillips curve without oil prices for one-year-ahead IE are displayed in Table A4 in the Appendix, and with oil prices are displayed in Table 3. For convenience, we define the models in the tables as follows. Model 1 - Normal Distribution and FW Method, Model 2 - Normal Distribution with constant threshold, Model 3 - Normal Distribution and AO Method, Model 4 - Student's t Distribution and FW Method, Model 5 - Student's t Distribution with constant threshold, Model 6 -Student's t Distribution with AO method, Model 7 - Ordered Probit model with normal distribution and AO method, Model 8 - Ordered Probit model with normal distribution and FW method, Model 9 - Ordered Probit model with student's t distribution and FW method, Model 10- Ordered Probit model with student's t distribution and AO method.

The regression results show that three-months-ahead IE has turned out to be significant in predicting CPI-C and CPI-U in models 1, 2, 3, 4, 5, and 6 without oil prices in Table A3. It was also observed that the quantified IE have more predictive power for predicting CPI-C and CPI-U than CPI-IW. While checking the predictive power in the models with oil prices, it was observed that three-months-ahead IE have turned out to be significant in predicting either CPI-C or CPI-U or both in models 1, 2, 3, 4, and 5 with oil prices in Table 2. Further, the three-months-ahead IE has turned out to be significant in predicting CPI-U with and without oil prices in the models 9 and 10. The past inflation appears to be statistically significant, and the output gap did not appear to be statistically significant in the models with three-months-ahead IE.

[9] We started the analysis with the data from 2008 onwards. However, we found a structural break in December 2013 in CPI-IW, CPI-Urban, and CPI-combined, which makes the data series (2008-2023) non-stationary. Hence, for fitting in the Phillips curve, we confined the data from December 2013 to September 2023, which is stationary.

The analysis of the forecasting ability of one-year-ahead IE revealed that one-year-ahead IE has turned out to be statistically significant for predicting CPI-IW, CPI-C and CPI-U in the models 8 and 10 with and without oil prices (Tables 3 and A4). The one-year-ahead IE also turned out to be statistically significant for predicting any of the CPI-IW, CPI-C and CPI-U as per the other models in Tables 3 and A4. When oil price is included in the model, the explanatory power has slightly improved, and the output gap appears statistically significant for CPI-C and CPI-U. However, the past inflation did not appear to be statistically significant in the models with one year ahead IE.

It was observed from the study that the models with three-months-ahead IE seem to have a better fit than the models with one-year-ahead IE. The value of the coefficients of the three-months-ahead IE and one-year-ahead IE are higher in models 7, 8, 9, and 10 than that of other models (Tables 2, A3, 3, and A4). This implies that the qualitative IE quantified by ordered probit models has better predictive power than the quantified IE by other methods. Further, the results show that households' IE are more effective in predicting CPI-U and CPI-C than CPI-IW.

Table 2: Phillips curve with oil prices with IE three months ahead IE

	Model 1			Model 2			Model 3			Model 4			Model 5		
	CPI-IW	CPI-C	CPI-U	CPI-IW	CPI-C	CPI-U	CPI-IW	CPI-C	CPI-U	CPI-IW	CPI-C	CPI-U	CPI-IW	CPI-C	CPI-U
Three months ahead IE	0.05	0.01*	0.09	0.18	0.33*	0.30	0.09	0.09*	0.09*	0.04	0.09*	0.08	0.17	0.32	0.30
Inflation (-1)	0.65***	0.63***	0.59***	0.65***	0.63***	0.59***	0.60***	0.63***	0.59***	0.65***	0.63***	0.60***	0.65***	0.64***	0.59***
Output Gap	3.99	-5.53	-4.66	3.52	-5.53	-4.74	4.49	-5.51	-4.65	3.60	-5.49	-4.67	3.47	-5.48	-4.74
Oil Price	0.01	0.02	0.02*	0.01	0.02	0.02*	0.00	0.02	0.02*	0.01	0.02	0.02*	0.01	0.02	0.02*
C	1.72***	1.62***	1.79***	1.72***	1.61***	1.78***	1.87***	1.62***	1.80***	1.72***	1.60***	1.78***	1.71***	1.58***	1.78***
Adjusted R-squared	0.51	0.69	0.65	0.51	0.69	0.65	0.53	0.69	0.65	0.51	0.70	0.65	0.51	0.69	0.65
Number of observations	40	40	38	40	40	38	40	40	38	40	40	38	40	40	38
	Model 6			Model 7			Model 8			Model 9			Model 10		
	CPI-IW	CPI-C	CPI-U	CPI-IW	CPI-C	CPI-U	CPI-IW	CPI-C	CPI-U	CPI-IW	CPI-C	CPI-U	CPI-IW	CPI-C	CPI-U
Three months ahead IE	0.09	0.08*	0.09	0.29	0.29	0.40*	0.19	0.28	0.46*	0.09	0.27	0.44*	0.29	0.27	0.39*
Inflation (-1)	0.59***	0.63***	0.59***	0.60***	0.59***	0.58***	0.59***	0.59***	0.58***	0.60***	0.59***	0.59***	0.60***	0.59***	0.58***
Output Gap	4.39	-5.47	-4.63	3.51	-6.14	-4.75	3.52	-6.16	-4.73	3.43	-6.15	-4.72	3.51	-6.15	-4.73
Oil Price	0.00	0.02	0.02*	0.01	0.03	0.02*	0.01	0.03	0.02*	0.01	0.03	0.02*	0.01	0.03	0.02*
C	1.90***	1.60***	1.79***	2.21***	1.86***	1.80***	2.03***	1.91***	1.82***	2.05***	1.84***	1.80***	2.21***	1.84***	1.77***
Adjusted R-squared	0.53	0.69	0.65	0.39	0.62	0.66	0.39	0.62	0.66	0.39	0.62	0.66	0.39	0.62	0.66
Number of observations	40	40	38	39	39	38	39	39	38	39	39	38	39	39	38

* (p<0.05),**(p<0.01),***(p<0.001)

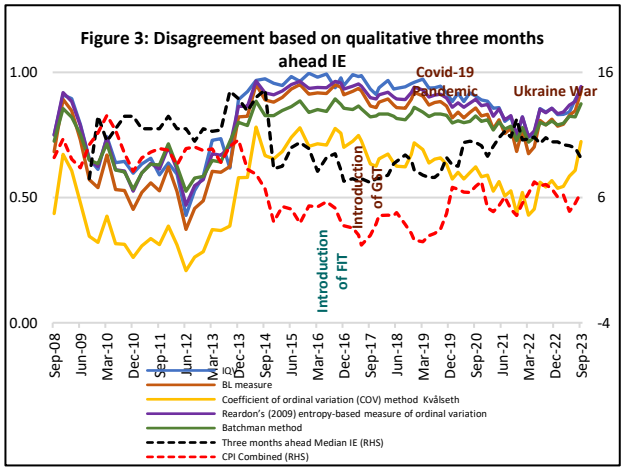
Table 3: Phillips curve with oil prices with one-year-ahead IE

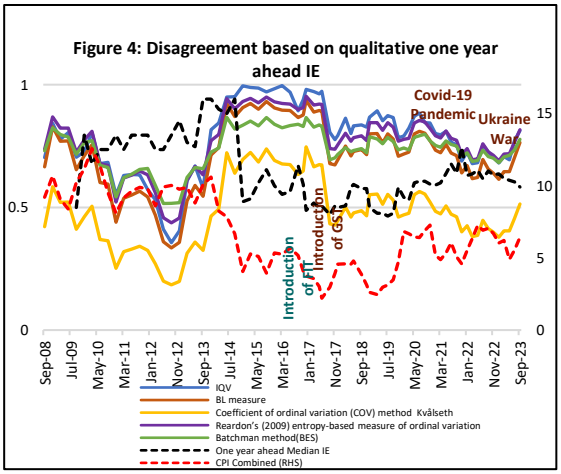
	Model 1			Model 2			Model 3			Model 4			Model 5		
	CPI-IW	CPI-C	CPI-U	CPI-IW	CPI-C	CPI-U	CPI-IW	CPI-C	CPI-U	CPI-IW	CPI-C	CPI-U	CPI-IW	CPI-C	CPI-U
One year ahead IE	0.09	0.22**	0.25***	0.26***	0.27***	0.26***	0.32**	0.23	0.29***	0.09	0.16	0.30***	0.25***	0.25***	0.26***
Inflation (-1)	0.12	0.13	-0.07	0.03	0.04	-0.13	-0.09	0.10	-0.13	0.12	0.21*	-0.09	0.06	0.08	-0.13
Output Gap	6.10	16.35***	12.75***	4.19	14.82***	12.42***	5.54	-15.53**	12.37***	6.10	16.35***	12.35***	4.68	14.88***	-12.24***
Oil Price	0.00	0.04*	0.04*	-0.01	0.03*	0.03*	0.01	0.04	0.03*	0.00	0.04	0.03*	-0.01	0.04*	0.03*
C	4.28***	3.57***	4.27***	4.02***	3.69***	4.44***	4.48***	3.66***	4.44***	4.28***	3.49***	4.27***	3.86***	3.55***	4.40***
Adjusted R-squared	0.04	0.31	0.33	0.22	0.418	0.41	0.22	0.307	0.41	0.04	0.24	0.36	0.20	0.38	0.40
Number of observations	40	40	35	40	40	35	40	40	35	40	40	35	40	40	35
	Model 6			Model 7			Model 8			Model 9			Model 10		
	CPI-IW	CPI-C	CPI-U	CPI-IW	CPI-C	CPI-U	CPI-IW	CPI-C	CPI-U	CPI-IW	CPI-C	CPI-U	CPI-IW	CPI-C	CPI-U
One year ahead IE	0.26**	0.15	0.36***	1.26**	0.84**	0.85***	1.29**	0.99**	1.08***	1.34**	1.06**	1.17***	1.39***	0.10*	1.04***
Inflation (-1)	-0.05	0.20	-0.13	-0.00	0.06	-0.09	0.01	0.07	-0.08	0.08	0.07	-0.08	-0.00	0.07	-0.09
Output Gap	5.50	-15.76**	-12.16	4.11	14.84***	12.31***	4.17	14.86***	12.23***	4.16	14.85***	12.16***	4.03	14.81***	-12.21***
Oil Price	0.01	0.04	0.03***	-0.02	0.04	0.03*	-0.02	0.04	0.03***	-0.01	0.04	0.03*	-0.01	0.04	0.03*
C	4.52***	3.56***	4.44*	4.04***	4.09***	4.31***	4.53***	4.30***	4.62***	4.53***	4.32***	4.64***	3.89***	4.32***	4.59***
Adjusted R-squared	0.17	0.23	0.42	0.13	0.26	0.38	0.12	0.26	0.37	0.12	0.26	0.37	0.13	0.26	0.38
Number of observations	40	40	35	38	38	35	38	38	35	38	38	35	38	38	35

* (p<0.05),**(p<0.01),***(p<0.001)

5.4 Disagreement among Respondents

Figure 3 and Figure 4 depict the disagreements calculated based on the three-months-ahead and one-year-ahead qualitative IE, respectively. The disagreement was lower during the high inflation phase of 2008 to 2013 (pre-inflation targeting period) and comparatively higher during the subsequent low inflation phase i.e. 2014 onwards (post-inflation targeting period). Though the disagreement started gradually reducing from 2017 onwards, the high inflation episode happened in 2022–23 due to geopolitical tensions causing an increase in the disagreement. Moreover, the Standard Deviation (SD) of three months ahead and one-year-ahead IE, i.e., the measure of disagreement for quantitative IE, has also increased during the post-inflation targeting period (Figure A4 in Appendix). This supports the fact that the sharp inflation changes in either direction may lead to a rise in the disagreement of IE (Mankiw et al., 2003).





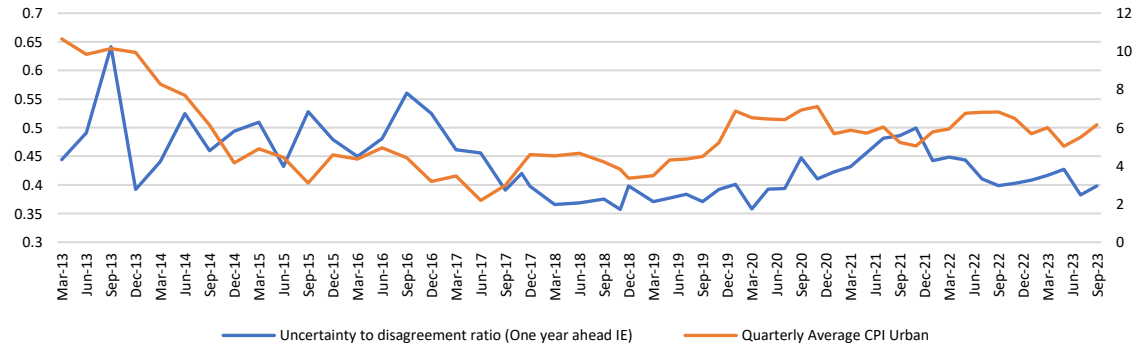
It was observed that while analyzing the item-wise three-months-ahead IE, in the past few years, the disagreement was higher for housing prices, followed by household durables and the cost of services (Figure A5 in the Appendix). The respondents had comparatively lower and the same level of disagreement on the IE of food products and non-food products during most of the period. The disagreement on general IE was comparatively lower than disagreement on the IE of other items.

The study on the disagreement of one year ahead IE revealed that, the disagreement on general IE was found to be comparatively lower from 2016 onwards. The disagreement on

housing prices and household durables was also higher (Figure A6 in the Appendix). The disagreement on food products and non-food products was similar in the recent period. In general, for items like food products and non-food products, households expect higher inflation with less uncertainty. While they expect comparatively lower inflation for household durables with comparatively higher uncertainty. Moreover, the respondents are comparatively highly uncertain and expect higher IE about housing prices.

Further, we have studied the relationship between uncertainty and disagreement. Studies have proved that uncertainty and disagreement do not always move in coordination (Glas and Hartmann, 2016; Binder, 2017; Zhao, 2021). The concordance between uncertainty and disagreement was verified by using the ratio of uncertainty to disagreement as proposed by Zhao (2021). The uncertainty and disagreement were calculated based on equations 16 and 17. Figure 5 portrays the ratio of uncertainty to disagreement for one year ahead IE and the average CPI – U. It was observed that uncertainty has increased during the period of inflation reduction as a part of the implementation of flexible inflation targeting (FIT) and during the outbreak of COVID–19 pandemic and the geopolitical tensions.

Figure 5: Uncertainty to disagreement ratio



6. Conclusion

Central banks monitor the inflation expectations of various agents including households, as these expectations play a crucial role in influencing actual inflation. While the overall IE are available for various countries, the item wise IE are also available in addition to the overall IE for Indian households. As they are available in qualitative terms and due to difficulties in quantifying them, they were less explored in the literature. Moreover, the studies have

proved that the quantitative IE available at aggregate level are generally biased and not rational. In such scenario, this study aimed to gain insights from the qualitative IE available at aggregate level and at item-wise level. Further, as uncertainty plays a crucial role in the formation of IE, the study investigated the pattern of uncertainties and disagreements associated with households' IE during various macro-economic episode in India and the factors affecting them.

Our findings indicate that the qualitative IE, both at the aggregate level and the item-specific level, provides valuable insights for policy formulation. Indian households have diverse opinions on the IE of various items, and they are influenced by various macroeconomic shocks differently. While forming overall IE, households give higher weightage for food products, cost of services and non-food products. Furthermore, the quantified three-months-ahead IE and one-year-ahead IE were found to be statistically significant in predicting inflation. The demographic characteristics of the respondents influence their qualitative IE and the associated uncertainty. Further, the study revealed that, the inflation shocks in either direction resulted in heightened disagreements on the households' IE.

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Appendix

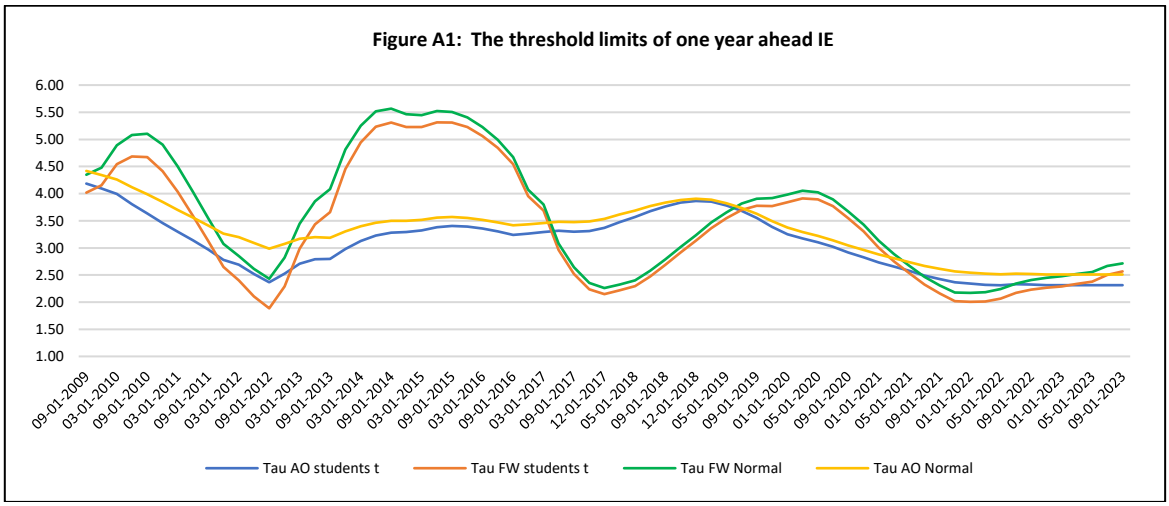
Figure A1: The threshold limits of one year ahead IE
6.00
5.50
5.00
4.50
4.00
3.50
3.00
2.50
2.00
1.50
1.00
09-01-2009
03-01-2010
09-01-2010
03-01-2011
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Tau FW Normal
Tau AO Normal

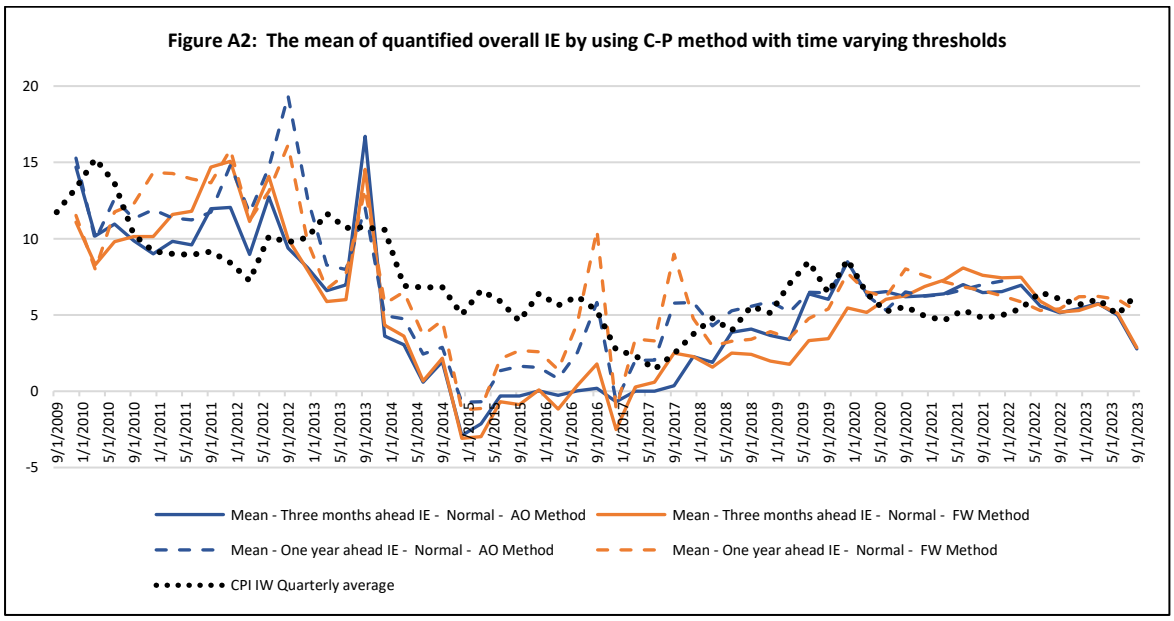
Figure A2: The mean of quantified overall IE by using C-P method with time varying thresholds
20
15
10
5
0
-5
9/1/2009
1/1/2010
5/1/2010
9/1/2010
1/1/2011
5/1/2011
9/1/2011
1/1/2012
5/1/2012
9/1/2012
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1/1/2022
5/1/2022
9/1/2022
1/1/2023
5/1/2023
9/1/2023
Mean - Three months ahead IE - Normal - AO Method
Mean - Three months ahead IE - Normal - FW Method
Mean - One year ahead IE - Normal - AO Method
Mean - One year ahead IE - Normal - FW Method
CPI IW Quarterly average

Figure A3: The mean of quantified overall IE by using ordered probit method

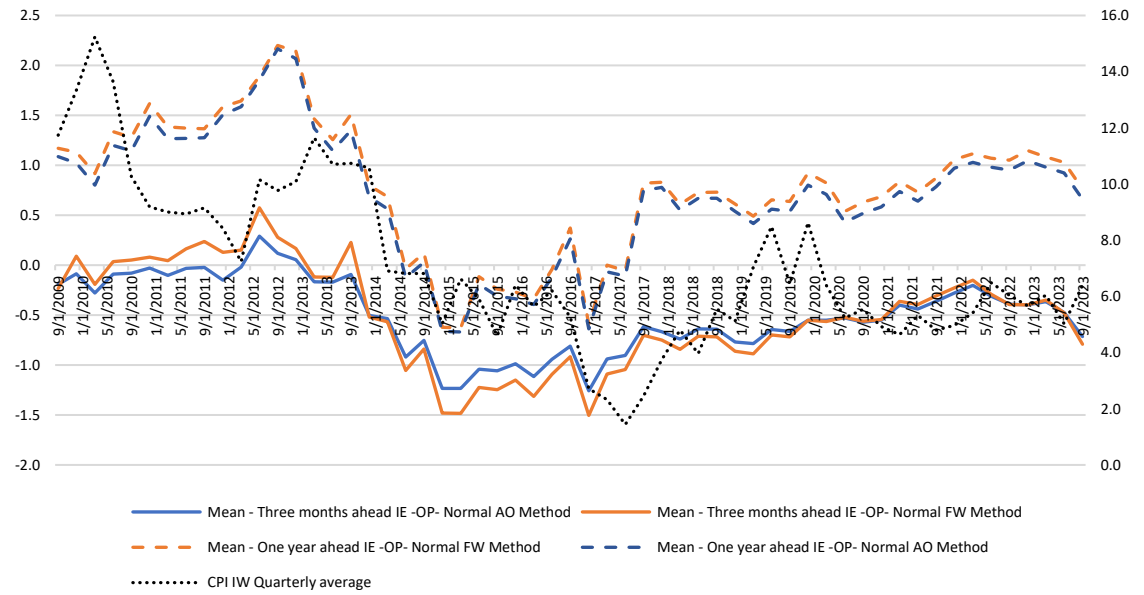
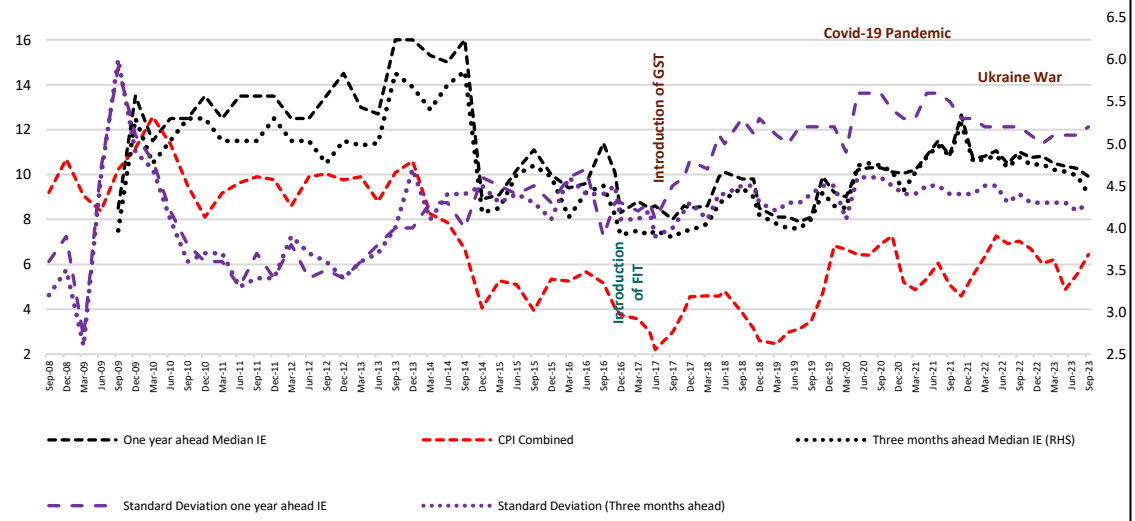
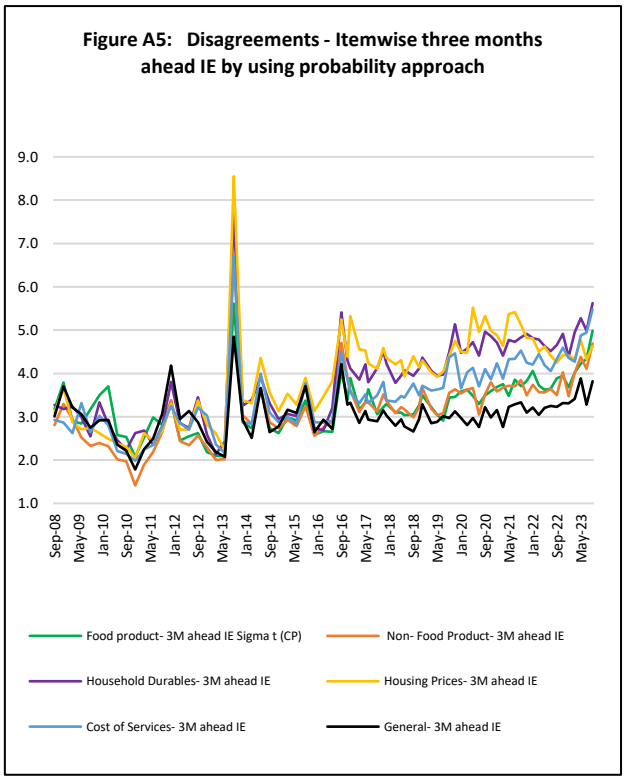


Figure A4: Disagreement based on quantitative three months ahead and one year ahead IE





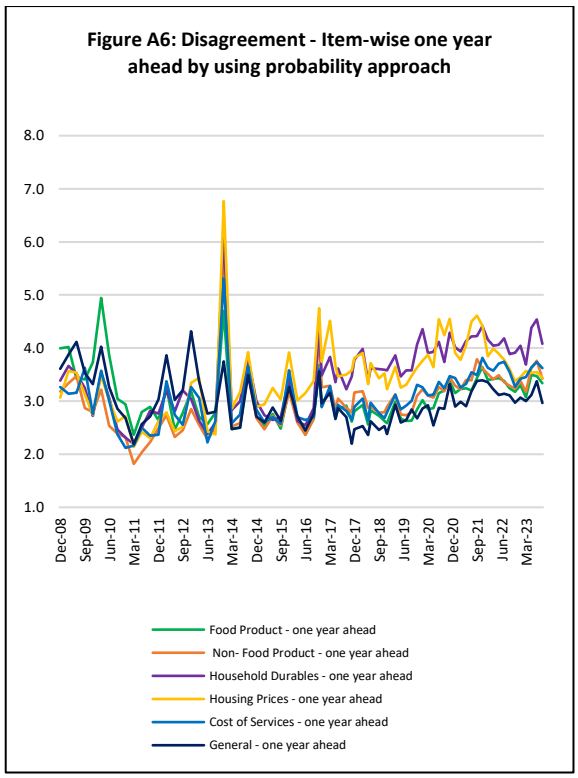


Table A1: Correlation of item-wise IE with overall IE [IE and Disagreement]

	Correlation with overall IE		Correlation with disagreements of overall IE	
Item	Three months Ahead	One year Ahead	Three months Ahead	One year Ahead
General	1	1	1	1
Food products	0.95	0.92	.78	.77
Non - food products	0.94	0.96	.83	.50
Household Durables	0.87	0.79	.69	.32
Housing	0.73	0.74	.64	.31
Cost of services	0.95	0.94	.72	.60

Table A2: Estimated coefficients of the Ordered Probit Model of three-months-ahead ahead IE

	Students t - FW method		Students t - AO method		Normal - FW method		Normal - AO method	
Variable	Expectation equation	Uncertainty equation	Expectation equation	Uncertainty equation	Expectation equation	Uncertainty equation	Expectation equation	Uncertainty equation
Age								
Below 40	0.03*	0.03**	0.02*	0.03**	0.03**	0.03**	0.02**	0.027**
40 to 60	-0.03	0.04***	-0.02*	0.03**	-0.02***	0.03***	-0.02**	0.03**
Above 60	Base	Base	Base	Base	Base	Base	Base	Base
Gender								
Male	-0.27***	-0.074***	-0.15***	-0.07***	-0.19***	-0.08***	-0.15***	-0.07***
Female	Base	Base	Base	Base	Base	Base	Base	Base
Occupation								
Daily wages	Base	Base	Base	Base	Base	Base	Base	Base
Financial sector	-0.18***	0.02	-0.12***	-0.03**	-0.13***	0.03**	-0.12***	-0.03**
Housewife	-0.21***	-0.06***	-0.12***	-0.10***	-0.15***	-0.06***	-0.13***	-0.10***
Other category	-0.08***	-0.01	-0.05***	-0.05***	-0.05***	0.03	-0.05***	-0.05***
Other employees	-0.10***	-0.02	-0.07***	-0.06***	-0.07***	-0.01	-0.07***	-0.06***
Retired persons	-0.01	0.04**	-0.02*	-0.01	-0.00	0.05***	-0.03*	-0.01
Self employed	-0.17***	-0.00***	-0.11***	-0.05***	-0.12***	0.01	-0.11***	-0.05***
City	✔	✔	✔	✔	✔	✔	✔	✔
Time	✔	✔	✔	✔	✔	✔	✔	✔
Threshold levels								
Cut 1	-2.11		-1.39		-1.69		-1.40	
Cut 2	-0.80		-0.69		-0.77		-0.70	

Table A3: Phillips curve without oil prices with three-months-ahead IE

	Model 1			Model 2			Model 3			Model 4			Model 5		
	CPI-IW	CPI-C	CPI-U	CPI-IW	CPI-C	CPI-U	CPI-IW	CPI-C	CPI-U	CPI-IW	CPI-C	CPI-U	CPI-IW	CPI-C	CPI-U
Three months ahead IE	0.06	0.12**	0.11**	0.21	0.40**	0.39**	0.09	0.11**	0.12**	0.05	0.11**	0.11**	0.21	0.40**	0.39**
Inflation (-1)	0.63***	0.61***	0.56***	0.63***	0.61***	0.57***	0.59***	0.61***	0.56***	0.63***	0.61***	0.57***	0.63***	0.62***	0.57***
Output Gap	4.63	-4.10	-3.31	4.10	-4.10	-3.37	4.80	-4.09	-3.30	4.23	-4.03	-3.28	4.09	-4.01	-3.34
C	1.79***	1.65***	1.84***	1.79***	1.64***	1.83***	1.90***	1.65***	1.85***	1.79***	1.63***	1.83***	1.78***	1.60***	1.82***
Adjusted R-squared	0.52	0.68	0.63	0.52	0.68	0.63	0.54	0.68	0.63	0.52	0.68	0.63	0.52	0.68	0.63
Number of observations	40	40	38	40	40	38	40	40	38	40	40	38	40	40	38
	Model 6			Model 7			Model 8			Model 9			Model 10		
	CPI-IW	CPI-C	CPI-U	CPI-IW	CPI-C	CPI-U	CPI-IW	CPI-C	CPI-U	CPI-IW	CPI-C	CPI-U	CPI-IW	CPI-C	CPI-U
Three months ahead IE	0.10	0.10**	0.11**	0.38	0.40	0.52	0.26	0.38	0.59	0.13	0.38	0.56**	0.38	0.37	0.50**
Inflation (-1)	0.58***	0.61***	0.56***	0.58***	0.57***	0.55***	0.58***	0.57***	0.56***	0.58***	0.57***	0.56***	0.58***	0.57***	0.56***
Output Gap	4.69	-4.01	-3.25	4.05	-4.52	-3.36	4.08	-4.53	-3.33	4.02	-4.50	-3.31	4.05	-4.49	-3.32
C	1.94***	1.63***	1.84***	2.33***	1.87***	1.84***	2.08***	1.93***	1.87***	2.11***	1.84***	1.84***	2.32***	1.84***	1.81***
Adjusted R-squared	0.54	0.68	0.63	0.41	0.60	0.63	0.41	0.60	0.63	0.41	0.60	0.63	0.41	0.60	0.63
Number of observations	40	40	38	39	39	38	39	39	38	39	39	38	39	39	38

* (p<0.05),**(p<0.01),***(p<0.001)

Table A4: Phillips curve without oil prices with one-year-ahead IE

	Model 1			Model 2			Model 3			Model 4			Model 5		
	CPI-IW	CPI-C	CPI-U	CPI-IW	CPI-C	CPI-U	CPI-IW	CPI-C	CPI-U	CPI-IW	CPI-C	CPI-U	CPI-IW	CPI-C	CPI-U
One year ahead IE	0.09	0.22**	0.24***	0.25***	0.27***	0.25***	0.31**	0.24	0.28***	0.09	0.16	0.29***	0.25***	0.252** *	0.25***
Inflation (-1)	0.12	0.10	-0.05	0.04	0.01	-0.12	-0.09	0.07	-0.12	0.12	0.18	-0.07	0.07	0.045	-0.11
Output Gap	6.24	-13.61**	-10.48**	3.73	-12.25**	-10.24**	5.99	-13.11**	-10.27**	6.24	-13.66**	-10.21**	4.26	-12.29**	-10.11**
C	4.30***	3.72***	4.26***	3.95***	3.83***	4.42***	4.53***	3.78***	4.42***	4.30***	3.63***	4.26***	3.80***	3.69***	4.38***
Adjusted R-squared	0.07	0.27	0.27	0.24	0.38	0.36	0.24	0.28	0.36	0.07	0.20	0.31	0.21	0.34	0.35
Number of observations	40	40	35	40	40	35	40	40	35	40	40	35	40	40	35
	Model 6			Model 7			Model 8			Model 9			Model 10		
	CPI-IW	CPI-C	CPI-U	CPI-IW	CPI-C	CPI-U	CPI-IW	CPI-C	CPI-U	CPI-IW	CPI-C	CPI-U	CPI-IW	CPI-C	CPI-U
One year ahead IE	0.25***	0.17	0.35***	1.25***	0.83**	0.82***	1.28**	0.98**	1.02***	1.34**	1.04**	1.13***	1.38***	0.99**	1.00***
Inflation (-1)	-0.05	0.17	-0.13	0.02	0.04	-0.08	0.03	0.04	-0.07	0.03	0.04	-0.07	0.02	0.04	-0.08
Output Gap	5.96	-13.26**	-10.13**	3.52	-12.45**	-10.15**	3.58	-12.45**	-10.10**	3.57	-12.43**	-10.04**	3.46	-12.42**	-10.08**
C	4.57***	3.67***	4.42***	3.93***	4.24***	4.29***	4.42***	4.45***	4.60***	4.43***	4.46***	4.61***	3.79***	4.46***	4.56***
Adjusted R-squared	0.19	0.21	0.37	0.15	0.22	0.33	0.13	0.22	0.32	0.13	0.22	0.32	0.15	0.22	0.33
Number of observations	40	40	35	38	38	35	38	38	35	38	38	35	38	38	35

* (p<0.05),**(p<0.01),***(p<0.001)