

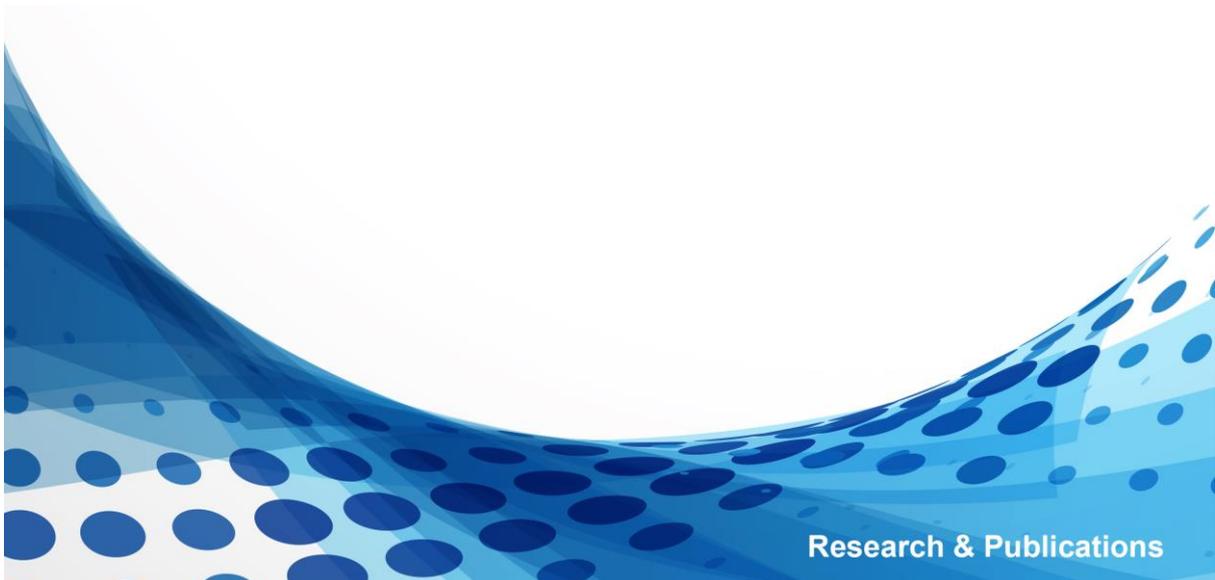


INDIAN INSTITUTE OF MANAGEMENT AHMEDABAD

IIMA
Working Paper

Determinants of Disagreement: Learning from Indian Inflation Expectations Survey of Households

Gaurav Kumar Singh
Tathagata Bandyopadhyay



Research & Publications

Determinants of Disagreement: Learning from Indian Inflation Expectations Survey of Households

Gaurav Kumar Singh
Tathagata Bandyopadhyay

January 2021

The main objective of the working paper series of the IIMA is to help faculty members, research staff and doctoral students to speedily share their research findings with professional colleagues and test their research findings at the pre-publication stage. IIMA is committed to maintain academic freedom. The opinion(s), view(s) and conclusion(s) expressed in the working paper are those of the authors and not that of IIMA.

Determinants of Disagreement: Learning from Indian Inflation Expectations Survey of Households

Gaurav Kumar Singh*, Tathagata Bandyopadhyay*

ABSTRACT

This study explores the determinants of disagreement in households' belief on future inflation. Households commonly show strong information rigidity as a consequence of stickiness in their information update (Mankiw and Reis, 2002, 2006). This paper contributes to the understanding of the formation of disagreement of the Indian households by investigating the effects of - day to day purchasing experiences of the agents, the intensity of news about inflation in the media, and central bank transparency. We find the positive effects of their recent price experiences, media influence, and inflation targeting on lowering the disagreement. Female and Young people tend to exhibit stronger effects in comparison to their counterparts.

KEYWORDS

Survey expectations, Inflation forecasts, Forecast disagreement

JEL D840, E31, E37

1. Introduction

Since Milton Friedman's famous presidential address to the American Economic Association in 1968, inflation expectation has been playing a prominent role in the analysis of monetary policy. "How much expectations matter, whether they are adaptive or rational, how quickly they respond to changes in the policy regime, and many related issues have generated heated debate and numerous research studies" (Mankiw, Reis, and Wolfers, 2004). Surprisingly, however, until around 2000, one obvious fact is routinely ignored that everyone does not have the same expectation. The reason for this oversight is, till 90's, the standard macroeconomic theory is dominated by the models that assume economic agents form expectations rationally, i.e., all agents share the same information set, and conditional on it they form expectations using the same forecasting model. So everyone has the same expectation, and naturally, there is no room for disagreement. However, with survey data gaining acceptance in the macroeconomics literature, pronounced time-variation in disagreement is considered to be a stylized fact of the survey responses (cf. Mankiw et al. (2004), Capistran and Timmermann (2009), Doornik, Fritsche, and Slacalek (2012), Mokinski, Sheng, and Yang (2015), Andrade, Crump, Eusepi, and Moench (2016), Brito, Carriere-Swallow, and Gruss (2018)).

Mankiw et al. (2004), having noted that the disagreement is correlated with a number of important macroeconomic variables, suggest that "disagreement may be a key to macro-economic dynamics." This view concurs well with the theoretical models proposed by Lucas (1973) and Townsend (1983) where heterogeneity in agents' beliefs

*Indian Institute of Management, Ahmedabad (IIMA)

play a key role. Recently, [Falck, Hoffmann, and Hurtgen \(2019\)](#) cite an empirical evidence to demonstrate that the level of disagreement may have a strong moderating effect on the outcome of a monetary policy decision. “A contractionary 100 bps U.S. monetary policy shock leads to an increase in inflation and inflation expectations of up to 0.7 percentage points in times of high disagreement, whereas in times of low disagreement it leads to a significant decline in these variables of around 0.8 percentage points.” Thus, tightening monetary policy fails to generate the intended effect of lowering inflation and inflation expectations when disagreement is high. [Brito et al. \(2018\)](#) argue that recognizing the determinants of disagreement is important because, “disagreement about the future may lead to misallocation of resources and impose welfare costs, ... Second, disagreement about future inflation is thought to provide a proxy for the degree to which inflation expectations are well anchored, and is thus important for the conduct of monetary policy.” Further, in the recent macroeconomics literature the theoretical models assuming agents with heterogeneous beliefs are growing ([Brock and Hommes \(1997\)](#), [Souleles \(2004\)](#), [Malmendier and Nagel \(2016\)](#), [Armantier, Nelson, Topa, van der Klaauw, and Zafar \(2016\)](#)). Empirical properties of disagreement are crucial to confront such models. For efficient conduct of monetary policy, it is, thus, important to recognize the plausible determinants of disagreement, and also, to understand the process of disagreement formation.

As noted by [Lamla and Maag \(2012\)](#), on the empirical side, the literature on the determinants of disagreement is relatively small and mostly centres on professional disagreement.² Most importantly, however, almost all studies on disagreement are based on survey data from the developed economies. Disagreement being a manifestation of economic and social behaviour of the economic agents, the determinants of disagreement and the process of its formation in a developing country like India may be very different from what have been observed in the developed economies. The main contribution of this paper is to bring this distinction into the fore. Our empirical findings based on IESH data³, vindicate this presumption. For example, IESH data show that disagreement is negatively correlated with inflation rate contrary to the findings⁴ in developed economies. This being a surprise finding, we offer an explanation by invoking existing theories⁵ of expectation formation. More importantly, our empirical findings suggest, as opposed to the changes in macroeconomic variables, the day to day purchasing experiences of the agents, their idiosyncratic characteristics, the intensity of media coverage of news about inflation, and inflation targeting by the central bank

²See for example, [Ciro and Zapata \(2019\)](#), [Brito et al. \(2018\)](#), [Oliveira and Curi \(2016\)](#), [Dovern et al. \(2012\)](#), [Patton and Timmermann \(2010\)](#), [Capistran and Timmermann \(2009\)](#), [Lahiri and Sheng \(2008\)](#), [Batchelor \(2007\)](#), [Fritsche and Döpke \(2006\)](#), [Giordani and Söderlind \(2003\)](#) and references therein. For empirical research on household disagreement, see [Lyziak and Sheng \(2018\)](#), [Johannsen \(2014\)](#), [Badarinza and Gross \(2012\)](#), [Badarinza and Buchman \(2009\)](#), [Mankiw et al. \(2004\)](#), [Branch \(2004, 2007\)](#). Also, some of the studies have considered disagreement in both professional and household, such as [Alexander Ballantyne and Rankin \(2016\)](#), [Siklos \(2013\)](#), [Lamla and Maag \(2012\)](#), [Ehrmann, Eijffinger, and Fratzscher \(2012\)](#), [Mankiw et al. \(2004\)](#) among others.

³The Reserve Bank of India (RBI), has been conducting quarterly Inflation Expectations Survey of Households (IESH) since September 2005. The survey elicits responses on households’ inflation expectations for next quarter and one year ahead. Beginning with 4 metros, the survey has subsequently been expanded to 18 cities in a phase-wise manner, where 500 respondents are picked from a metro and 250 respondents from a non-metro city. The empirical analysis presented here consider data collected from twelve cities (4 metro and 8 non-metro) to ensure a reasonably long time horizon.

⁴See [Cukierman and Wachtel \(1979\)](#), [Valev and Carlson \(2003\)](#), [Carroll \(2003\)](#), [Mankiw et al. \(2004\)](#), and [Souleles \(2004\)](#) for evidence of a positive correlation.

⁵See [Coibion, Gorodnichenko, and Kamdar \(2018\)](#) for a survey on how economic agents form their expectations.

influence disagreement directly. In other words, the agents, in order to form their inflation expectations, do not seem to follow the changes in the macroeconomic variables; rather, they pick up signals from media and their day to day purchasing experiences. Also, we find that the household forecasts are biased, and they tend to overpredict during the high inflation regime. The empirical results are presented in Sections 4 & 5.

The paper is organized as follows. In Section 2, we explore the patterns in the time variation of disagreement from the data using graphs and charts. In Section 3, we identify a set of plausible determinants of disagreement from the existing literature, and posit a series of hypotheses about their effects on it. For formulation of hypotheses we invoke existing theories of inflation expectations formation. The hypotheses are then tested in Section 4 using the IESH data. Finally, in Section 5, we test whether there is an evidence of bias in the inflation forecasts affecting disagreement, and if so, how is it related to the actual inflation.

2. Data, Measure & Patterns of Disagreement

2.1. Data & Measure of Disagreement

The IESH collects inflation expectations data by asking quarter-ahead, and year-ahead directional change of “prices in general” in one of the following categories: whether it is going to “increase more than the current rate” (C_1), “increase similar to the current rate” (C_2), “increase less than the current rate” (C_3), “no change” (C_4) or “decline” (C_5). Let F_i denote the fraction of household responses in the category C_i , $i = 1, 2, \dots, 5$. For qualitative inflation forecasts, various competing measures of disagreement are proposed in the literature. However, there does not seem to be a consensus among the researchers about which one is appropriate. These measures of variability are based on either quantified expectations (Dasgupta and Lahiri (1992), Mankiw et al. (2004)), or ordinal responses (Ehrmann et al. (2012), Bachmann, Elstner, and Sims (2013)) or nominal responses (Thomas (2010), Lamla and Maag (2012)). For our empirical analysis we use index of qualitative variation (IQV), a measure based on nominal responses. For responses classified into K categories, it is defined as $\frac{K}{K-1}(1 - \sum_{i=1,2,\dots,K} p_i^2)$, where p_i is the fraction of responses in the i th category. It varies between 0 and 1, and is equal to 1 when p_i ’s are all equal, and equal to 0 when one of the p_i ’s is equal to 1. Thomas (2010) observes that IQV outperforms other measures for five-category qualitative response data.

For the empirical analysis presented here we consider one quarter ahead household inflation forecasts data for the period 2010 : Q3 (IESH: round 21) to 2019 : Q3 (IESH: round 57). Although the survey started in 2005 : Q3 (round 1), it became stable only in 2008 : Q3 (round 13) (Das, Lahiri, and Zhao, 2018). Further, we avoid the highly volatile period, 2008 : Q4 (round 14) to 2010 : Q2 (round 20), caused by the global financial crisis.

2.2. Patterns of Disagreement

Figure 1 shows a series of segmented vertical bars across different rounds, each bar representing the response fractions in five categories mentioned above. On the same

diagram, we plot the quarterly inflation rate (IR)⁶. Notice that, during the high inflation regime⁷, F_1 varies between 0.65 to 0.83, while the combined fractions of responses in the categories C_1 and C_2 between 0.86 to 0.96. However, with the onset of the low inflation regime, F_1 and F_2 gradually decrease. From 2018 onward, with increase in IR , F_1 and F_2 both show an increasing trend. Notice that, during the high inflation regime, the agents' inflation forecasts show a tendency to persist, and are biased towards the category C_1 .

Figure 1. Response Fractions (F_1, F_2, F_3, F_4, F_5) of Inflation Forecasts and Inflation Rate (IR)

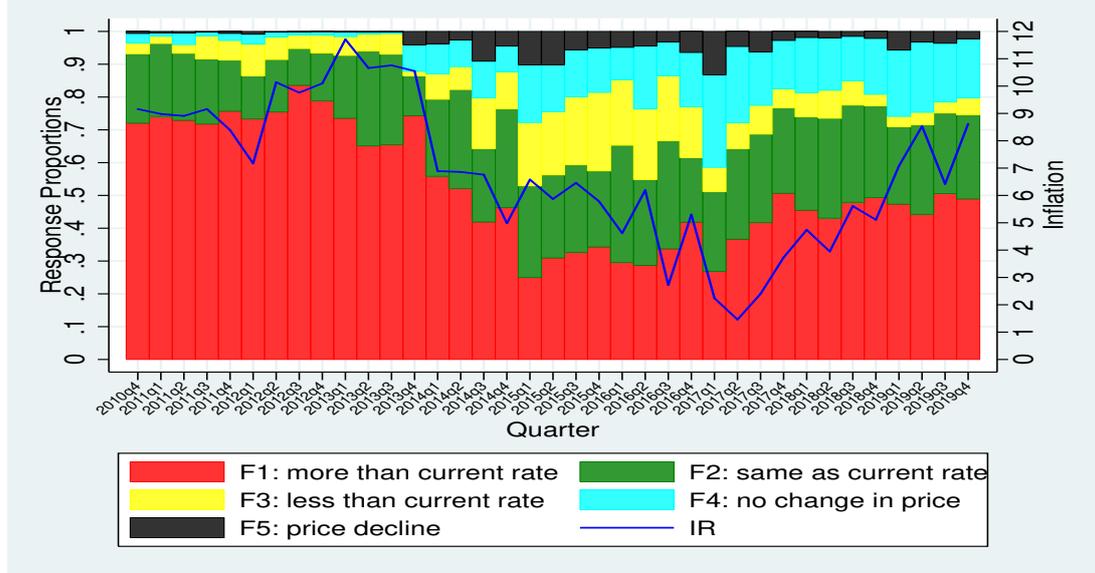
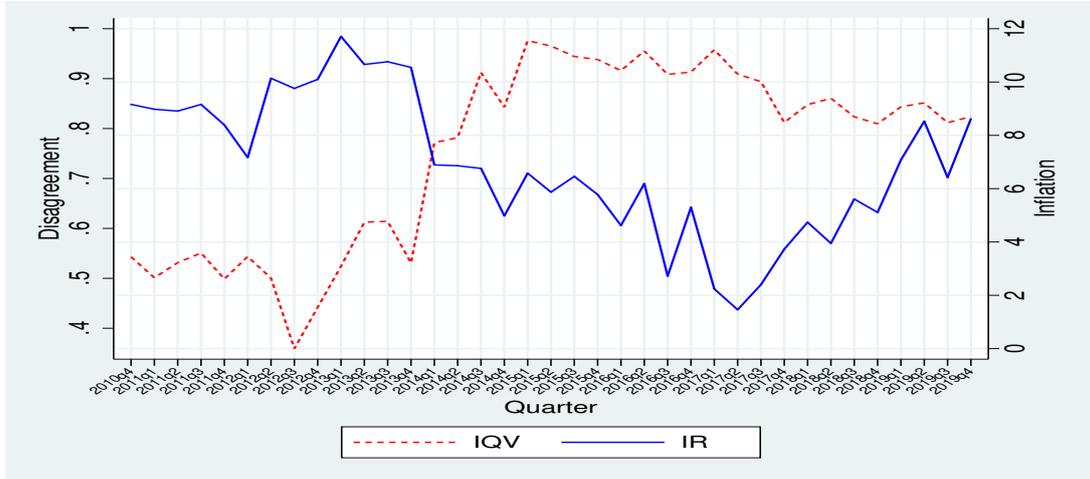


Figure 2 exhibits the plots of IQV and IR against rounds. Clearly, lower IQV occurs with higher IR and vice versa. It matches with our observations from Figure-1. Figure 3 is the scatter plot of IQV against IR . For low values of IR , a slight non-linear pattern is visible, otherwise, IQV shows a steady decreasing trend with increase in IR . For developed economies, as noted above, disagreement is found to have a positive correlation with IR which is in clear contrast with the pattern observed in IESH data. Recently, Lamla and Maag (2012) observe a non-linear relationship between disagreement and IR when analyzing inflation expectations survey data collected from German households. These patterns are a complex interaction of the effects of change in IR on the heterogeneity of the agents' information sets, choice of their loss functions for forecasting, uncertainty about their choice of a forecasting model, and finally on the differential interpretations of the information available to them, which we discuss in Section 3.

⁶Our measurement of IR is based on consumer price index for industrial worker i.e. CPI-IW. This study focuses on the urban households of India so CPI-IW is the most relevant consumer price index that mimic the prevailing inflation rate for the IESH respondents (Das et al. (2018)). In India, CPI-IW is published on monthly basis. We measure quarterly IR in two-steps. First, we compute the average of monthly CPI-IW for each quarter Q , say, $CPIIW_Q$. Then, the inflation rate for the quarter Q , say, IR_Q , is defined as $IR_Q = \frac{CPIIW_Q - CPIIW_{Q-4}}{CPIIW_{Q-4}}$. Note that the consumers' quarterly Inflation rate is measured as the four-quarter change in the consumer price index.

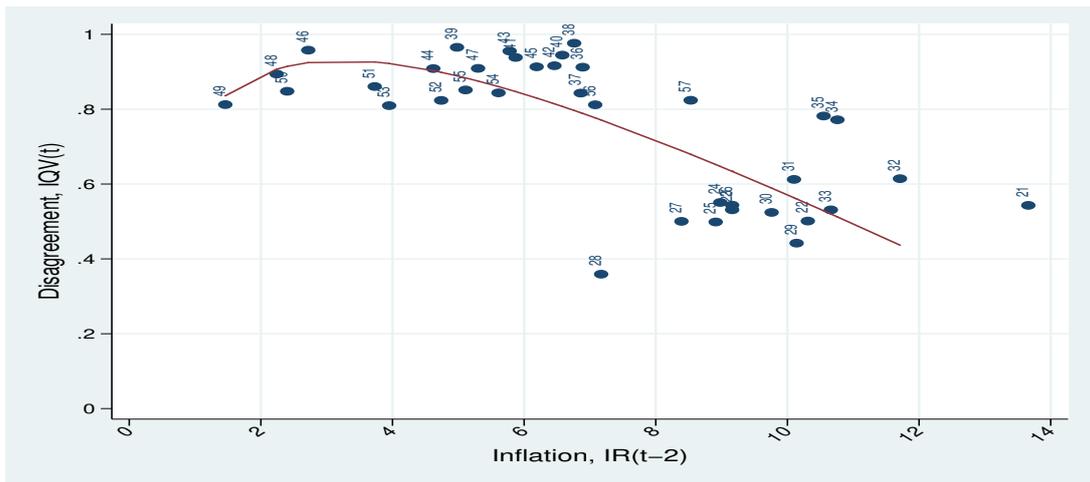
⁷From 2010 : Q2 till the end of 2013 the IR was hovering around 10. In 2014 : Q1 it suddenly dropped to 6% and hovered around the same for most of the subsequent quarters. In our empirical analysis, we consider the period upto 2013 : Q4 as **high inflation regime**, and the period spanning 2014 : Q1 to 2019 : Q3 as **low inflation regime**. See Benes, Clinton, George, John, Kamenik, Laxton, Mitra, Nadhanael, Wang, and Zhang (2017) (Section III) for an overview.

Figure 2. Disagreement (IQV) and Inflation (IR)



Note: Disagreement data is matched to the inflation quarter on which the forecast is made.

Figure 3. Scatter Plot of Quadratic Fit of Disagreement (IQV) and latest published Inflation (IR)



Figures 4 and 5, respectively, exhibit the effects of age and gender on the disagreement. The values plotted are deviations from the average *IQV*. The observed pattern suggests that the disagreement among the seniors⁸ (see Figure 4) is the maximum followed by the middle aged and the young. Also, the disagreement among the males (see Figure 5) is found to be more than among the females. Thus, the age and the gender seem to affect disagreement.

Figure 4. Disagreement deviation (Age), 4-quarter moving-average

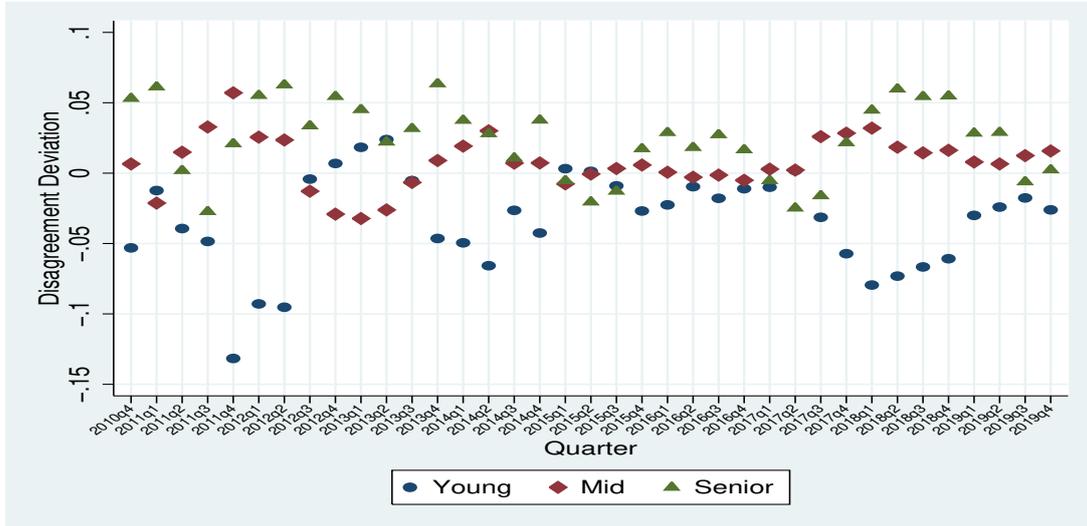
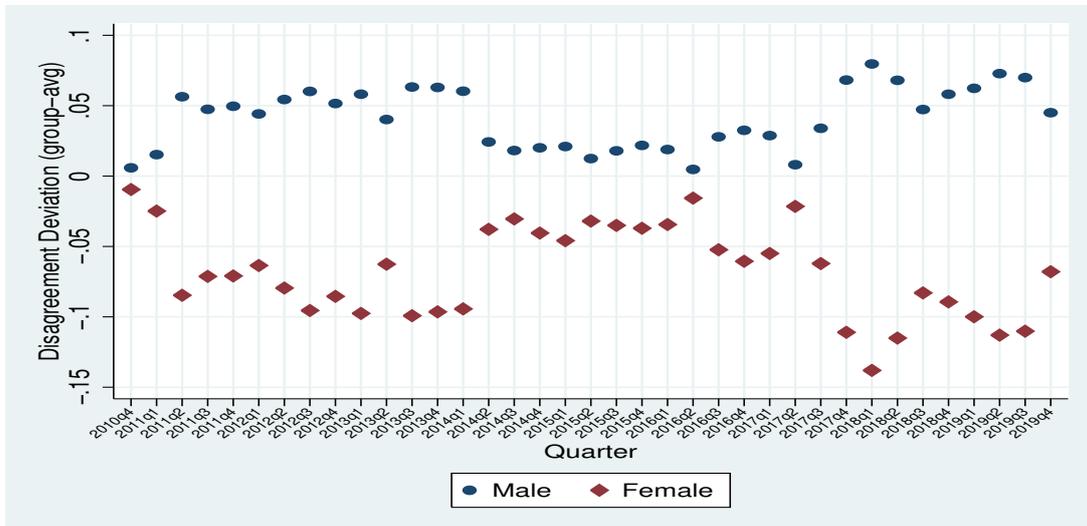


Figure 5. Disagreement deviation (Sex), 4-quarter moving-average



3. Determinants of Disagreement

Disagreement is known to be caused by the differences in the subjective beliefs of the agents about the future inflation. Following the publication of the seminal paper

⁸Young: age ≤ 30 years, Middle-aged: age > 30 but ≤ 50 years, Senior: age > 50 years

by [Mankiw et al. \(2004\)](#), a variety of explanations for disagreement are proposed in the literature. Central to these is, the agents use heterogeneous information sets. However, agents having access to the same information set, may still differ because of the differences in their demographic characteristics like age, gender, occupation, education and income etc. Also, the agents having access to the same information set and having the same demographic characteristics may still disagree because their expectation-formation processes may be different. Various models are proposed in the literature to describe this process. Notable among them are: the sticky information model ([Mankiw and Reis, 2002](#)), which assumes that the agents update their information intermittently due to costs associated with acquiring and processing the information; the epidemiological models ([Carroll, 2003](#)), which assume that the agents encounter news about inflation probabilistically over time resulting in epidemiological dynamics of aggregate expectations; the noisy information models ([Woodford, 2001](#)), which assume that agents form expectations based on noisy private signals; and the adaptive learning models ([Evans and Honkapohja, 2001](#)) which assume that agents may form expectations using some form of adaptive learning. The process may also be influenced by the agents' switching between different forecasting models ([Branch, 2004, 2007](#)) in different time periods, or using asymmetric loss functions for forecasting inflation leading to over- and under predictions ([Capistran and Timmermann \(2009\)](#)).

Researchers study the effects of a set of potential explanatory variables on disagreement in order to understand the disagreement formation process. In the following, we list a set of potential explanatory variables which may affect the disagreement. For each variable, we posit a hypothesis about its plausible effect on disagreement invoking the existing theories.

3.1. Macroeconomic Variables

We consider the following macroeconomic variables: the inflation rate (IR), the inflation volatility (IV), and the relative price variability (RPV). [Mankiw et al. \(2004\)](#), in their seminal paper, recognize them as the key macroeconomic variables affecting disagreement.

3.1.1. Inflation Rate (IR)

As mentioned above, survey data from advanced economies suggest a positive correlation between *IR* and disagreement, which [Mankiw et al. \(2004\)](#) explain by invoking the sticky information model ([Mankiw and Reis, 2002, 2006](#)). They note that: "This fanning out of inflation expectations following a change in inflation is consistent with a process of staggered adjustment of expectations". However, theories of rational inattention ([Sims, 2003](#)) and theories of rational predictor selection ([Branch, 2004, 2007](#)) suggest that with rising inflation level incentives to track inflation may rise and, thus, resulting in less disagreement. Also, depending on the level of inflation, the rational agents may use asymmetric loss functions for inflation prediction ([Capistran and Timmermann, 2009](#)), and thus, leading to over- or under- prediction, which in turn may affect disagreement. The effect of IR is, thus, a complex interaction of all these effects acting in opposite directions.

Following [Mankiw et al. \(2004\)](#) we posit:

H_1 : With rising inflation disagreement tends to increase.

3.1.2. Inflation Volatility (IV)

Mankiw et al. (2004) observe that “Disagreement rise when inflation changes sharply—in either direction”. In other words, higher values of IV^9 are associated with higher disagreement. The explanation for the effect of IV on disagreement is similar to the inflation rate.

We posit:

H_2 : Increase in inflation volatility leads to higher disagreement.

3.1.3. Relative Price Variability (RPV)

The RPV^{10} captures the variation of inflation rates across different sub-components of the overall consumption basket of the consumers, and thus, increase in RPV brings more heterogeneity in the information sets of the agents. As observed by Souleles (2004) and Bryan and Venkatu (2001a,b), while responding to the survey, the agents may not have the official inflation rate in mind, but may rather forecast the inflation based on the observed inflation of the sub-components of their private consumption basket. Consequently, an increase in RPV is expected to propel a rise in forecast disagreement.

Thus we hypothesize:

H_3 : With increase in relative price variability disagreement rises.

3.2. Other Variables of Interest

3.2.1. Lag-Disagreement

Lamla and Maag (2012) argue that if agents do not absorb any news, no information updating takes place, and disagreement is solely due to the dispersion of prior beliefs. For such agents, the current level of disagreement is primarily determined by the previous level. Figures 1 & 2 above clearly exhibit a tendency of disagreement to persist. Persistence in disagreement is a function of information updating. If the agents update their information in a staggered manner, we expect the lag-disagreement to be correlated with the current disagreement. Also, longer the agents take to update the information, stronger is the persistence, and higher is the correlation between the current and lag-disagreements.

So our next hypothesis is:

H_4 : Lag-disagreement affects the current disagreement.

⁹Inflation volatility essentially captures the extent of short-term fluctuations in inflation. As the measure of IV , we employ the difference between two most recent changes in IR in two successive rounds. To elaborate further, assume D_t be the change in IR between two successive rounds, viz. $IR_t - IR_{t-1}$ ($= D_t$) then $IV_t = D_t - D_{t-1}$.

¹⁰CPI-IW inflation is derived from a representative basket of consumption comprising six different groups: (I) Food, (II) Pan, Supari, Tobacco and Intoxicants, (III) Fuel Light, (IV) Housing, (V) Clothing, Bedding Footwear and (VI) Miscellaneous. If all groups have the same inflation as the overall inflation, there is no price variability among the groups. RPV captures the dispersion in inflation among the groups as follows:

$$RPV = \sqrt{\sum_i w_i * (\pi_t - \pi_{t,i})^2} \quad (1)$$

where i is a group in consumption basket of CPI-IW, π_t is CPI-IW inflation and $\pi_{t,i}$ is inflation for group i and w_i is weight of group i in CPI-IW consumption basket. Clearly RPV with value 0 implies no variability amidst the different groups of CPI-IW.

3.2.2. Media

In a recent paper, [Lamla and Maag \(2012\)](#) observe that the media has an important role in the formation of disagreement of the households. Common people get information about inflation mainly from the media, like TV and newspapers ([Blinder and Krueger, 2004](#)). [Carroll \(2003\)](#) observes that with more media coverage of inflation, the agents' inflation forecasts tend to converge more. Recently, [Lamla and Vinogradov \(2019\)](#) observe that the expectations of the consumers who receive news on monetary policy differ significantly from those who do not. Thus increased media coverage creates homogeneity in the information sets of the households leading to less disagreement about inflation expectations. We consider Google Trends (*GTREND*)¹¹ for the key word "inflation" as a proxy for the time variation of intensity of media coverage about inflation. Following [Badarinza and Gross \(2012\)](#), we posit that with increasing intensity of information flow agents tend to agree more.

So our next hypothesis is:

H_5 : Increasing intensity of media coverage of inflation lowers disagreement.

3.2.3. Central Bank's Inflation-Targeting (IT)

Inflation targeting¹² by Central Banks helps agents anchoring expectations about prices. [Brito et al. \(2018\)](#) study the effects of central bank transparency including inflation targeting on disagreement among the professional forecasters. They find empirical evidence of reduction of disagreement following the adoption of inflation targeting. Also, the reduction is found to be significant, especially for the developing countries, who started from a low level of transparency and a high level of inflation. In the light of poor performance of India in Central Bank transparency and independence¹³ ([Dincer and Eichengreen, 2014](#)), we posit that the inflation targeting (IT) announced by RBI¹⁴ for the first time in 2016 leads to a significant reduction of disagreement.

Our next hypothesis is:

H_6 : Inflation targeting has led to the reduction of disagreement.

3.2.4. Other Macroeconomic variables - Food and Fuel inflation

Food and Energy are relatively inelastic components in a household's consumption basket. While analyzing data from the Consumption Expenditure Survey, [Johannsen \(2014\)](#) observe that, households with low levels of expenditure display higher heterogeneity in their relative expenditures on food and energy. [Coibion and Gorodnichenko \(2015\)](#) find that households who on average spend more money on gasoline and therefore purchase gasoline more frequently adjust their inflation forecasts by more in response to oil prices fluctuations than do other households. [Cavallo, Cruces,](#)

¹¹ *GTREND* is (scaled) quarterly-volume of search for the key word 'inflation' under news category in India.

¹² See [Mishkin \(2000\)](#) for a discussion.

¹³ 2 out of 15 during 1998-2005 and 3 during 2006-2010

¹⁴ On February 20, 2015, the RBI and Government of India (GoI) reach into Monetary Policy Framework Agreement (MPFA) on flexible-inflation targeting (FIT). FIT was conceived on the recommendation of the Expert Committee formed for strengthening the Monetary Policy Framework (January, 2014). MPFA sets an initial target of inflation below 6 percent (by January 2016) for RBI to reign the inflation. The inflation is measured through an year-on-year change in the monthly CPI-C (consumer price index-combined) in percentage terms. Going forward, the inflation target is set at 4 percent with a permissible variation of 2 percent from the target. Later, FIT was ordained by a parliamentary proclamation in 2016Q3. The current target of FIT is promulgated for five years till 2021 since its inception in 2016.

and Perez-Truglia (2017) document that consumers benchmark their expectations on inflation based on their memories of supermarket prices. Since food and energy are the two most volatile components of CPI, its volatility leads to dispersed experiences of inflation for different demographic groups. Thus, the price volatility in these two categories measured by the food and the fuel inflation rates are expected to bring added variability in the households' expected inflation.

Thus our hypothesis is,

H_7 : Price volatility in food and fuel leads to more disagreement.

3.2.5. Demographic Characteristics

As stated at the outset, heterogeneity in agents' prior beliefs plays a key role in causing disagreement about the future inflation. In a recent paper, Capistran and Timmermann (2009) argue that disagreement is caused by the biased beliefs of the agents about the future inflation, and individual bias is clearly idiosyncratic in nature. In this context, the interpretation bias considered by Kandel and Zilberfarb (1999) is worth mentioning. Recently, Malmendier and Nagel (2016) extend the adaptive learning models to incorporate age-dependent updating of expectations in the events of inflation surprises. In Michigan Survey of Consumers (*MSC*) data¹⁵ they find that young individuals, compared to the older individuals, update their expectations more strongly since recent experiences form a greater share of their accumulated lifetime history. In our empirical investigation, we consider age and gender of the respondents as proxies for the idiosyncratic characteristics, and study its effects on disagreement.

Thus we hypothesise,

H_8 : The age and gender of the agents affect disagreement.

4. Empirical Analysis

4.1. Modeling Disagreement: Aggregated Data

We start with a base model for IQV, which is given by,

$$IQV_t = \beta_0 + \beta(IR_{t-2}, IV_{t-2}, RPV_{t-2}) + u_t, \quad (2)$$

where IR_{t-2} , IV_{t-2} and RPV_{t-2} are the values of IR , IV and RPV respectively at quarter $t - 2$ instead of $t - 1$. This is in order to account for the publication lag of macroeconomic information. Note that IQV_t is disagreement in IESH data (collected at time $t - 1$) that are the forecasts about the movement of IR at time t relative to that at time $t - 1$. For modeling the nonlinear relationship between IQV and IR as observed in Figure 3, we add IR_{t-2}^2 to the model. However, the high correlation (0.97) between IR_{t-2} and IR_{t-2}^2 leads to nonsensical estimates of the regression coefficients of both IR_{t-2} and IR_{t-2}^2 . We thus, drop IR_{t-2}^2 from the model. In the first column of Table 1 the estimates of the regression coefficients, and the corresponding p-values are reported. IR is found to have a strong significant negative effect on IQV contradicting the hypothesis H_1 . In other words, the disagreement seems to decrease

¹⁵MSC is conducted every month (since 1978) for US households by the Survey Research Center at the University of Michigan. The surveys solicits consumers response regarding their current and future financial standings and their thoughts on the present and near future state of the economy.

with increase in IR. Also, IV and RPV are found to be non-significant contradicting the hypotheses H_2 and H_3 . The model has adjusted R^2 equal to 0.397. Notice that, the DA test and the Q test¹⁶, both reject the null hypothesis practically at all level of significance.

We next augment the base model by adding lag- IQV ($LIQV$), the IQV of the previous quarter, as an explanatory variable. The revised estimates of the model parameters are shown in the second column of Table 1. Clearly, $LIQV$ shows a strong significant positive effect on IQV supporting the hypothesis H_4 , and also with its inclusion all three macroeconomic variables become non-significant. Notice that the \bar{R}^2 is more than doubled, and both DA and Q tests fail to reject the null hypothesis. In the light of the above results, it seems that unlike the professional forecasters, the common people do not seem to monitor the changes in the macroeconomic variables over time for forecasting inflation. The results also indicate that disagreement among the agents is strongly persistent. In other words, the agents do not update the information about inflation regularly.

We augment the model further by adding the explanatory variables, $GTREND$, IT ¹⁷, $IR(food)_{t-1}$ and $IR(fuel)_{t-1}$ ¹⁸. As stated above, $GTREND$ captures the intensity of information flow from media about inflation. IT captures the effect of the central bank transparency. The variables $IR(food)_{t-1}$ and $IR(fuel)_{t-1}$ directly affect the day to day buying experiences of the common people. The estimate of the revised model indicates that with the inclusion of these new variables, $LIQV$ becomes non-significant. However, the variance inflation factor (VIF) of $LIQV$ is found to be very high (11.66) indicating the presence of multicollinearity. A regression of $LIQV$ on the remaining variables of the model yields a very high R^2 value (= 0.914). Thus, we drop $LIQV$ from the final model.

The estimates of the final model are shown in the fourth column. As expected, the estimates of all the four coefficients, including that of IT , are negative and strongly significant, thus, supporting the hypotheses H_5 , H_6 and H_7 . The adjusted R-squared (\bar{R}^2) for the model is 0.909. Also, both DA and Q tests fail to reject the null hypothesis with high p-values. Finally, there is no indication of multicollinearity, the VIF values are all being close to 3.

The final model suggests that the time variation of disagreement among the households is caused by the day to day purchasing experiences, the intensity of media coverage about inflation, and the central bank transparency. The interesting facts that come out from this empirical study are, none of the macroeconomic variables has a significant effect on the disagreement, disagreement is highly persistent (the correlation between IQV and $LIQV$ is high and equal to 0.93), and if the variables $GTREND$, IT , $IR(food)$ and $IR(fuel)$ are included the effect of lag-disagreement becomes non-

¹⁶Durbin's alternative (DA) tests is used for testing the null hypothesis of no autocorrelation of errors when the regressors include lagged dependent variables. This is an extension of commonly used Durbin-Watson (DW) test that assumes strict exogeneity of regressors. Portmanteau (Q) test checks for the regression residuals being white-noise and the corresponding null hypothesis is that errors are white-noise.

¹⁷A dummy variable equal to 1 from 2016 first quarter onward, 0 otherwise.

¹⁸ $IR(food)_{t-1}$ is quarterly inflation rate for Food group of CPI-IW. Similarly, $IR(fuel)_{t-1}$ is quarterly inflation rate for Fuel group of CPI-IW. Food and Fuel group constitutes 36.29% and 5.58% of CPI-IW, respectively. These two groups are given special attention in literature as they are more influential (and commonly more volatile) than other groups of the consumption basket in shaping the consumers' views on inflation.

Table 1. Aggregate Results

	(1)	(2)	(3)	(4)
	<i>IQV</i>	<i>IQV</i>	<i>IQV</i>	<i>IQV</i>
<i>IR</i> _{<i>t</i>-2}	-0.041*** (0.000)	0.004 (0.336)	-0.000 (0.978)	
<i>IV</i> _{<i>t</i>-2}	0.001 (0.775)	-0.002 (0.567)	-0.001 (0.669)	
<i>RPV</i> _{<i>t</i>-2}	-0.003 (0.740)	-0.004 (0.280)	-0.003 (0.443)	
<i>LIQV</i>		0.955*** (0.000)	0.245 (0.232)	
<i>GTREND</i>			-0.002* (0.033)	-0.002*** (0.000)
<i>IT</i>			-0.104+ (0.056)	-0.152*** (0.000)
<i>IR(food)</i> _{<i>t</i>-1}			-0.009+ (0.060)	-0.014*** (0.000)
<i>IR(fuel)</i> _{<i>t</i>-1}			-0.022*** (0.000)	-0.029*** (0.000)
Constant	1.058*** (0.000)	0.024 (0.803)	0.897** (0.002)	1.193*** (0.000)
DA	0.000	0.074	0.559	0.790
Q	0.000	0.433	0.615	0.769
\bar{R}^2	0.397	0.853	0.908	0.909
Observations	37	37	37	37

p-values in parentheses

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: All equations are estimated over the period 2001Q3 to 2019Q3. Estimates are through Newey-West regression with lag 3 (Newey and West, 1987). Lag is chosen as per $.75T^{\frac{1}{3}}$ criteria. IR_{t-2} is the most recent published inflation rate, computed as the quarterly average of monthly index on an year-on-year basis. IV_{t-2} mimics the Inflation-Volatility and is measured as the difference in change-in-inflation. RPV_{t-2} is relative-price-variability that captures the dispersion across different groups of the consumption basket. $LIQV$ is lag-disagreement and reflects the persistence in disagreement. $GTREND$ proxy the volume of media information as captured through Google Trends data as volume of searches on keyword “inflation” under news category. IT dummy proxies the advent of flexible inflation targeting in India, 1 (true/presence) for 2016Q1 and onward, and 0 (false/absence) otherwise. Inflation $IR(Food)_{t-1}$ and $IR(Fuel)_{t-1}$ is the CPI-IW inflation for Food and Fuel group, respectively, and are matched with the survey-round to mimic the Households’ recent experiences on price volatility. Autocorrelation for all the models is checked with Durbin’s alternative (DA) test as lagged dependent variable is included among the regressors. Null hypothesis of DA test is that there is no autocorrelation at any order. For all the models, except model-(1), the null hypothesis of no autocorrelation could not be rejected. For all models, Portmanteau (Q) test for regression residuals being white-noise are performed and null hypothesis of errors being white-noise couldn’t be rejected, except for model-(1).

significant. This model offers a very useful insight to the policy makers about the formation of disagreement among the households.

4.2. Models for Disagreement: Disaggregated Data

In order to assess the impact of the demographic characteristics on the disagreement, we divide the responses in each round into six groups each representing a combination of age¹⁹ and gender²⁰. Let IQV_{it} denote the IQV measured for the i -th group in round t . We, thus, have a pooled time-series cross-section data with 6 cross-section units in each of the 37 time points. We consider unit fixed effects regression models (Angrist and Pischke (2009), Imai and Kim (2019)) for the analysis of the data. The common representation of such a model is,

$$Y_{it} = \alpha_i + \beta X_{it} + \epsilon_{it}, \quad (3)$$

where Y_{it} represents the dependent variable, X_{it} the set of explanatory variables, β the vector of regression parameters, and ϵ_{it} the disturbance term. Equation (3) is a fixed effects model (FEM) since the intercepts are allowed to differ across groups, but are time invariant. Also the vector of regression parameters β do not vary across units over time. The households in the six groups are likely to be subject to various common observable and unobservable disturbances leading to a contemporaneous correlation between ϵ_{it} 's. Also, ϵ_{it} 's are likely to be serially correlated over time. In order to incorporate both the contemporaneous and lagged cross-sectional dependence into the model Driscoll and Kraay (1998) assume that the disturbance term ϵ_{it} is generated as:

$$\epsilon_{it} = \lambda_i f_t + \mu_{it} \quad (4)$$

$$f_t = \rho f_{t-1} + \nu_{it}, \quad (5)$$

where, μ_{it} and ν_{it} are independent and identically distributed normal random variables with mean zero. Cross-sectional dependence is induced in the disturbances by the unobserved common factor f_t , which is present in all cross-sectional units. Since an autoregressive process of order one with auto correlation coefficient ρ generates f_t , both contemporaneous and lagged cross-sectional dependence are incorporated into the model.

For our empirical study, to begin with, we consider regression model (3) for IQV_{it} with X_{it} representing the vector of explanatory variables considered in column (3) of Table 1, and α_i 's representing the fixed effects due the three dummies, two for age²¹ and one for gender²². The OLS estimates of the regression coefficients are consistent. However, for drawing inferences about the regression coefficients, we need

¹⁹Young: age ≤ 30 years, Middle-aged: age > 30 but ≤ 50 years, Senior: age > 50 years.

²⁰Male and Female

²¹"Mid = 1" for middle aged, "= 0" otherwise, "Senior = 1" for seniors, "= 0" otherwise

²²"Fem = 1" for female, "= 0" otherwise

consistent estimates of its standard errors. In the presence of cross-sectional and serial dependence, the OLS estimates of the standard errors are inconsistent, and also highly biased in finite samples. In a time series context, the serial correlation in errors is commonly corrected by the [Newey and West \(1987\)](#) HAC (heteroskedasticity and autocorrelation consistent) estimators of standard errors. However, [Driscoll and Kraay \(1998\)](#) observe that, for pooled cross-section and time-series data, the HAC estimator would result in inconsistent estimates of standard errors because it ignores the cross-sectional dependence. Also, they observe that, erroneously ignoring cross-sectional correlation may lead to severely biased estimates of standard errors, and thus, to incorrect inferences. For drawing inferences, we thus use estimates of standard errors proposed by [Driscoll and Kraay \(1998\)](#)²³ correcting for both cross-sectional and serial dependence.

The OLS estimates of the regression coefficients are shown in column (1) of [Table 2](#). Not surprisingly, like in the case of aggregated data, the estimates of coefficients of IR_{t-2} , IV , RPV_{t-2} and $LIQV$ come out as non-significant. The coefficients of all other explanatory variables are significant including those of age and gender dummies, thus, supporting the hypotheses H_8 . Column (2) shows the estimates of the coefficients and the corresponding P-values after dropping the four non-significant variables from the model. The change in \bar{R}^2 after dropping the non-significant variables is negligible. The model estimates reconfirm our findings based on the aggregated data. The variables capturing the day to day purchase experiences of the agents, the media coverage about inflation, and inflation targeting by the central bank have significant effects on the disagreement with a negative sign. The additional insights that the analysis of disaggregated data provides are, the seniors and middle aged people show significantly more disagreement compared to the young ones, and the males tend to disagree significantly more compared to the females.

5. Bias

In [Sections 2 & 4](#) above, we have observed that the disagreement tends to decrease with increase in inflation rate which is in contrast with the findings for developed economies. We present here an empirical support for the observed phenomenon. If the agents use asymmetric loss functions for forecasting inflation then the agents may over- or under- predict depending on the inflation regime. It naturally leads to a bias in the forecasts as noted by [Capistran and Timmermann \(2009\)](#). Now, we address the following question: whether the IESH data exhibit a bias in the inflation forecasts, and if so, how is it related to the actual inflation? Finally, we relate our findings to the relationship between IQV and IR as observed in the IESH data.

[Figure 6](#) shows the plots of the change in IR between two successive rounds, viz. $IR_t - IR_{t-1}$ ($= D_t$, say) and the fractions of households' forecasts, say, F_{1t} , F_{2t} and F_{3t}^* in the three categories, say, C_1 , C_2 and C_3^* , respectively,²⁴ on the same chart. Notice that the IESH data are simply the forecasts at time $t - 1$ about the movement of IR at time t relative to that at time $t - 1$. On the other hand, the sign of D_t

²³implemented in Stata (cf. [Hoechle \(2007\)](#)) as *xtscc* program.

²⁴“More than the current rate” in red (C_1), “Same as the current rate” in green (C_2) and “Less than the current rate” in yellow (C_3^*)

Table 2. Disaggregate Results

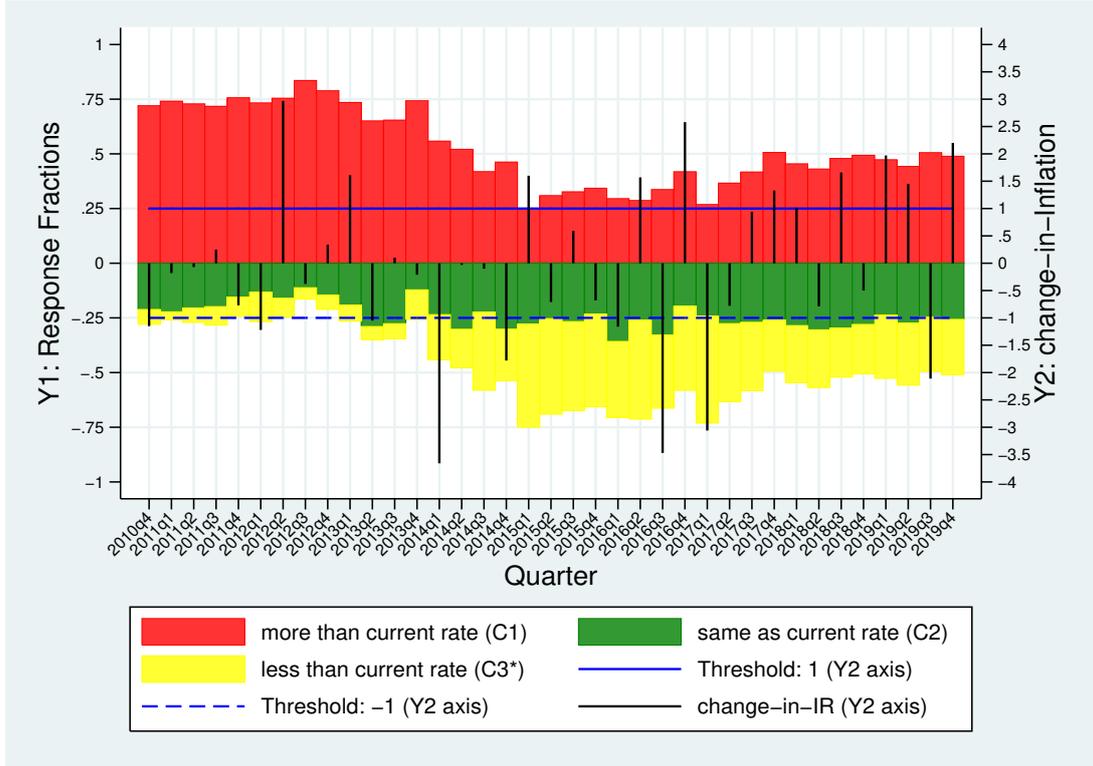
	(1)	(2)
	<i>IQV</i>	<i>IQV</i>
<i>IR</i> _{<i>t</i>-2}	-0.000 (0.982)	
<i>IV</i> _{<i>t</i>-2}	-0.001 (0.627)	
<i>RPV</i> _{<i>t</i>-2}	-0.003 (0.443)	
<i>LIQV</i>	0.208 (0.226)	
<i>GTREND</i>	-0.002** (0.009)	-0.002*** (0.000)
<i>IT</i>	-0.115* (0.018)	-0.157*** (0.000)
<i>IR(food)</i> _{<i>t</i>-1}	-0.010* (0.022)	-0.014*** (0.000)
<i>IR(fuel)</i> _{<i>t</i>-1}	-0.024*** (0.000)	-0.029*** (0.000)
<i>Mid</i>	0.013* (0.026)	0.017*** (0.001)
<i>Senior</i>	0.010* (0.044)	0.013** (0.002)
<i>Fem</i>	-0.031*** (0.000)	-0.039*** (0.000)
Constant	0.947*** (0.000)	1.201*** (0.000)
\bar{R}^2	0.907	0.902
Observations	222	222

p-values in parentheses

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: All equations are estimated over the period 2001Q3 to 2019Q3. Estimates are through [Driscoll and Kraay \(1998\)](#) regression implemented in Stata program *xtscc* ([Hoechle, 2007](#)). Variables *IR*_{*t*-2}, *IV*_{*t*-2}, *RPV*_{*t*-2}, *LIQV*, *GTREND*, *IT*, *IR(Food)*_{*t*-1} and *IR(Fuel)*_{*t*-1} have the same interpretation as give in the Table 1 note (also see section 3 for a detailed description).

Figure 6. Change in Inflation (D) and Response fractions (F_1, F_2, F_3^*)



captures the observed movement of IR at time t relative to time $t - 1$. We would like to verify whether the forecasts about the movement of IR are in consonance with the observed changes in the sign of D_t over time.

Clearly, a change in IR may not be perceived by the agents from their day to day experiences unless it exceeds a threshold, say, θ (Bakhach, Tsang, and Jalalian, 2016). For our empirical analysis, and for the sake of simplicity, we assume θ to be equal to 1 for the high inflation regime, and equal to 0.5 for the low inflation regime. Notice that, in the high inflation regime, the fraction of times IR increases by more than unity, i.e., $D_t > 1$, is equal to $2/13$, and the resulting 95% confidence interval is given by $[0, 0.26]$. In the low inflation regime, the corresponding ($D_t > 0.5$) fraction is $11/24$, and the resulting 95% confidence interval is given by $[0.39, 0.66]$. Interestingly, however, in the high-inflation regime, the proportion of agents forecasting an increase in IR varies between 0.65 and 0.83 which is much higher than 0.26. Evidently it suggests that the agents tend to overpredict inflation in the high inflation regime. On the other hand, in the low-inflation regime, it varies between 0.25 and 0.56, which is in perfect agreement with the actual change in IR , and hence, there does not seem to be any evidence of bias.

Thus, during the high inflation regime, the forecasters seem to exhibit an upward bias, resulting in a very high concentration of the forecasts in categories C_1 and C_2 , but mostly in C_1 , thus, leading to a low level of disagreement. In contrast, during the low inflation regime, the agents' forecasts are evenly spread out across different categories, thus, resulting in a higher level of disagreement. The tendency to overpredict during the high inflation regime causes the inverse relationship between

IQV and IR as observed in the IESH data.

6. Concluding Remarks

Here we summarize our findings. Clearly, the disagreement as measured by IQV exhibits a strong tendency to persist over time, which is also evident from the high positive correlation ($= 0.93$) between IQV and lag- IQV . This indicates the presence of information rigidity in updating the beliefs by the agents. Also, the agents do not seem to follow the changes in the key macroeconomic variables, like IR , IV and RPV over time to adjust their inflation forecasts. On the other hand, they seem to adjust their forecasts based on the information gathered from their day to day purchase experiences and the news about inflation captured by the variables $IR(food)_{t-1}$, $IR(fuel)_{t-1}$ and $GTREND$, respectively. Finally, the demographic characteristics of the agents, like age and gender, do have a significant effect on the disagreement. Females agree more than the males and younger people agree more than the older people.

Further, the *IESH* data exhibit a high negative correlation ($= -0.77$) between IQV and IR . Following [Capistran and Timmermann \(2009\)](#), it seems that the agents adopt asymmetric loss functions for forecasting inflation. Our empirical analysis suggests that the agents tend to overpredict during the high-inflation regime resulting in high concentration of forecasts in a few categories. On the other hand, the forecasts are evenly spread out across different categories during the low inflation regime, thus, leading to low disagreement during the high inflation regime and high disagreement during the low inflation regime.

Finally, we would like to raise a caveat about the significant negative effect of IT on disagreement. Notice that (cf. [Figure 2](#)) the formal announcement of inflation targeting by the government is followed by a sustained but short period of low inflation, the lowest being observed in 2017 : $Q2$. There is a plausibility that the low inflation may be caused by variables other than IT , which are unobservable or are hard to measure, like the central bank communication strategy to public ([Coibion, Gorodnichenko, and Weber, 2019](#)) or the degree of central bank independence²⁵. [Mishkin \(2000\)](#) observes that the latter is critical for inflation targeting to be effective, especially for the emerging economies. As noted by [Capistran and Ramos-Francia \(2010\)](#), if these factors are not controlled for, their effects may be wrongly attributed to IT .

Finally, to the best of our knowledge, this is the pioneering study of time variation of disagreement about inflation forecasts among the Indian households. This paper provides key insights about the formation of disagreement, and thus, would help the policy makers in conducting monetary policy more effectively. More importantly, some of our findings are novel and typical for an emerging economy like India, and are at variance with the findings in developed economies. Given the fact, that most of the published studies on disagreement are based on the survey data from the developed economies, we believe, our paper would enrich the current literature on disagreement.

²⁵By central bank independence, we mean a strong institutional commitment to insulate the central bank from legislators' influence, and giving the central bank exclusive control over the setting of monetary policy instrument.

References

- Alexander Ballantyne DJ, Christian Gillitzer, Rankin E (2016) Disagreement about inflation expectations. Research Discussion Paper 2016-02, Reserve Bank of Australia
- Andrade P, Crump RK, Eusepi S, Moench E (2016) Fundamental disagreement. *Journal of Monetary Economics* 83:106 – 128, , URL <http://www.sciencedirect.com/science/article/pii/S0304393216300794>
- Angrist J, Pischke JS (2009) *Mostly Harmless Econometrics: An Empiricist's Companion*
- Armantier O, Nelson S, Topa G, van der Klaauw W, Zafar B (2016) The price is right: Updating inflation expectations in a randomized price information experiment. *The Review of Economics and Statistics* 98(3):503–523, , URL https://doi.org/10.1162/REST_a.00499, https://doi.org/10.1162/REST_a.00499
- Bachmann R, Elstner S, Sims ER (2013) Uncertainty and economic activity: Evidence from business survey data. *American Economic Journal: Macroeconomics* 5(2):217–49, , URL <http://www.aeaweb.org/articles?id=10.1257/mac.5.2.217>
- Badarınza C, Buchman M (2009) inflation perceptions and expectations in the euro area: The role of news. Working papers 1088, European Central Bank
- Badarınza C, Gross M (2012) Information flows and disagreement. Working Paper Series 1475, European Central Bank, URL <https://EconPapers.repec.org/RePEc:ecb:ecbwps:20121475>
- Bakhach A, Tsang E, Jalalian HR (2016) Forecasting directional changes in the fx markets.
- Batchelor R (2007) Bias in macroeconomic forecasts. *International Journal of Forecasting* 23(2):189–203, URL <https://EconPapers.repec.org/RePEc:eee:intfor:v:23:y:2007:i:2:p:189-203>
- Benes J, Clinton K, George A, John J, Kamenik O, Laxton D, Mitra P, Nadhanael G, Wang H, Zhang F (2017) Inflation-forecast targeting for india : An outline of the analytical framework
- Blinder AS, Krueger AB (2004) What does the public know about economic policy, and how does it know it? Working Paper 10787, National Bureau of Economic Research, , URL <http://www.nber.org/papers/w10787>
- Branch W (2004) The theory of rationally heterogeneous expectations: Evidence from survey data on inflation expectations. *Economic Journal* 114(497):592–621, URL <https://EconPapers.repec.org/RePEc:ecj:econjl:v:114:y:2004:i:497:p:592-621>
- Branch W (2007) Sticky information and model uncertainty in survey data on inflation expectations. *Journal of Economic Dynamics and Control* 31(1):245–276, URL <https://EconPapers.repec.org/RePEc:eee:dyncon:v:31:y:2007:i:1:p:245-276>
- Brito S, Carriere-Swallow Y, Gruss B (2018) Disagreement about future inflation: Understanding the benefits of inflation targeting and transparency. Working Paper 18/24, International Monetary Fund
- Brock WA, Hommes CH (1997) A rational route to randomness. *Econometrica* 65(5):1059–1095, URL <http://www.jstor.org/stable/2171879>
- Bryan MF, Venkatu G (2001a) The curiously different inflation perspectives of men and women
- Bryan MF, Venkatu G (2001b) The demographics of inflation opinion surveys. *Economic Commentary* (Oct):2, URL <http://EconPapers.repec.org/RePEc:fip:fedcec:y:2001:i:oct15>
- Capistran C, Ramos-Francia M (2010) Does inflation targeting affect the dispersion of inflation expectations? *Journal of Money, Credit and Banking* 42(1):113–134, URL <https://EconPapers.repec.org/RePEc:mcb:jmoncb:v:42:y:2010:i:1:p:113-134>
- Capistran C, Timmermann A (2009) Disagreement and Biases in Inflation Expectations. *Journal of Money, Credit and Banking* 41(2-3):365–396, URL <https://ideas.repec.org/a/mcb/jmoncb/v41y2009i2-3p365-396.html>
- Carroll CD (2003) Macroeconomic expectations of households and professional forecasters. *the Quarterly Journal of economics* pp 269–298
- Cavallo A, Cruces G, Perez-Truglia R (2017) Inflation Expectations, Learning, and Super-

- market Prices: Evidence from Survey Experiments. *American Economic Journal: Macroeconomics* 9(3):1–35, URL <https://ideas.repec.org/a/aea/aejmac/v9y2017i3p1-35.html>
- Ciro JCG, Zapata JCA (2019) Disagreement in inflation expectations: empirical evidence for Colombia. *Applied Economics* 51(40):4411–4424, , URL <https://ideas.repec.org/a/taf/applec/v51y2019i40p4411-4424.html>
- Coibion O, Gorodnichenko Y (2015) Is the phillips curve alive and well after all? inflation expectations and the missing disinflation. *American Economic Journal: Macroeconomics* 7(1):197–232, , URL <https://www.aeaweb.org/articles?id=10.1257/mac.20130306>
- Coibion O, Gorodnichenko Y, Kamdar R (2018) The formation of expectations, inflation, and the phillips curve. *Journal of Economic Literature* 56(4):1447–91, , URL <https://www.aeaweb.org/articles?id=10.1257/jel.20171300>
- Coibion O, Gorodnichenko Y, Weber M (2019) Monetary policy communications and their effects on household inflation expectations. Working Paper 25482, National Bureau of Economic Research, , URL <http://www.nber.org/papers/w25482>
- Cukierman A, Wachtel P (1979) Differential Inflationary Expectations and the Variability of the Rate of Inflation: Theory and Evidence. *American Economic Review* 69(4):595–609, URL <https://ideas.repec.org/a/aea/aecrev/v69y1979i4p595-609.html>
- Das A, Lahiri K, Zhao Y (2018) Inflation expectations in india: Learning from household tendency surveys. Working Papers 2018-03, Towson University, Department of Economics, URL <https://EconPapers.repec.org/RePEc:tow:wpaper:2018-03>
- Dasgupta S, Lahiri K (1992) A comparative study of alternative methods of quantifying qualitative survey responses using napm data. *Journal of Business & Economic Statistics* 10(4):391–400, URL <http://EconPapers.repec.org/RePEc:bes:jnlbes:v:10:y:1992:i:4:p:391-400>
- Dincer NN, Eichengreen B (2014) Central Bank Transparency and Independence: Updates and New Measures. *International Journal of Central Banking* 10(1):189–259, URL <https://ideas.repec.org/a/ijc/ijcjou/y2014q1a6.html>
- Dovern J, Fritsche U, Slacalek J (2012) Disagreement Among Forecasters in G7 Countries. *The Review of Economics and Statistics* 94(4):1081–1096, URL <https://ideas.repec.org/a/tpr/restat/v94y2012i4p1081-1096.html>
- Driscoll J, Kraay A (1998) Consistent covariance matrix estimation with spatially dependent data. *Rev Econ Stat* 80:549–560
- Ehrmann M, Eijffinger S, Fratzscher M (2012) The role of central bank transparency for guiding private sector forecasts*. *The Scandinavian Journal of Economics* 114(3):1018–1052, , URL <https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1467-9442.2012.01706.x>, <https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1467-9442.2012.01706.x>
- Evans GW, Honkapohja S (2001) *Learning and Expectations in Macroeconomics*. Princeton University Press
- Falck E, Hoffmann M, Hurtgen P (2019) Disagreement about inflation expectations and monetary policy transmission. *Journal of Monetary Economics* , URL <http://www.sciencedirect.com/science/article/pii/S0304393219301515>
- Fritsche U, Döpke J (2006) When do forecasters disagree? an assessment of german growth and inflation forecast dispersion. *International Journal of Forecasting* 22:125–135,
- Giordani P, Söderlind P (2003) Inflation forecast uncertainty. *European Economic Review* 47(6):1037–1059, URL <https://EconPapers.repec.org/RePEc:eee:eecrev:v:47:y:2003:i:6:p:1037-1059>
- Hoechle D (2007) Robust standard errors for panel regressions with cross-sectional dependence. *Stata Journal* 7:281–312,
- Imai K, Kim IS (2019) When should we use unit fixed effects regression models for causal inference with longitudinal data? *American Journal of Political Science* 63(2):467–490, , URL <https://onlinelibrary.wiley.com/doi/abs/10.1111/ajps.12417>, <https://onlinelibrary.wiley.com/doi/pdf/10.1111/ajps.12417>
- Johannsen BK (2014) Inflation experience and inflation expectations: Dispersion and disagreement within demographic groups. Working papers 89, FEDS, URL <https://ssrn.com/>

- abstract=2529160
- Kandel E, Zilberfarb BZ (1999) Differential Interpretation Of Information In Inflation Forecasts. *The Review of Economics and Statistics* 81(2):217–226, URL <https://ideas.repec.org/a/tpr/restat/v81y1999i2p217-226.html>
- Lahiri K, Sheng X (2008) Evolution of forecast disagreement in a Bayesian learning model. *Journal of Econometrics* 144(2):325–340, URL <https://ideas.repec.org/a/eee/econom/v144y2008i2p325-340.html>
- Lamla MJ, Maag T (2012) The role of media for inflation forecast disagreement of households and professional forecasters. *Journal of Money, Credit and Banking* 44(7):1325–1350, URL <https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1538-4616.2012.00534.x>, <https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1538-4616.2012.00534.x>
- Lamla MJ, Vinogradov DV (2019) Central bank announcements: Big news for little people? *Journal of Monetary Economics* 108:21 – 38, URL <http://www.sciencedirect.com/science/article/pii/S0304393219301473>, Central Bank Communications: From Mystery to Transparency May 23–24, 2019 Annual Research Conference of the National Bank of Ukraine Organized in cooperation with Narodowy Bank Polski
- Lucas R (1973) Some international evidence on output-inflation tradeoffs. *American Economic Review* 63(3):326–34, URL <https://EconPapers.repec.org/RePEc:aea:aecrev:v:63:y:1973:i:3:p:326-34>
- Malmendier U, Nagel S (2016) Learning from Inflation Experiences. *The Quarterly Journal of Economics* 131(1):53–87, URL <https://ideas.repec.org/a/oup/qjecon/v131y2016i1p53-87.html>
- Mankiw NG, Reis R (2002) Sticky information versus sticky prices: A proposal to replace the new keynesian phillips curve*. *The Quarterly Journal of Economics* 117(4):1295–1328, URL <http://dx.doi.org/10.1162/003355302320935034>, [/oup/backfile/content_public/journal/qje/117/4/10.1162/003355302320935034/2/117-4-1295.pdf](http://oup/backfile/content_public/journal/qje/117/4/10.1162/003355302320935034/2/117-4-1295.pdf)
- Mankiw NG, Reis R (2006) Pervasive stickiness. *American Economic Review* 96(2):164–169, URL <https://app.dimensions.ai/details/publication/pub.1064524675>
- Mankiw NG, Reis R, Wolfers J (2004) Disagreement about inflation expectations. In: *NBER Macroeconomics Annual 2003, Volume 18*, The MIT Press, pp 209–270
- Mishkin FS (2000) Inflation targeting in emerging-market countries. *The American Economic Review* 90(2):105–109, URL <http://www.jstor.org/stable/117201>
- Mokinski F, Sheng XS, Yang J (2015) Measuring disagreement in qualitative expectations. *Journal of Forecasting* 34(5):405–426, URL <https://onlinelibrary.wiley.com/doi/abs/10.1002/for.2340>, <https://onlinelibrary.wiley.com/doi/pdf/10.1002/for.2340>
- Newey W, West K (1987) A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica* 55(3):703–08, URL <https://EconPapers.repec.org/RePEc:ecm:emetrp:v:55:y:1987:i:3:p:703-08>
- Oliveira LV, Curi A (2016) Disagreement in expectations and the credibility of monetary authorities in the brazilian inflation targeting regime. *EconomiA* 17(1):56–76, URL <http://hdl.handle.net/10419/179612>
- Patton AJ, Timmermann A (2010) Why do forecasters disagree? Lessons from the term structure of cross-sectional dispersion. *Journal of Monetary Economics* 57(7):803–820, URL <https://ideas.repec.org/a/eee/moneco/v57y2010i7p803-820.html>
- Siklos PL (2013) Sources of disagreement in inflation forecasts: An international empirical investigation. *Journal of International Economics* 90(1):218–231, URL <https://ideas.repec.org/a/eee/inecon/v90y2013i1p218-231.html>
- Sims C (2003) Implications of rational inattention. *Journal of Monetary Economics* 50(3):665–690, URL <https://EconPapers.repec.org/RePEc:eee:moneco:v:50:y:2003:i:3:p:665-690>
- Souleles NS (2004) Expectations, Heterogeneous Forecast Errors, and Consumption: Micro Evidence from the Michigan Consumer Sentiment Surveys. *Journal of Money, Credit and Banking* 36(1):39–72, URL <https://ideas.repec.org/a/mcb/jmoncb/v36y2004i1p39-72.html>
- Thomas M (2010) Essays on inflation expectation formation
- Townsend R (1983) Forecasting the forecasts of others. *Journal of Political Economy* 91(4):546–

- 88, URL <https://EconPapers.repec.org/RePEc:ucp:jpolec:v:91:y:1983:i:4:p:546-88>
- Valev N, Carlson J (2003) Sources of dispersion in consumer inflation forecasts. *Applied Economics Letters* 10:77–81,
- Woodford M (2001) Imperfect Common Knowledge and the Effects of Monetary Policy. NBER Working Papers 8673, National Bureau of Economic Research, Inc, URL <https://ideas.repec.org/p/nbr/nberwo/8673.html>
- Łyziak T, Sheng X (2018) Disagreement in consumer inflation expectations. Tech. rep.