Asymmetries in Inflation Expectations:
A Study Using IESH Quantitative Survey Data

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Abstract

This paper studies quantitative data from Reserve Bank of India's Inflation Expectations Survey of Households. We argue that the persistent upward bias in household expectations is mainly the result of three types of asymmetries. First, the cross-sectional impact of aggregate price shocks is asymmetric: For example, older workers in non-financial industries tend to be more pessimistic than younger workers or those in the financial industry. Second, the effects of price changes of different categories of consumption goods are asymmetric: We find that energy and food price inflation have a disproportionately large effect on household inflation perceptions and expectations. Third, households adapt their expectations to actual inflation rate asymmetrically: The rate of adaptation is much higher when inflation is unexpectedly high.

JEL Classifications: D84 E31 C25 C43

Keywords: Asymmetry; cross-sectional heterogeneity; food and energy price

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1. Introduction

Household surveys have long been used to measure consumers' perceptions and expectations of economic conditions. There is a large literature on this topic. Apart from studies on survey design (e.g., Bruine de Bruin et al. (2012)), many more concern the expectation formation process and the information content of household expectations (e.g., Pfajfar and Santoro (2010)). Abundant evidence indicates that household expectations are unlikely to be fully rational and unbiased. Instead, heterogeneity is often found to drive the dynamics and dispersion of household expectations[1]. However, not many studies on this topic use data from developing economies. In a recent study, Abbas et al. (2014) find in Pakistan data that "inflation expectations are systematically exaggerated, and this biasedness is entrenched for low-income, less educated, female and younger respondents".

We look at household inflation expectations from one of the most important developing economies and document three forms of asymmetry that contribute to the observed misalignment between actual and expected inflation. Specifically, we focus on inflation perceptions and expectations reported in the Inflation Expectations Survey of Households (IESH), a quarterly survey conducted by Reserve Bank of India since 2005. To our knowledge, no other published research article has used household-level data from this survey. We conduct several exercises:

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

First, we examine the dynamics of quantitative perceptions and expectations in the aggregate. Consistent with what reported in scholarly journals and popular press, we find notable pessimism in these simple aggregates. This is so even during 2011 to 2013, when actual inflation rate is relatively stable around eight to ten percent. We then proceed to analyze household-level data in an attempt to uncover possible reasons for the observed pessimism. Specifically, we first examine the cross-sectional distribution of household inflation expectations and how it changes over time. Then, we identify characteristics common to the group of households with highly pessimistic views on inflation. Next, we study the expectation formation process using both household-level data and aggregate data. In particular, we examine the sensitivity of household inflation expectations to food and energy price inflation.

Our results suggest that three forms of asymmetry explain, at least partially, the misalignment between expectations and reality. First, the cross-sectional impact of aggregate price shocks is asymmetric: For example, older workers in non-financial industries tend to be more pessimistic than younger workers or those in the financial industry. Second, the effects of price changes of different categories of consumption goods are asymmetric: We find that energy and food price inflation have a disproportionately large effect on household inflation perceptions and expectations. Third, households adapt their expectations to actual inflation rate asymmetrically: The rate of adaptation is much higher when inflation is unexpectedly high. Overall, our results show the usefulness of the survey and the resulting measures of household inflation expectations. Despite somewhat common misconception, especially in popular media, observed biases in inflation expectation measures do not render them useless. Quite to the contrary, our results based on the survey highlight structural factors affecting household inflation expectations. Proper interpretation and understanding of the signals embedded in the survey responses are key to making use of the survey results.

The rest of the paper is organized as follows: Section 2 introduces the Inflation Expectations Survey of Households. In Section 3, we provide a comprehensive comparison of quantitative inflation perceptions and expectations with associated actual values. The next section study the process of expectation formation, where we report both the results from household-level analysis and the results from aggregate-level analysis. Concluding remarks are presented in Section 5.

2. Background and Data

The Reserve Bank of India (RBI) introduced quarterly IESH from September 2005. Since its inception, the primary purpose of this survey has been to collect information regarding regional heterogeneities of inflation expectations of urban households. The initial two rounds of the survey covered 2,000 households, 500 each from four major metro cities viz., New Delhi, Chennai, Kolkata, and Mumbai, which represents four geographical zones (North, South, East, and West). Survey questions in the first two rounds solicited only qualitative responses of household’s expectation on general prices for the next quarter and a year ahead. Additionally, expectations of prices for food products, house rents and services were also collected. The questions on changes in price in relation to the prevailing inflation rate were asked for five different scales: (i) price increase similar to current rate; (ii) price increase more than current rate; (iii) price increase less than current rate; (iv) no change in prices; and (iv) decline in prices.

The depth of IESH was enhanced considerably from the third round. In terms of geographical coverage, IESH was extended to eight more cities. 500 households from each metro city and 250 households from each of the remaining eight cities were selected in the sample, bringing the total sample size to 4000 households. Each geographical zone was represented by three cities - North: Delhi, Jaipur, Lucknow; South: Chennai, Bangalore, Hyderabad; East: Kolkata, Guwahati, Patna; and West: Mumbai, Ahmedabad, Bhopal. The 5-scale qualitative responses were further augmented to include household's expectation on non-food products and household durables. As a major extension, quantitative responses on the expected rate of inflation for the next three months and one year were also solicited from this round. Therefore, the scope of the survey focused on seeking (i) qualitative responses on price changes (general prices as well as prices of specific product groups) in next three months and next one year and (ii) quantitative responses on three-month-ahead and one-year-ahead inflation rates[2]. From the ninth round in September 2007, a question on the respondents' perception of current inflation rate was also added. Till September 2012 (29th round), the survey was conducted in 12 cities. From round 30, (quarter ended December 2012) four more cities have been added viz., Kolhapur, Nagpur, Thiruvananthapuram and Bhubaneswar. A sample of 250 households is selected from each of these cities so as to achieve a total sample size of 5,000 from 16 cities.

The survey design is primarily a purposive one and uses quota sampling. Households are chosen in a way to get adequate geographical representation of the city and a mix of gender, age and employment status of households. The male and female ratio in the sample is usually 3:2 and respondents are over 18 years of age (RBI (2010)). The respondent categories include financial sector employees, other employees, self-employed, housewives, retired persons, daily workers and others. The target quota selection apparently does not have any statistical basis. Overall sample

[2] Quantitative responses to these questions are limited to integers between 1% and 16%. Responses lower than 1% is recorded as 1% and responses higher than 16% is recorded as 16%.

coverage is broadly kept as per the target in all the rounds. From September 2008, the representation of housewives was increased to 30% (as shown in Table 1). The sample is chosen in a way to cover the city uniformly and different areas of cities are chosen for each survey round.

<< Table 1 here >>

Due to the significant changes the survey went through since 2005, we do not use the data before the survey was considered stabilized in 2008Q3. So the data set used here covers the period of 2008Q3 to 2015Q1 and contains 117,418 individual responses. In addition to information contained in the survey, we also use actual inflation rate data. For each of the 16 cities covered in the survey, we have the corresponding city-wise CPI-IW (industrial workers) inflation rates. For overall inflation rates, we have the CPI-IW inflation, WPI (wholesale price index) inflation, CPI inflation (which is now targeted by RBI), as well as CPI inflation for food, vegetables, services, and energy.

3. Exploring Survey Expectations

3.1. An examination of the aggregates

We derive aggregate inflation expectations and compare them with the official statistics for the country as a whole as well as for each city. Figure 1 shows this comparison. The plots in the left column show the comparison between survey respondents' currently perceived inflation and actual inflation; the middle column and the right column show the comparison between 3-month-ahead and 1-year-ahead inflation expectations and ex post actual values, respectively. For brevity, in addition to the plots of the overall series, we only present the plots for four major cities: Chennai, Delhi, Kolkata, and Mumbai.

<< Figure 1 here >>

Four main observations can be made based on the figure. First, there is a strikingly high level of similarity between perceptions of the current inflation rate and expectations of future inflation rate, regardless of whether the latter is about 3-months into the future or 1-year into the future. Second, for most of the quarters in our sample period, there is a significant amount of upward bias in both perceptions and expectations. This is clearly seen in the plots of the country-level series. Even during the relatively stable period from 2010Q3 to 2014Q2 when actual inflation stayed in between 8% to 10%, expectations were consistently higher. This is particularly so for 1-year-ahead expectations, which stayed nearly 3% above the actuals. Third, noted heterogeneity is observed across cities. For example, perceptions and expectations of respondents from Kolkata seem to be tracking actual inflation rates fairly well, while those of the respondents from Mumbai tend to be considerably higher than actual inflation. On the other hand, there are important similarities in perceptions and expectations across different cities. For example, for all the cities, there was a large drop in perceptions and expectations during 2009, while for Chennai and Mumbai, city-level actual inflation rates did not drop by a large amount, and for Kolkata, city-level inflation rate actually increased. Finally, we note that aggregate inflation perceptions and expectations respond to the official statistic asymmetrically: Take perceptions as an example, when there is a notable drop in the actual rate, as was the case in late 2008 and late 2014, perceptions drop almost contemporaneously. But when there are only minor changes in the actual rate, such as during 2011 to 2013, perceptions do not respond much, despite being several percentage points higher than the actual rate.

While the amount of overestimation in inflation expectations seems significant, it is not unique to India, nor is it unique to households. Campelo et al. (2015) reviewed similar household surveys for six individual countries and the Euro area as a whole and found upward bias in household expectations everywhere. [3] Figure 2 one-quarter ahead compares household expectations with professional forecasts for India and the United States. Household expectations are from the University of Michigan's consumer sentiment survey. To be consistent with their Indian counterparts, the simple average of household expectations are used. Professional forecasts for India are obtained from the RBI's Survey of Professional Forecasters on Macroeconomic Indicators (SPF). The RBI has been conducting the survey since September 2007. We use the quarterly inflation forecasts reported in the survey. Professional forecasts for the U.S. are obtained from the U.S. Survey of Professional Forecasters available from the Federal Reserve Bank of Philadelphia. From Figure 2, we can see that household inflation expectations tend to be persistently higher than the actual rates for both the U.S. and India. In the Indian case, from 2008Q4 to 2015Q2, the average of actual inflation rate is 9.63%; the average of household expectations is 11.11%; and the average of professional forecasts is 9.56%. In the U.S. over the 28 quarters, the average of actual inflation is 1.62%; the average of Michigan mean is 3.99%; and the average of professional forecasts is 2.11%. In relative terms, overestimation is even more significant in the United States.

<< Figure 2 here >>

These observations are consistent with what reported in several studies, including Pfajfar and Santoro (2010), Carrillo and Emran, M. Shahe (2012), Lamla and Lein (2014), among others. As it is costly to obtain new information on inflation, households do not always keep their information

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

set up-to-date. However, the frequency at which household information set is updated is not fixed. As the analysis in the rest of the paper suggests, households that are more sensitive to price changes (e.g., poor households) may update their information set more frequently, so are those that are capable of obtaining and interpreting information more easily (e.g., with higher education level). In addition, more frequent update may happen during periods with relatively more intensive coverage of inflation related news (e.g., when there are notable changes in the actual inflation rates). It is worth noting that while there is a clear inconsistency between observed inflation perceptions and expectations and what would be consistent with traditional full-information rational expectation hypothesis, what we observe is likely more than animal spirit. In fact, households expectation formation may well be structural, as discussed in Mankiw and Reis (2002), Mankiw, N. Gregory et al. (2003), and more recently Pfajfar and Santoro (2013). In a separate study, we look deeper into the expectation formation process where we estimate the behavioral rule used by Indian households conditional on the direction and magnitude of changes in actual inflation rate.

3.2. An examination of the distributions

While comparing aggregate inflation perceptions and expectations to the associated actual values is informative, it does not in any way reveal the distribution of perceptions and expectations across households. It is important to also study this cross-sectional dispersion, particularly so when a significant amount of pessimism is observed in the aggregate data. We want to understand the source of this pessimism: Is it a reflection of aggregate shock that affect all the households, or is it a reflection of perceptions and expectations of only some of the households? If the latter is more likely the case, what common attributes do these pessimistic households share?

We therefore present in Figure 3 a set of histograms showing the distribution of household quantitative responses separately for each and every quarter in our sample period. Figure 3a shows inflation perceptions, while Figure 3b and 3c show 3-month-ahead and 1-year-ahead expectations, respectively. One prominent feature that is immediately noticeable across all three figures is the high level of concentration of responses in the highest response category, i.e., inflation is or expected to be "> 16%". This congregation does not only appear in quarters with relatively high actual inflation rates, such as late 2009 to early 2010, but also appear in quarters with stable and lower actual inflation rates, such as late 2010 to mid-2014. Not until nearly the end of our sample period, 2014Q4, do we see a significant decrease in the percentage of survey respondents with perception/expectation higher than 16%. In addition, we note that the concentration of these pessimistic responses were not present before 2009Q4, and that the level of concentration of such responses are higher in expectations than perceptions.

<< Figure 3 here >>

We proceed by putting all the survey responses into two groups: those who believe inflation is or is expected to be more than 16%; and those who do not hold such a belief. By comparing the two groups, we obtain some descriptive results on if respondents in the first group share some common characteristics. As described before, we have information on survey respondents' location of residence (city), age group, employment category, and gender. Our analysis find that the two groups of respondents are not systematically different in terms of age, employment, and gender composition. However, there are significant differences in terms of location of residence. In Table 2, we list the numbers (in the left column, labeled N) and percentages (in right column, labeled %) of responses in each group (16% or below vs. above 16%) for inflation perceptions, 3-month-ahead inflation expectations, and 1-year-ahead inflation expectations, alongside each city's average actual inflation rate during the sample period. The percentages are calculated with all the responses reported in a group as total. From the table, we can see that respondents living in Bangalore, Jaipur, and Mumbai give a disproportionally high number of "> 16%" responses, while those living in Chennai and Kolkata give a disproportionally low number of such responses. For example, only 3.8% of the "16% or below" responses are from respondents living in Bangalore, but 13.1% of "> 16%" responses come from Bangalore. In fact, we can see that almost half of all 6700 responses from Bangalore throughout the entire sample period are in the "> 16%" category, while the average actual inflation rate in Bangalore is only 9.36% for the same time period. On the other hand, residents of Kolkata gave only 1470 "> 16%" responses, out of 13500 total responses for the sample period, when average inflation rate in the city is 8.83%, merely 0.53% lower than that of Bangalore.

<< Table 2 here >>

To further understand the discrepancy between observed inflation perceptions and expectations and the characteristics of survey respondents, we run a set of regressions using household-level data, where the dependent variable is the difference between actual inflation rate and its perception/expectation, i.e., the forecast error, and the independent variables include a set of dummy variables for each survey round (quarter), city, age group, gender, and employment category. In order to reveal the importance of each characteristic of respondents in explaining their forecast errors, we estimate six models with different independent variables. Model 1 to 5 have a set of dummy variables on the right-hand-side representing survey round (model 1), city (model 2), age group (model 3), gender (model 4), or employment category (model 5), respectively. Model 6 contains all the right-hand-side variables used in models 1 to 5 simultaneously. Table 3 reports the results from these regressions. Note that we only report results obtained using inflation perceptions, since qualitatively similar results are obtained using inflation expectations. For each model, we report the coefficient of each independent variable (while omitting all the quarterly dummies) and the number of observations and adjusted R squares. One, two, or three stars after the coefficient denote significance at 5%, 1%, and 0.1% level. From these results, we can see that a large proportion of the forecast errors can be explained by survey respondents' characteristics, as model 6 has an adjusted R squared of 0.47. However, the largest part of the explained forecast errors are explained by the set of quarterly dummy variables, as model 1 shows. This means that most systematic pessimism and optimism in inflation expectations are common to all the survey respondents and vary only over time. The second largest part of the explained forecast errors are explained by respondents' location of residence. But compared with model 1, model 2 has much lower explanatory power, with adjusted R squared of 0.11 compared with model 1's 0.38. Other individual characteristics, including age group, gender, and employment category, while are indeed significant, account for less than 1% of the total forecast errors. Among these characteristics, older age, female, and employment in non-financial industries are closely associated with a higher level of pessimism. We conducted this same exercise but only using data before 2009Q3 and after 2014Q3. As Figure 1 shows, there are no obvious concentration of "16% or more" responses during these quarters. Age and employment category are no longer significant when our models are estimated using this subsample. Collectively, these results show that aggregate shocks do not impact population cohorts symmetrically: It is not that being an old daily worker leads to bias in inflation expectations, rather, it is the disproportionally negative impact of aggregate shocks on this cohort that result in high expectations.

<< Table 3 here >>

This observation leads to a natural, though somewhat ad-hoc, experiment: By simply discarding the extreme responses, i.e., “> 16%”, one may obtain less biased estimates of inflation perceptions and expectations. We briefly demonstrate this in Figure 4, where we compare aggregate quantitative inflation perceptions derived using all available responses (dotted line) and responses excluding the extreme “> 16%” (solid line) with actual inflation rates (dashed line). From the figure, we can see that perceptions derived without using the “>16 %” responses, while having similar dynamics with that derived using all available responses, do seem largely free of bias during the sample period. In particular, during the period of late 2011 to early 2014, where actual inflation rate is stable around 9.5% to 10%, perceptions derived without using the extreme responses seem to be quite accurate. It is worth noting that this demonstration is only meant to show the potential source of bias in aggregate data. We do not suggest the use of this method in formal statistical analysis. More sophisticated adjustments are necessary to properly process the quantitative responses from the survey. In fact, it has long been standard practice in the U.S. to report inflation expectations after adjusting the raw survey responses. As an example, Curtin (1996) details the procedure used to estimate price expectations from the University of Michigan Survey of Consumers.

<< Figure 4 here >>

3.3. Aggregation of inflation expectations

Another factor that may potentially bias inflation expectations on the aggregate level lies in the process of aggregation. As the scale of spending and its sensitivity to sentiment vary across population cohorts depending on the socio-demographic characteristics of the cohort members, we argue that a simple average of individual inflation expectations would fail to provide an accurate picture of inflation expectations in the aggregate. Therefore, we attempt to construct an aggregate and a city-level inflation expectations measure by weighting individual inflation expectations in the IESH survey according to the consumption profile of a typical individual with the same socio-demographic characteristics.

As discussed above, the survey covers households of 12 cities, 3 cities each from the four geographical regions. Let π_{it}^{e} be the city-level aggregated inflation expectation for the i^{th} city and t^{th} quarter, $i = 1$ to 12 (16) and $t =$ 2008Q3 to 2015Q1. However, π_{it}^{e} within a city is observed across a heterogeneous mix of respondents, whose inflation expectations vary across gender, age and employment status. We maintain that this cross-sectional variation of inflation expectations is critically important and any measure of aggregation should incorporate this distributional heterogeneity by taking some kind of weighted average across households. Obviously, an un-weighted aggregation may not reflect the true dimension of inflation expectations in a city. For example, Souleles (2004) suggested weights that could reflect "the scale of spending by different groups of people, or the sensitivity of their spending to their sentiment". In this context, we propose a weighted aggregation formula, using consumption expenditure as weight. Recent evidence using micro-survey data suggests that there is positive cross-sectional association between households spending and inflation expectation. Particularly, the urban, educated, working-age and high income households are likely to spend more when they expect an increase in inflation (D'Acunto et al. (2015)). Also, theoretically, higher inflation expectations provide greater incentive to spend now due to lower real interest rates, given fixed nominal interest rates (Ichiue and Nishiguchi (2015)).

We use consumption data as reported in the "Employment and Unemployment Situation in India, 2011-12" of National Sample Survey Office (NSSO), Government of India. First, we select data of those urban centers of NSSO survey that match with 12(16) cities of IESH. Next, we match four broad household categories as "self-employed", "regular wage/salary earning", "casual labor" and "others". [4] Accordingly, seven categories IESH respondents are grouped to create aforementioned four matched categories as "self-employed"; "financial and other employees" as equivalent to "regular wage/salary earning" group; "daily workers" as "casual labor"; and "housewives, pensioners and others" in the "others" category. Third, within each household category, we group NSSO data by various age classes and work out their average consumption, matching with IESH age groups. There are nine such classes: (1) up to 25 years, (2) 25 to 30 years, (3) 30 to 35 years, (4) 35 to 40 years, (5) 40 to 45 years, (6) 45 to 50 years, (7) 50 to 55 years, (8)

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[4] (i) *Self-employed* are those who worked in household enterprises (self-employed) as own-account worker; worked in household enterprises (self-employed) as an employer; worked in household enterprises (self-employed) as helper; did not work owing to sickness though there was work in household enterprise; did not work owing to other reasons though there was work in household enterprise.

(ii) *Regular wage/ salaried employee* worked as regular wage/salaried employee; did not work owing to sickness but had regular salaried/wage employment; did not work owing to other reasons but had regular salaried/wage employment but not working.

(iii) *Casual labor* worked as casual labor in public works other than MGNREG public works; worked as casual labor in Mahatma Gandhi NREG public works; worked as casual labor in other types of works; did not work owing to sickness (for casual workers only).

(iv) *Others* include people who sought work or did not seek but was available for work (for usual status approach); attended educational institutions; attended to domestic duties only; attended to domestic duties and was also engaged in free collection of goods (vegetables, roots, firewood, cattle feed, etc.), sewing, tailoring, weaving, etc. for household use; rentiers, pensioners, remittance recipients, etc.; not able to work owing to disability; did not seek but was available for work; and others (including beggars, prostitutes, etc.).

55 to 60 years, and (9) 60 years and above. Lastly, we aggregate inflation expectation as follows: Let the average share of monthly consumption expenditure of an individual in k^{th} age group belonging to j^{th} category of households in i^{th} city be c_{ijk} and his/her corresponding inflation expectation at quarter t be π^e_{ijkt}. Then aggregate inflation expectation of the i^{th} city for the quarter t can be expressed as $\pi^e_{it} = \sum_{j=1}^{4} \alpha_{ij} \sum_{k=1}^{9} c_{ijk} \pi^e_{ijkt}$, such that $\sum_{j=1}^{4} \alpha_{ij} = 1, \sum_{k=1}^{9} c_{ijk} = 1$, where α_{ij} is the share of j^{th} category of households in the i^{th} city[5]. Finally, overall inflation expectation π^e_t for quarter t is estimated as $\pi^t_e = \sum_{i=1}^{12} w_i \pi^e_{it}$, where w_i is the weight of the i^{th} city in CPI-IW such that $\sum_{i=1}^{12} w_i = 1$. The same exercise is repeated separately using consumer durables and non-durables. Since the survey records individual responses in intervals, we have to assign each individual response a value. For a response between 1% and 16%, the mid-point of the response category is used. For example, if someone responds that the current inflation rate is between 2% and 3%, we assign the rate 2.5% to him. 0.5% is assigned to individuals responding with "<1%" and 16.5% is assigned to individuals responding with ">16%". Individuals who respond with "No idea" are ignored. The series of aggregate expectations is calculated quarter-by-quarter.

Compared with aggregate and city-level measures of inflation expectations derived using equally-weighted average, the arguably more accurate measures obtained using this weighting procedure account for variations in the scale of consumption spending across socio-demographic groups, though the differences are salient in general, especially at city-level. We do not find systematic differences between measures of inflation expectations based on weights derived using

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[5] Ideally this should have been done by gender. But estimates of urban households' categories (α_{ij}) by cities/states are made available by NSSO in aggregate form, not by gender.

total consumption, durable goods consumption, or non-durable goods consumption. These observations suggest that the characteristics of inflation expectations we discussed in previous subsections are unlikely to be merely artifacts of aggregation bias.

4. Expectation Formation

The previous section discussed asymmetric responses of households' perceptions and expectations to aggregate inflation shocks as well as asymmetric impact of aggregate inflation shocks across population segments. In this section, we shift our attention to the expectation formation process. We study the process using household-level data in this subsection and conduct aggregate-level analysis in the next subsection.

4.1. Analysis using Household-Level Data: Role of Food and Energy Inflation

The hypothesis we want to examine here is that, in forming perceptions and expectations of the overall rate of inflation, whether households give disproportionally large or small weight to food and energy price inflation relative to their weight in household consumption bundle. This issue has received much attention in recent years both in India and in other countries, see Eapen and Nair (2012), Pandey et al. (2013), Guha and Tripathi (2014) for discussions related to India, as well as Bruine de Bruin et al. (2011) and references therein for discussions of other economies. In our exercises below, we not only look at aggregate perceptions and expectations but also analyze individual responses from the IESH survey.

To check if food and energy price inflation have disproportional effect on household inflation perceptions and expectations, we look at whether after controlling for observed household characteristics, the addition of energy and food inflation leads to significant improvement in the model's explanatory power. More specifically, we first estimate a set of baseline models using household-level data, where the dependent variable is household inflation perceptions/expectations, and the independent variables include four lags of actual inflation rate, plus dummy variables for location of residence, age group, gender, and employment category. Then, we add food and/or energy inflation variable to the right-hand-side, and examine the coefficient(s) of the added variable(s), its statistical significance, and the increase (or decrease, when the increase is negative) in the model's adjusted R squared as a result of this addition. This exercise is conducted separately for perceptions, 3-month-ahead expectations, and 1-year-ahead expectations; also separately for each city, in addition to all the cities together. Table 4 shows the results, where for each city, the first row shows the effect of both food and energy inflation; the second row shows the effect of energy inflation only; and the third row shows the effect of food inflation only. For most of the cities, as well as for all the cities as a whole, both food price inflation and energy price inflation have significant effect even after actual and lagged inflation rate and observed respondent characteristics are controlled for. In most cases, the addition of food or energy inflation does not lead to a large increase in the model's explanatory power. However, there are a few important exceptions. Taking inflation perception as an example, the addition of energy price inflation results in an incremental adjusted R squared of more than 5% for Bangalore, Guwahati, and Kolhapur. For Bhubaneswar, Chennai, and Thiruvananthapuram, this addition leads to more than 10% increase in the model's explanatory power. Among these cities, residents of Bhubaneswar and Guwahati give disproportionally smaller weight to energy price inflation (i.e., coefficient is negative), while those living in the other cities give disproportionally larger weight to energy price inflation. Including food price inflation leads to incremental adjusted R squared in excess of 5% for models of Bangalore, Bhubaneswar, Chennai, and Hyderabad. For Kolkata and

Nagpur, the increase exceeds 10%. Among residents of these cities, those from Chennai, Hyderabad, Kolkata, and Nagpur give disproportionally small weight to food price inflation, while others give disproportionally larger weight. When both food and energy inflation are controlled for, as much as 17% increase in explanatory power (from a baseline of only 4%, as in the case of Bangalore) can be observed. Other cities whose residents are much affected by these two consumption categories include Bhubaneswar, Chennai, Kolhapur, Kolkata, Nagpur and Thiruvananthapuram.

<< Table 4 here >>

While one may be tempted to interpret these results as an artifact of animal spirit, there may be other reasons. The CPI-IW (industrial workers) measure with a base year of 2001 is computed with weighting diagrams derived from the results of the Working Class Family Income and Expenditure Surveys conducted during 1999-2000. If the consumption bundle of households today is significantly different than what used to compute the index, one would expect to see households attaching disproportional weights to certain consumption groups such as food and/or energy. The CPI measure introduced in January 2011 uses consumption bundles developed from the results of consumer expenditure survey of 2004 to 2005. The new combined CPI measure should represent a better measure of the actual price changes. In the future, as sufficient amount of data become available, further analysis will be possible, especially on the aggregate level.

4.2. Analysis using Aggregate Data: Rate of Adaptation

We proceed by analyzing expectation formation on the aggregate level. Specifically, we are interested in whether the process of expectation formation on the aggregate level is consistent with the hypothesis discussed in Frankel (1975). The hypothesis is that short-run inflation expectations are affected by two factors. The first factor is the deviation of (most recently observed) actual inflation rate from its expected values. The second factor is how the actual inflation rate differs from its long-run expectation. Using the same notation as in the previous section, let y_t^* be the expectation of y_t, the model is $y_{t+1}^* - y_t^* = \alpha + \beta(y_t - y_t^*) + \gamma(\bar{y}_t - y_t) + u_t$, where $\bar{y}_t$ is a measure of long-run inflation expectations and u_t is the error term. Since the IESH does not collect information on long-run expectations, we use five-year-ahead forecasts from RBI's Survey of Professional Forecasters on Macroeconomic Indicators (SPF). RBI has been conducting the survey since September 2007. Note that when $\gamma = 0$, this model becomes the standard adaptive expectations model, which states that people update their expectations based on the most recently observed difference between the actual and their expectations. We consider this specification as well as the one where $\gamma \neq 0$. Given the limited length of our time series, we conduct this analysis using pooled city-level data. For each city, we construct the city-level expectations and perceptions as simple average of individual expectations and perceptions. Actual inflation rates are also city-specific.

When γ is assumed to be zero, β is estimated to be 0.18 when y_t^* is three-month-ahead expectations. Using one-year-ahead expectations, we estimate β to be 0.19. Both estimates are statistically significant at 1% and both models have adjusted R squared of 0.1. This shows that people do adapt their expectations to reality. However, not everyone make the adjustment in every quarter. If we are willing to assume the framework of Carroll (2003), this estimate suggests that only about 20% of people adapt to the latest actual inflation rate each quarter, while the rest simply stick to their expectations formed in the past. Of course, as this framework precludes partial adjustment, it is unlikely to provide a complete picture of the expectation formation process.

When the deviation of actual inflation rate from both the short-run expectation and long-run expectation are allowed in the model, i.e., $\gamma \neq 0$, we are able to account for a much larger proportion of variations. In both the model of three-month-ahead and one-year-ahead inflations, adjusted R squared doubles. β is estimated to be around 0.4 and γ is estimated to be around 0.37. Again, both coefficients are significant at 1% level. These estimates help us better understand the expectation formation process: People do not just naively adapt to most recent actual inflation rate. Their behavior is consistent with them having a belief that in the long run, actual inflation fluctuates around some long-run expected value. When current actual inflation rate is below what is expected to be the "normal" rate in the long run, $\gamma(\bar{y}_t - y_t) > 0$, and $y^*_{t+1} > y^*_t$, i.e., people expect higher inflation rate.

5. Concluding Remarks

In this paper, we examine the quantitative inflation perceptions and expectations reported in the Inflation Expectations Survey of Households from the RBI. Consistent with prior findings and evidence from other countries and regions around the world, our results also reveal significant and persistent pessimism in household perceptions and expectations. This pessimism is then identified to be the result of large number of unusually high ("> 16%") responses. Subsequent examinations of the data reveal that disproportionally large number of such responses come from residents in only a few cities. In terms of socio-demographic characteristics, we find that respondents who are older, female, or working in non-finance industries tend to be more pessimistic. We demonstrate that by simply discarding these extreme responses, one obtains significantly less biased estimates of inflation perceptions and expectations.

In addition, we look into the hypothesis that energy price inflation and/or food price inflation may have an effect on household inflation perception and expectation that is disproportional to their weight in household consumption bundles. We find evidence supporting this hypothesis: After controlling for actual inflation rates and observed respondent characteristics, the addition of food and/or energy price inflation is generally statistically significant, and provides a large increase in the model's explanatory power for several cities. We also studies the information source of inflation expectations and find that people base their expectations on both past actual inflation rates and short-run forecasts of inflation. Long-run forecasts of inflation do not seem to add additional information after short-run forecasts are used. One important result from our exercises is that, while a certain percentage of households adapt their expectations to the latest actual value each quarter, this rate of adaptation is not constant. When inflation rate is unexpectedly high, i.e., when households under-predict inflation, a much larger proportion of households update their expectations. This explains the apparent lack of adaptation when inflation decreases modestly, while expectations shoot up rapidly following increasing actual inflation.

Overall, our results suggest that the observed difference between actual inflation rate and household perceptions and expectations may be the result of three forms of asymmetry. First, aggregate shocks impact households asymmetrically. Apart from location of residence, older age, female, and employment in non-financial industries seem to be attributes that are common to (head of) households affected more negatively by aggregate shocks. This explains the large number of highly pessimistic expectations observed even during periods where actual inflation rate is low or decreasing. The second asymmetry is demonstrated by the disproportional weight households seem to attach to food and energy price inflation. While this may be simply animal spirit, it may also be a result of the difference between currently household consumption patterns and the now

15-years-old weighting diagrams used in computing the price index. The third is that households respond to changes in actual inflation asymmetrically. Perceptions and expectations change quickly to reflect large increases in actual inflation rate. But when actual inflation rate is stable, households do not seem to be updating their information set frequently, which explains the persistent upward bias during 2011 to 2013.

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Table 1. Target Quota in the Sample (Percent)

This table shows the target percentage of respondents from each category of employment status before and after September 2008. Information in this table is from Tyagi (2009) and Reserve Bank of India (2010).

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

Table 2. Number and Percentage of Respondents Giving Extreme Responses

This table shows the number and percentage of respondents from each city who gave quantitative responses that inflation is >16%, compared with the percentage of those who gave lower responses. The percentages are with respect to the total number of responses that inflation is >16%, and that inflation is no more than16%, respectively.

City	Perception				3-Month Expectations				1-Year Expectations				Average Actual Inflation
	≤16%		>16%		≤16%		>16%		≤16%		>16%		
	N	%	N	%	N	%	N	%	N	%	N	%	
Ahmedabad	5,899	6.4	855	3.5	5,509	6.2	988	3.9	4,760	5.9	1,731	5.3	9.28
Bangalore	3,495	3.8	3,233	13.1	3,229	3.6	3,209	12.6	2,896	3.6	3,530	10.8	9.36
Bhopal	6,294	6.8	451	1.8	6,015	6.8	529	2.1	5,534	6.9	907	2.8	9.42
Bhubaneswar	2,247	2.4	268	1.1	2,175	2.5	177	0.7	2,040	2.5	313	1.0	7.64
Chennai	12,380	13.3	1,083	4.4	11,984	13.5	1,218	4.8	11,595	14.4	1,560	4.8	9.37
Delhi	11,369	12.3	2,028	8.2	10,480	11.8	2,531	9.9	9,416	11.7	3,217	9.8	8.4
Guwahati	5,702	6.1	975	4.0	5,539	6.3	1,032	4.0	5,241	6.5	1,208	3.7	8.85
Hyderabad	5,717	6.2	1,034	4.2	5,343	6.0	1,309	5.1	5,025	6.2	1,566	4.8	8.49
Jaipur	3,803	4.1	2,936	11.9	3,766	4.3	2,734	10.7	2,925	3.6	3,547	10.8	8.55
Kolhapur	1,061	1.1	1,418	5.8	885	1.0	1,535	6.0	829	1.0	1,560	4.8	8.28
Kolkata	11,963	12.9	1,470	6.0	11,532	13.0	1,278	5.0	11,040	13.7	1,686	5.2	8.83
Lucknow	5,216	5.6	1,525	6.2	4,983	5.6	1,656	6.5	4,660	5.8	1,996	6.1	9.21
Mumbai	8,332	9.0	4,980	20.2	8,142	9.2	4,900	19.2	6,775	8.4	6,331	19.3	9.94
Nagpur	1,463	1.6	1,039	4.2	1,349	1.5	1,128	4.4	1,070	1.3	1,411	4.3	7.52
Patna	5,882	6.3	854	3.5	5,626	6.4	988	3.9	5,238	6.5	1,394	4.3	9.61
Trivandrum	1,942	2.1	493	2.0	1,917	2.2	296	1.2	1,407	1.7	767	2.3	11.27
Total	92,765	100.0	24,642	100.0	88,474	100.0	25,508	100.0	80,451	100.0	32,724	100.0	

Table 3. Regression Results: Forecast Errors on Individual Characteristics

This table shows the coefficient estimates of a set of models where the dependent variable is the difference between actual inflation rate and perceived inflation rate (individual quantitative data). Apart from the variables listed in the table, model 6 also contain a set of quarterly dummy variables for each quarter/round of survey. Coefficients suffixed by * are significant at 5% level; ** denotes significance at 1% level; *** denotes significance at 0.1%. Model 1 is the constant only model and is omitted to save space.

Variable Group	Variable	Model 2	Model 3	Model 4	Model 5	Model 6
City	Bangalore	-2.780***				-2.815***
	Bhopal	1.111***				1.068***
	Bhubaneswar	0.013				1.482***
	Chennai	0.450***				0.421***
	Delhi	-0.274***				-0.320***
	Guwahati	0.09				0.057
	Hyderabad	-0.757***				-0.823***
	Jaipur	-3.026***				-3.054***
	Kolhapur	-5.082***				-3.627***
	Kolkata	0.594***				0.599***
	Lucknow	-1.162***				-1.167***
	Mumbai	-2.590***				-2.633***
	Nagpur	-4.000***				-2.516***
	Patna	-0.916***				-0.932***
	Trivandrum	-3.191***				-1.645***
Age Group	25 to 30 years		0.048			0.082*
	30 to 35 years		-0.062			-0.052
	35 to 40 years		-0.114*			-0.118**
	40 to 45 years		-0.125*			-0.171***
	45 to 50 years		-0.266***			-0.274***
	50 to 55 years		-0.239***			-0.366***
	55 to 60 years		-0.340***			-0.336***
	60 years and above		-0.546***			-0.474***
Gender	Female			-0.287***		0.029
Employment Category	Other Employees				-0.047	-0.176***
	Self-Employed				-0.235***	-0.260***
	Housewife				-0.523***	-0.527***
	Retired Persons				-0.537***	-0.197**
	Daily Workers				-0.721***	-0.647***
	Other Category				0.316***	-0.092
Constant		-0.783***	-1.528***	-1.552***	-1.362***	-1.564***
Observations		117418	117308	117310	117308	117308
Adjusted R Square		0.100	0.001	0.001	0.003	0.452

Table 4. Effect of Energy and Food Price Inflation: Regressions with Individual-Level Data

This table shows the effect of CPI energy and food inflation. Inc. $\bar{R}^2$ is defined as the increase in $\bar{R}^2$ as a result of adding CPI energy and/or food inflation to the baseline model, which contains four lags of actual inflation rate and dummy variables for age group, employment category, gender, and city of residence. All models are estimated using individual-level data. Coefficients in bold are significant at 5%.

City	Perceptions				3-Month-Ahead Expectations				1-Year-Ahead Expectations			
	Baseline $\bar{R}^2$	Inc. $\bar{R}^2$	Coefficient		Baseline $\bar{R}^2$	Inc. $\bar{R}^2$	Coefficient		Baseline $\bar{R}^2$	Inc. $\bar{R}^2$	Coefficient	
			Energy	Food			Energy	Food			Energy	Food
		0.020	0.000	**-0.226**		0.018	**0.020**	**-0.257**		0.021	**0.064**	**-0.261**
All Cities	0.168	0.016	**0.038**		0.134	0.013	**0.064**		0.146	0.016	**0.108**	
		0.020		**-0.226**		0.018		**-0.274**		0.020		**-0.315**
		0.018	**-0.041**	0.025		0.035	**-0.170**	**-0.130**		0.030	**-0.081**	**-0.147**
Ahmedabad	0.116	0.018	**-0.053**		0.123	0.032	**-0.111**		0.101	0.025	-0.015	
		0.017		**0.059**		0.025		0.006		0.028		**-0.082**
		0.169	**0.651**	**0.741**		0.108	**0.488**	**0.601**		0.130	**0.529**	**0.565**
Bangalore	0.039	0.064	**0.533**		0.041	0.035	**0.392**		0.059	0.053	**0.439**	
		0.071		**0.616**		0.050		**0.508**		0.049		**0.463**
		0.029	**-0.132**	**-0.263**		0.024	**-0.144**	**-0.333**		0.010	**-0.090**	**-0.295**
Bhopal	0.020	0.014	**-0.106**		0.024	0.004	**-0.111**		0.020	-0.005	**-0.061**	
		0.018		**-0.226**		0.014		**-0.293**		0.006		**-0.270**
		0.106	**-2.347**	**0.730**		0.005	0.040	**0.608**		0.023	**-0.815**	**0.692**
Bhubaneswar	0.071	0.100	**-2.976**		0.067	0.002	**-0.485**		0.024	0.019	**-1.411**	
		0.070		**1.857**		0.005		**0.589**		0.020		**1.083**
		0.154	**0.396**	**-0.292**		0.194	**0.479**	**-0.345**		0.165	**0.439**	**-0.460**
Chennai	0.062	0.124	**0.479**		0.055	0.158	**0.577**		0.049	0.116	**0.570**	
		0.078		**-0.447**		0.098		**-0.533**		0.103		**-0.632**
		0.037	**0.135**	**0.336**		0.036	**0.124**	**0.352**		0.060	**0.252**	**0.452**
Delhi	0.129	0.019	0.002		0.115	0.019	-0.014		0.132	0.031	**0.074**	
		0.031		**0.223**		0.031		**0.247**		0.040		**0.240**
		0.074	**-0.330**	**0.242**		0.031	**-0.164**	**0.239**		0.031	**-0.094**	**0.342**
Guwahati	0.157	0.062	**-0.367**		0.182	0.021	**-0.200**		0.159	0.010	**-0.146**	
		0.024		**0.350**		0.021		**0.293**		0.027		**0.373**
		0.057	**0.106**	**-0.330**		0.040	**0.109**	**-0.201**		0.031	**0.108**	**-0.141**
Hyderabad	0.088	0.037	**0.130**		0.076	0.033	**0.124**		0.058	0.028	**0.118**	
		0.052		**-0.348**		0.035		**-0.219**		0.027		**-0.158**

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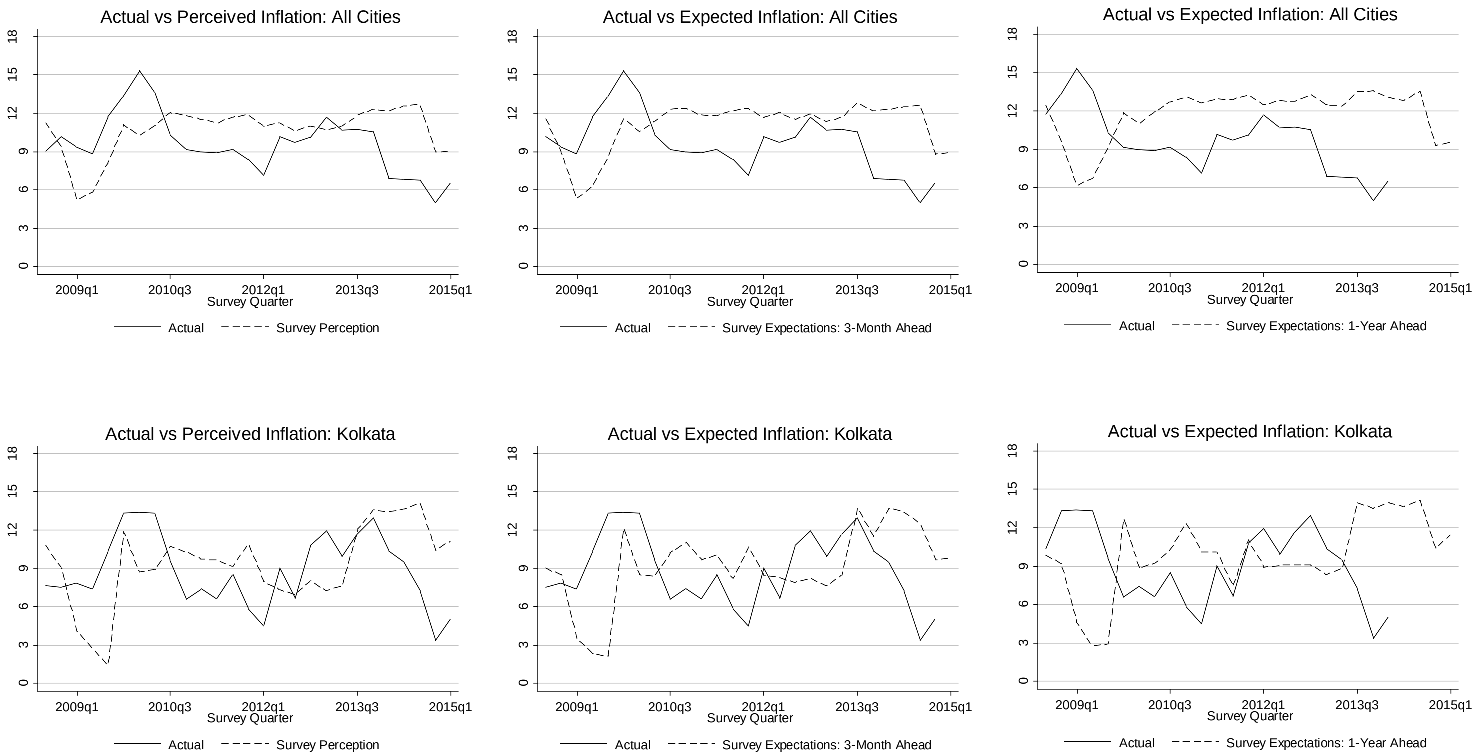
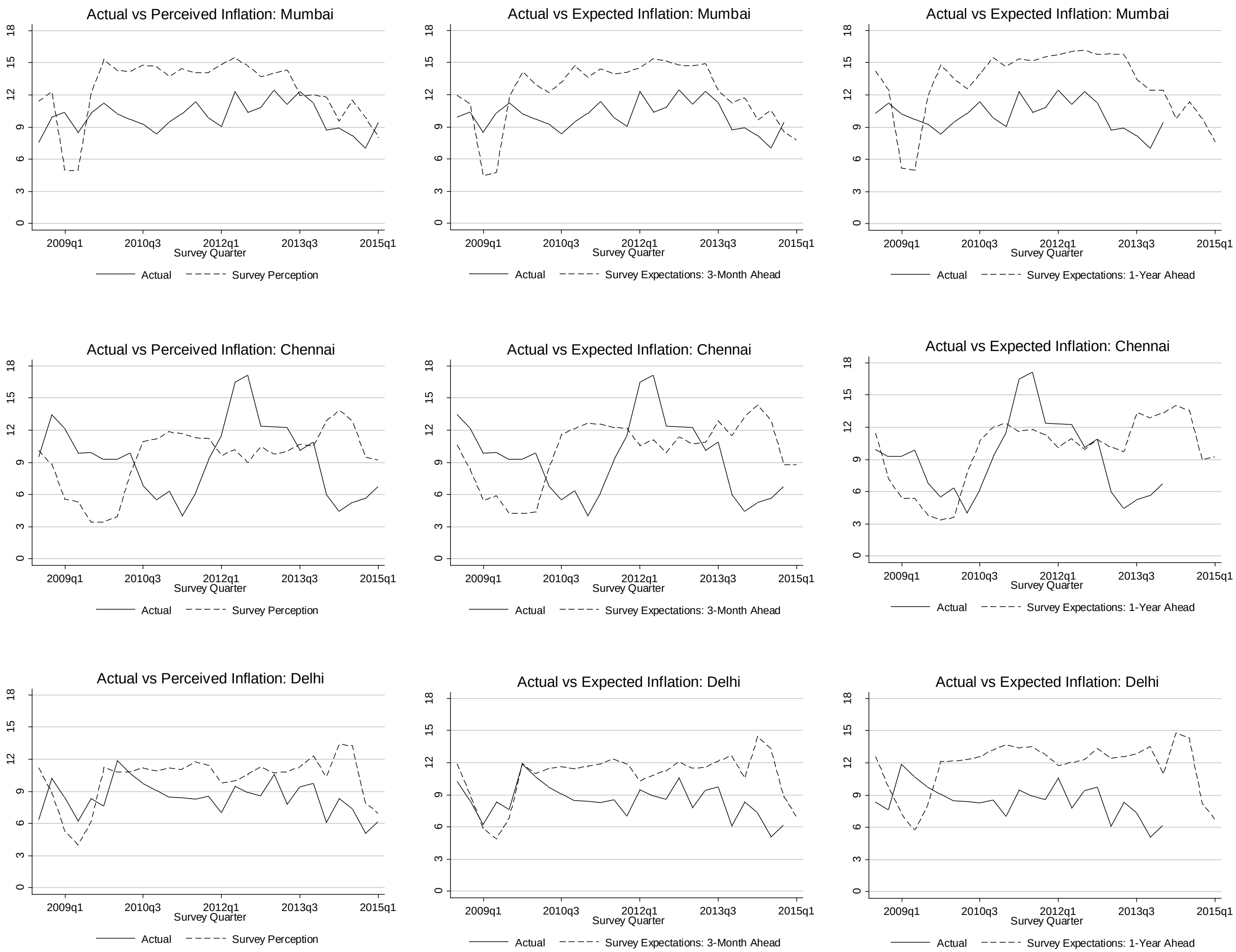
City	Perceptions				3-Month-Ahead Expectations				1-Year-Ahead Expectations			
	Baseline $\bar{R}^2$	Inc. $\bar{R}^2$	Coefficient Energy	Coefficient Food	Baseline $\bar{R}^2$	Inc. $\bar{R}^2$	Coefficient Energy	Coefficient Food	Baseline $\bar{R}^2$	Inc. $\bar{R}^2$	Coefficient Energy	Coefficient Food
		0.054	**0.174**	**-0.287**		0.032	**0.123**	**-0.233**		0.022	**0.108**	**-0.152**
Jaipur	0.104	0.038	**0.278**		0.063	0.023	**0.207**		0.075	0.017	**0.163**	
		0.043		**-0.408**		0.027		**-0.319**		0.017		**-0.227**
		0.105	**1.835**	**-0.314**		0.080	**1.701**	**-0.280**		0.073	**1.427**	-0.014
Kolhapur	0.097	0.097	**1.416**		0.177	0.075	**1.327**		0.152	0.073	**1.407**	
		0.026		**0.395**		0.021		**0.377**		0.037		**0.537**
		0.129	**-0.126**	**-0.961**		0.110	**-0.057**	**-1.012**		0.100	**-0.125**	**-0.981**
Kolkata	0.215	0.010	-0.019		0.145	0.009	**0.056**		0.149	0.008	-0.015	
		0.121		**-0.906**		0.108		**-0.987**		0.094		**-0.926**
		0.008	**0.094**	**-0.261**		0.004	0.008	**-0.174**		-0.001	0.015	0.014
Lucknow	0.073	0.001	0.026		0.077	0.001	-0.037		0.095	-0.001	0.018	
		0.006		**-0.198**		0.004		**-0.169**		-0.001		0.023
		0.061	**0.408**	**0.382**		0.070	**0.445**	**0.236**		0.119	**0.542**	**0.287**
Mumbai	0.101	0.032	**0.211**		0.093	0.062	**0.324**		0.085	0.106	**0.394**	
		0.009		**0.057**		0.025		**-0.119**		0.045		**-0.145**
		0.162	**-1.218**	**-1.340**		0.057	0.185	**-0.864**		0.033	**0.325**	**-0.656**
Nagpur	0.237	0.032	**-1.662**		0.263	0.000	-0.101		0.352	0.000	0.108	
		0.145		**-1.404**		0.057		**-0.854**		0.032		**-0.639**
		0.029	**-0.109**	**-0.267**		0.028	**-0.093**	**-0.266**		0.042	**0.044**	**-0.285**
Patna	0.087	0.002	**-0.038**		0.073	0.000	-0.022		0.041	0.009	**0.120**	
		0.021		**-0.217**		0.022		**-0.224**		0.041		**-0.305**
		0.120	**2.081**	**-0.523**		0.066	**1.299**	-0.067		0.161	**1.870**	**-0.191**
Trivandrum	0.211	0.100	**1.226**		0.069	0.066	**1.189**		0.057	0.159	**1.557**	
		0.036		**0.380**		0.043		**0.496**		0.095		**0.620**

Figure 1. Quantitative Survey Expectations and Actual Inflation Rates

This figure compares quantitative survey perception/expectation with the corresponding official statistics. The plots in the left column show the comparison between survey respondents' currently perceived inflation and the actual inflation; the middle column and the right column show the comparison between 3-month-ahead and 1-year-ahead inflation expectations and the ex post actual values, respectively.




Actual vs Perceived Inflation: Mumbai
Actual vs Expected Inflation: Mumbai
Actual vs Expected Inflation: Mumbai
Actual vs Perceived Inflation: Chennai
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0
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12
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2009q1
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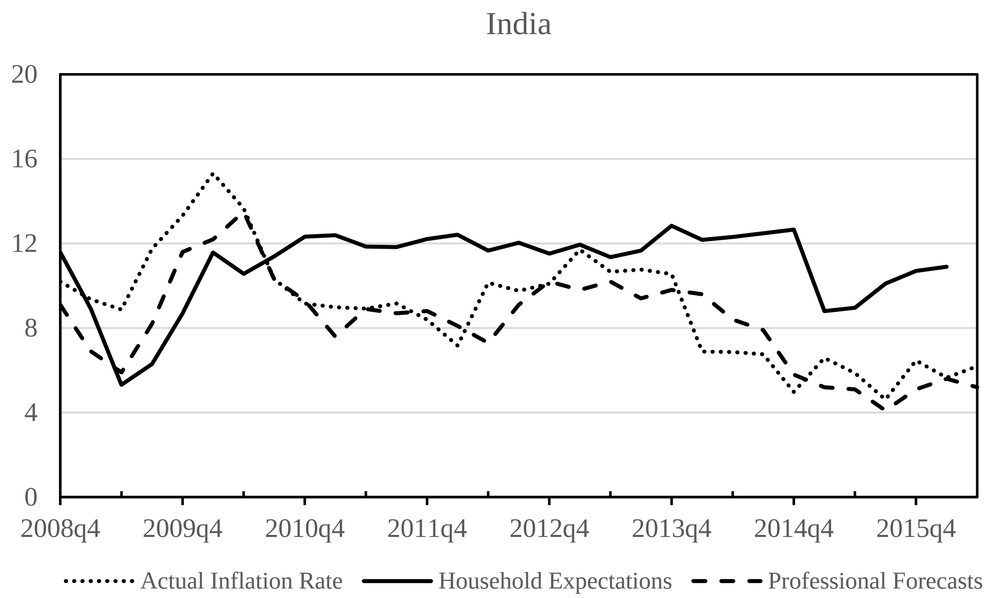
2012q1
2013q3
2015q1
Survey Quarter
Actual
Survey Perception
Survey Expectations: 3-Month Ahead
Survey Expectations: 1-Year Ahead

Figure 2. Households vs. Professionals

This figure compares one-quarter-ahead household inflation expectations and professional forecasts of inflation in India and the United States.



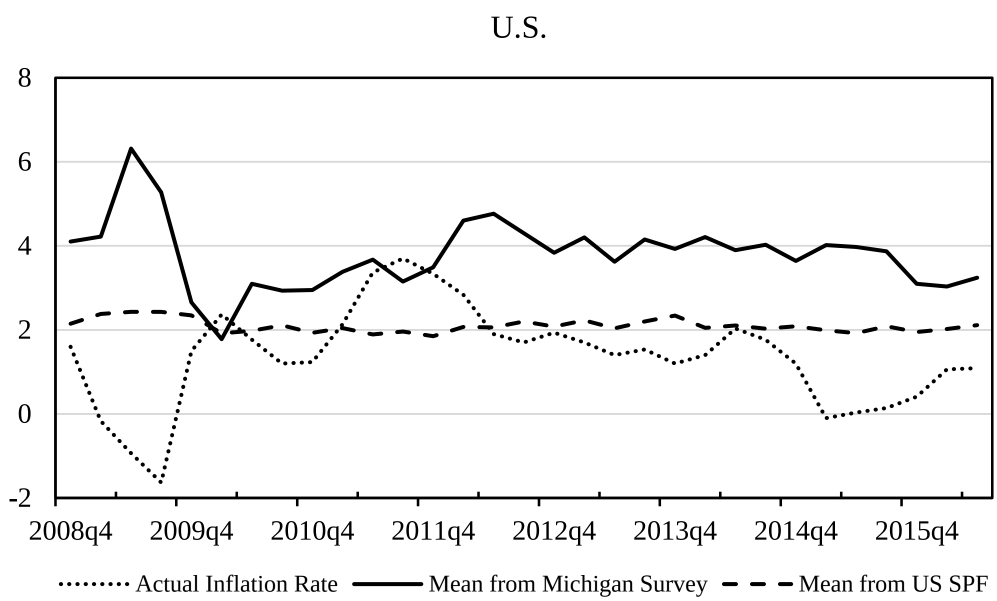


Figure 3. Distribution of Quantitative Responses

This figure shows how the distribution of quantitative responses evolves over time. For the responses to each question (perceptions (Figure 3a), 3-month-ahead expectations (Figure 3b), and 1-year-ahead expectations (Figure 3c)), histograms of the responses are shown for each quarter in the sample. Vertical axis shows the percentage of responses falling into each bin. Permissible responses are from 1 to 16. Solid vertical line shows the actual inflation rate. Dashed vertical line shows the mean of the distribution.

Figure 3a. Perceptions

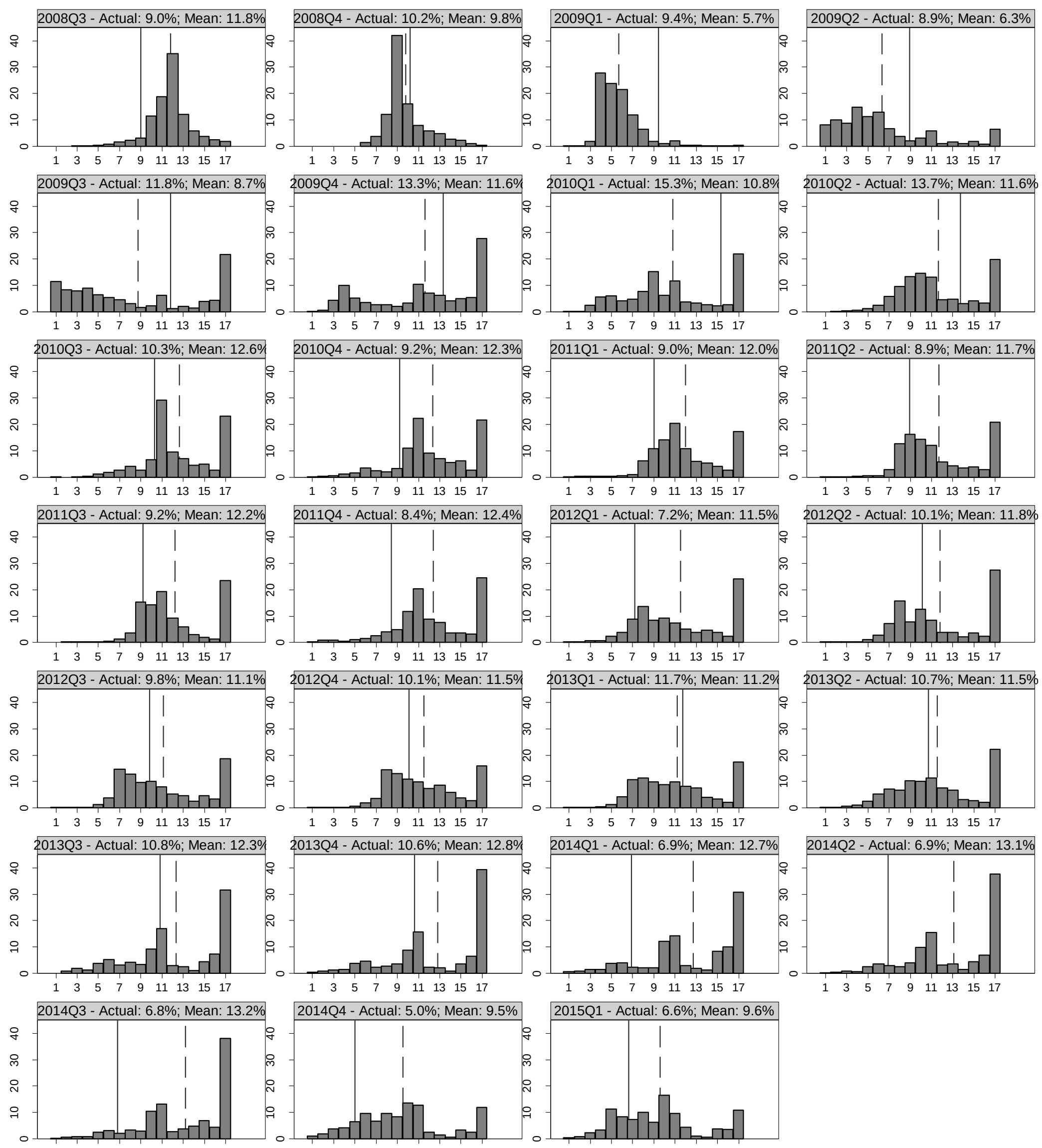


Figure 3b. 3-Month-Ahead Expectations

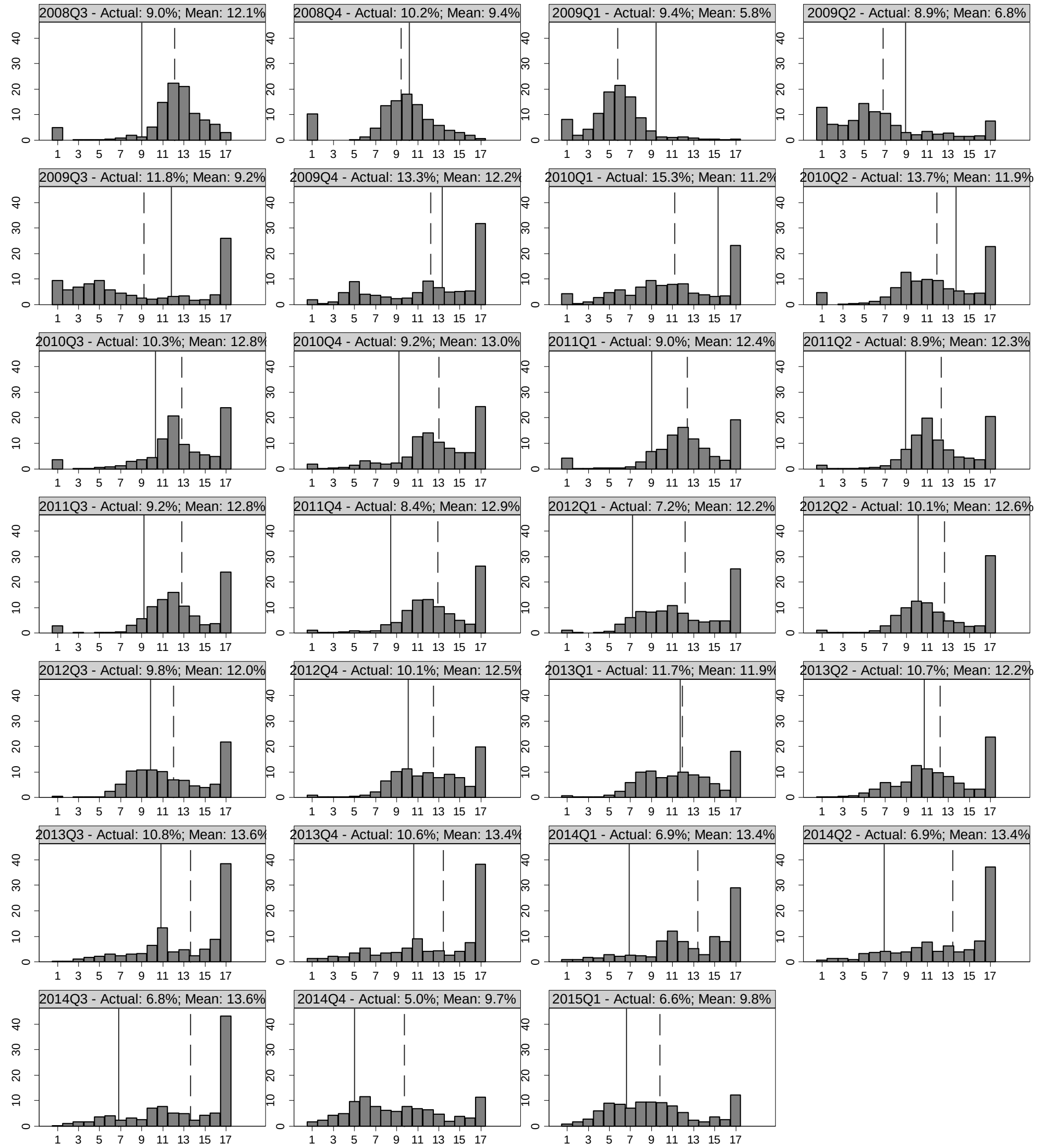


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Figure 3c. 1-Year-Ahead Expectations

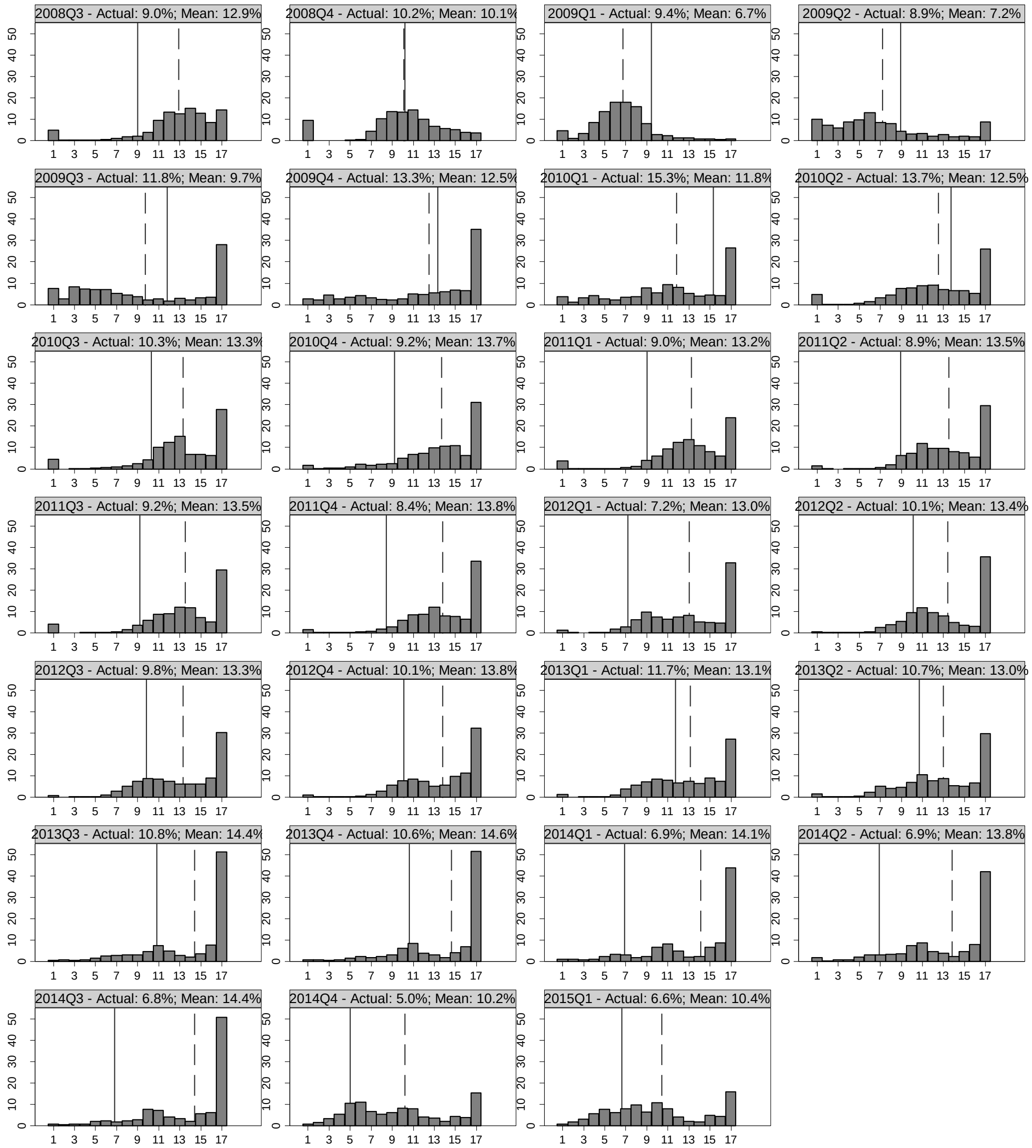

Figure 4. Quantitative Survey Perceptions without Using "> 16%" Responses

This figure compares quantitative survey perception with the corresponding official statistics. The solid line is the official statistic. The dotted line is the survey perception derived as the average of all the individual quantitative survey responses. The dashed line is the survey perception derived as the average of all the individual quantitative responses that give a perception of 15% or lower.

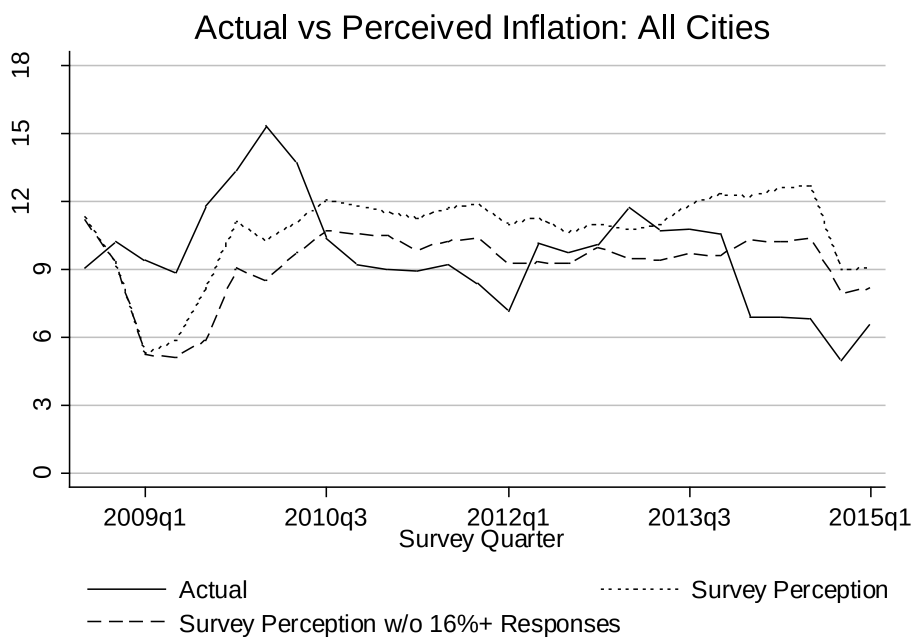

Figure 5. U.S. Household Inflation Expectations by Education Level

This figure contrasts one-year-ahead inflation expectations of respondents without a college degree or beyond with those without a high school diploma. Expectations are derived from U.S. Survey of Consumers, a monthly survey conducted by the University of Michigan.