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Learning from Household Tendency Surveys**

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Inflation Expectations in India: Learning from Household Tendency Surveys

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Abstract

Using a large household survey conducted by the Reserve Bank of India since 2005, we estimate the dynamics of aggregate inflation expectations over a volatile inflation regime. A simple average of the quantitative responses produces biased estimates of the official inflation data. We therefore estimate expectations by quantifying the reported directional responses. For quantification, we use the Hierarchical Ordered Probit model, in addition to the balance statistic. We find that the quantified expectations from qualitative forecasts track the actual inflation rate better than the averages of the quantitative forecasts, highlighting the filtering role of qualitative tendency surveys. We also report estimates of disagreement among households. The proposed approach is particularly suitable in emerging economies where inflation tends to be high and volatile.

Keywords: Hierarchical ordered probit model, Quantification, Tendency survey, Disagreement, Indian inflation.

JEL Classification: C25, D84, E3

¹ This paper is based on the keynote address on July 24, 2015 by Kajal Lahiri entitled “Measuring economy-wide inflationary expectations and their uncertainty from cross-sectional surveys” at the 9th Statistics Day Conference at the Reserve Bank of India, Mumbai on the occasion of the birth anniversary of P. C. Mahalanobis. The views expressed in the paper are those of the authors and do not represent the views of the institutions to which they belong. The authors are grateful to two anonymous referees for valuable comments, which improved the exposition of the paper.

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1. Introduction

Monitoring household inflation expectations and their diversity is of special significance to monetary authorities, especially in emerging economies.² These expectations, while usually found not to conform to the rational expectations doctrine, play an important role in people's day-to-day decision-making, cf. Armantier *et al.* (2015). Household expectations are difficult to measure, and are almost exclusively monitored using Consumer Tendency Surveys (CTS).³ To avoid being excessively demanding on lay persons and also for ease of data collection, these surveys traditionally ask for qualitative or directional forecasts only (e.g. will go up, stay the same or go down). However, some recently developed surveys also solicit quantitative responses that can be utilized to supplement these directional forecasts.⁴

Despite the widespread use of survey measures of inflation expectations, and in light of the oft-found sluggishness by households to adjust to new information, one unresolved issue is how best to aggregate the individual-level directional survey responses for the conduct of monetary policies. While there is a long strand of literature devoted to this issue, not much applied work has

² cf. Patra and Ray (2010).

³ Information from the financial market has been used in the literature to measure inflation expectations. However, such measures are often obtained under strong assumptions and are unlikely to be representative of household expectations, which are often found to be irrational. In addition, households are known to be sluggish in updating their information set.

⁴ See Curtin (2007, 2018) and United Nations (2015) for reviews of consumer surveys around the world in a historical perspective. Details about several such surveys in the US are reviewed in Bruine de Bruin *et al.* (2017) as well.

been done using these methodological developments in the context of emerging economies.⁵ This is a particularly important issue for a country like India, where inflation has been persistently high and food security has been a significant concern. When surveys report inflation expectations that differ substantially from the official data and vary systematically by socio-demographic groups, it is difficult for monetary authorities to use the reports to formulate policies because of distributional consequences. Nevertheless, one cannot readily dismiss the survey-based household expectations, since they could be rightfully different from the official statistics due to a number of reasons.⁶

This paper addresses the issue by experimenting with alternative quantification techniques using a uniquely structured *Inflation Expectations Survey of Households (IESH)* – a quarterly survey conducted by the Reserve Bank of India (RBI). This survey collects both qualitative and quantitative expectations independently, in the sense that the answers need not be mutually consistent.⁷ This feature sets our study apart from other recent attempts at measuring inflation expectations using qualitative survey data.⁸ It allows us to compare, contrast, and combine measures of inflation expectations based on both qualitative data and quantitative responses. By

⁵ See, among others, Fische and Lahiri (1981), Dasgupta and Lahiri (1992), Ash et al. (1998), Nardo (2003), Kakoska and Teksoz (2007), Lui et al. (2011), Proietti and Frale (2011), Breitung and Schmeling (2013), Vermeuleu (2014), Lahiri and Zhao (2015), and Kaufmann and Scheufele (2017) for developments in quantification methods over the last 30 years.

⁶ Curtin (2007, 2010) and Bruine de Bruin *et al.* (2017) document systematic differences in reported inflation expectations across several surveys in the United States and offer several rationalizations. See also Dräger (2016) and references therein for recent developments on sticky information and rational inattentiveness theories.

⁷ As a comparison, for example, in the University of Michigan's consumer sentiment survey, a respondent is first asked which direction the price level will change (if any), then by how much. This guarantees that, e.g., a qualitative response of increasing price level is always accompanied by a positive quantitative response.

⁸ For example, Rosenblatt-Wisch and Scheufele (2015) quantify the qualitative inflation expectations reported in the Swiss Consumer Survey using different variants of probability approach and regression approach. Ito and Kaihatsu (2016) quantify inflation and wage expectations of Japanese consumers using a modified version of the Carlson-Parkin (1975) method.

combining these diverse types of information, we obtain a potentially better estimate of aggregate household inflation expectations.

During our sample period from late 2008 to mid-2017, India experienced dramatic fluctuations in inflation. After a sharp increase in early 2010 from 9% to 15%, the inflation rate remained rather stable (around 9% to 10%) before it steadily declined to about 6% beginning 2014. The rate further declined over 2014-16 to a historically low level around 1%, only to rebound to over 5% in 2018Q1.⁹ Such dynamics present both an interesting case study, where we can observe household responses to these sudden changes, and a challenge for quantification, where the standard assumptions like unbiasedness and normality are unlikely to hold. We show that the qualitative responses and our approach to quantification perform well in this dynamic and challenging environment.

This same RBI data set was analyzed previously in Das *et al.* (2016), where we focused exclusively on the quantitative responses and their heterogeneities along socio-demographic and geographic dimensions.¹⁰ The aggregate inflation expectations derived from these quantitative responses were persistently biased. However, we found that the households whose expectations far exceed the official statistics might be providing an authentic description of their own experiences, given their relative socio-economic status and geographic location. We identified one source of these experiences to be the different food and energy prices faced by households. Ball *et al.* (2016) report a similar finding, where the relative price changes originated from the food and energy industries were found to partly explain the volatility in headline inflation. We concluded

⁹ Ball *et al.* (2016) provide careful and extensive documentation of inflation in India since 1994.

¹⁰ A few other researchers have used the aggregate-level data from the survey, cf., Ghosh et al. (2017). Das *et al.* (2016) includes additional references.

that policymakers should not simply discount or even discard the high inflation expectations reported by vulnerable segments of the population. To the contrary, such expectations are often informative.¹¹

In this paper, we build on these developments and obtain a potentially more useful estimate of aggregate inflation expectations from the qualitative responses in the IESH survey. We improve upon the existing quantification approaches in three aspects. First, we use a flexible Hierarchical Ordered Probit (HOPIT) model for quantification as proposed in Lahiri and Zhao (2015). This approach allows us to control for the socio-economic characteristics of survey respondents, in addition to relaxing the assumptions imbedded in the Carlson-Parkin (CP) procedure on the indifference thresholds (i.e., households' sensitivity to small changes in inflation) and the disagreement associated with the aggregate inflation expectation. Second, we argue that redefining the directional responses with respect to the inflation rate rather than the price level is more informative in high-inflation, high-volatility environments. In countries like India, where the inflation rates are persistently high and variable, this simple reformulation allows us to identify the turning points in inflation expectations much more easily and accurately. Finally, we consider quantifying not only the qualitative responses reported in the survey but also the directional signals implied by the quantitative responses. We can therefore compare the two sets of estimates based on the answers to two independent survey questions given by the same set of households. This approach also provides a scope for forecast combination, which could produce an even more accurate measure of inflation expectations. Even though our empirical results are limited by the IESH's focus on urban households, the procedure we develop to estimate household expectations

¹¹ Using data from Argentina, Cavallo *et al.* (2016) show that households use inflation statistics in a sophisticated way: When their own experiences differ from official statistics, households process the information in a way consistent with their own experiences.

should be of interest to a wide variety of audiences, in particular to policymakers and researchers who are primarily interested in using aggregate measures of expectations.

The IESH is introduced in the next section. We describe the quantification method and the HOPIT model in Section 3. Our empirical results are reported and discussed in Section 4. Finally, concluding remarks are offered in Section 5.

2. The Inflation Expectations Survey

In this study, we use the *Inflation Expectations Survey of Households* from the Reserve Bank of India. This is a quarterly survey started in 2005Q3 focusing on urban dwellers. Initially, the survey sampled 500 households from each of the four major metropolitan areas, Chennai, Delhi, Kolkata, and Mumbai. From the third round, the survey added 250 households from each of the following eight cities: Ahmedabad, Bangalore, Bhopal, Jaipur, Guwahati, Hyderabad, Lucknow, and Patna. Starting from 2012Q4, 250 households from each of the four new cities – Bhubaneswar, Kolhapur, Nagpur, and Thiruvananthapuram – have been added to the survey, bringing the total sample size up to 5000.¹² The survey design went through several significant changes since 2005, before it was stabilized in 2008Q3. Even though we do not use the data from the survey’s initial years, our sample, from 2008Q3 to 2017Q2, still has an unprecedented cross-sectional dimension of 4,000 to 5,000 individual responses per quarter.

While the IESH collects information on the identity of the respondents, the data used here is anonymized. However, we have information on each respondent’s gender, age group, employment category, and city of residence, all of which are reported in Block 1 of the survey. The age groups start from “younger than 25” and end at “60 or older” with groups in between spanning five years

¹²Three additional cities - Chandigarh, Raipur, and Ranchi - have been included in the survey since 2015Q1.

each (e.g., the second group is “25 to 30”). Employment categories include financial sector employees, other (sector) employees, self-employed, housewives, retired, daily workers, and others.

In Block 2, the survey asks for “expectations of respondent on prices in next 3 months,” and in Block 3, the survey asks for “expectations of respondents on prices in next one year.” In both blocks, respondents are asked to give qualitative responses about the price level in general (“general”) and of specific products or services, viz., “food products,” “non-food products,” “household durables,” “housing,” and “services.” Permissible responses are “i. Price increase more than current rate,” “ii. Price increase similar to current rate,” “iii. Price increase less than current rate,” “iv. No change in prices,” and “v. Decline in prices.”

Block 4 of the survey seeks quantitative responses on “respondent’s views on the following inflation rates”: “current inflation rate,” “inflation rate after 3 months,” and “inflation rate after one year.” Quantitative responses to questions in Block 4 are recorded as intervals from <1%, 1 – 2%, 2 – 3%, and so on, all the way to >16%. Unlike the previous two blocks, Block 4 only asks for expectations on the price level in general, not that of specific products or services. These quantitative responses are “the annual rate of the price change,” as specified on the survey questionnaire.

The quantitative responses on three-month- and one-year-ahead inflation rates are very similar, with the latter being slightly higher throughout our sample period. This is true for the qualitative responses as well. Over the entire sample, about 70% of the qualitative responses are the same at both horizons. Around 15% of the responses are higher at the longer horizon. Therefore, in the rest of the paper, we focus on the three-month-ahead expectations regarding the general price

level. Our quantification procedure applies equally well to the one-year-ahead expectations and the expectations for specific products or services.

Compared with well-known surveys of similar nature, such as the University of Michigan's consumer sentiment survey, a unique feature of the IESH is that the questions in each block do not depend on those in the other blocks. For example, in the IESH, a respondent can give a qualitative response in Block 2 stating that she expects the price level to decline, but then give a positive number as her quantitative response to the inflation rate question in Block 4. This aspect of the IESH allows us to study the consistency between respondents' quantitative and qualitative responses, and potentially use both types of data to estimate aggregate inflation expectations.

As for the actual values, among the four major consumer price indices in India – CPI for Urban Non-Manual Employees, CPI for Industrial Workers, CPI for Agricultural Laborers, and CPI for Rural Laborers – CPI for Industrial Workers (CPI-IW) is the most appropriate index for us given the IESH survey's focus on urban households. We calculate inflation rate as percent change from a year ago in CPI-IW, where the quarterly price index is the average of the monthly values. To give an up-to-date picture of inflation dynamics, we plot aggregate series up to 2018Q1 where appropriate. Our analysis based on individual responses is limited to the end of 2017Q2, beyond which we do not have data available.

3. Quantification Methods

Two standard quantification methods have been widely discussed in the literature and used in practice. The first is the bellwether balance statistic, due to Anderson (1952) and Theil (1952), defined as the percentage of survey respondents giving a positive (up) response minus the

percentage giving a negative response (down) plus 100.¹³ The second is the method due to Carlson and Parkin (1975). Both methods use only the percentages of respondents giving each type of possible responses. In order to fully utilize all available information from the survey about individual respondents, we use the method proposed in Lahiri and Zhao (2015). This method generalizes the Carlson-Parkin method using a hierarchical ordered probit (HOPIT) model, which nests the probability model implied by the Carlson-Parkin method as a special case. Since the probability model implied by the balance statistic is not a special case of the HOPIT model, we also calculate the balance statistic using our data set. The balance statistic also serves as a summary of the underlying data, where the percentage saying “same” (%Same) is the remaining component. Using the notion of spectral envelope, Proietti and Frale (2011) show that the balance statistic has a filtering role and extracts the underlying cycle imbedded in a time series of counts.

Let individual i 's true expectation about time period t be y_{it}^* . Our aim is to obtain an estimate of the economy-wide expectation y_t^* with the common factor assumption that $y_{it}^* = y_t^* + u_{it}$, $u_{it} \sim N(0, \sigma_{it}^2)$. Thus, for each t , σ_{it}^2 measures the variance of the idiosyncratic component of the individual forecasts. Given the structure of the IESH, let the individual quantitative response be $Y_{it} = y_{it}^* + \varepsilon_{it}$, which is assumed to be a noisy (ε_{it}) measure of y_{it}^* due to various factors, such as inter-personal differences in information sets, efficiency, recording errors, and strategic loss functions. Let the individual qualitative response be $y_{it} = \sum_{j=1}^J [j \times \mathbf{I}(\delta_{it}^{j-1} < y_{it}^* \leq \delta_{it}^j)] \in \{1, 2, 3, \dots, J\}$. The index J is simply the number of possible responses available to the individual.

¹³ The definition we use matches the way U.S. consumer sentiment is quantified. Depending on the application, the definition of a balance statistic may be presented in a different form, such as the percentage of survey respondents giving a positive response plus half of the percentage giving a neutral response, which is a simple linear transformation of the definition we use. The latter is often known as the diffusion index, used in the construction of PMI, see Lahiri and Monokrousos (2013).

Using this notation, we can write the fraction of respondents giving the response j in period t as $Frac_{jt} = N^{-1} \sum_{i=1}^N \mathbf{I}(\delta_{it}^{j-1} < y_{it}^* \leq \delta_{it}^j)$, where N_t is the total number of respondents in period t .

We normalize the two extreme unobserved thresholds $\delta_{it}^0 = -\infty$ and $\delta_{it}^J = \infty$ for all i and t , but others are estimated freely.

In this framework, we can see that y_{it} is a discretized version of Y_{it} and the variance of the error ε_{it} of the numerical forecasts is expected to be smaller than the error variance in the qualitative response model, cf. Lui et al. (2011). However, the hope is that the implicit censoring in y_{it} will act as a natural filter for the deviant forecasts. For the HOPIT model, we must have $\delta_{it}^{j-1} < \delta_{it}^j$ for all j . This restriction simply reflects a basic consistency in human perception.

People are either unable to perceive or indifferent toward small changes. For example, one may report that the inflation rate stays the same when it actually changes from, say, 2.0% to 2.01%.

Our task of quantification using the qualitative forecasts is therefore to estimate y_{it}^* using y_{it} . This is done in a two-step process. The first step is to estimate the HOPIT model. To complete the model's specification, we further assume that $\delta_{it}^j = \delta_{it}^{j-1} + \exp(X_{ij}\beta_j) \forall 1 < j < J$ and $\sigma_{it} = \exp(X_{ij}\gamma)$, which allow the thresholds and the variance to depend on respondent characteristics.

The assumption that δ_{it}^1 are all the same is simply a necessary normalization. The set of parameters $\{\beta_2, \beta_3, \dots, \beta_{J-1}, \gamma, y_t^*\}$ are estimated with maximum likelihood.¹⁴ Unfortunately, the scale of y_t^* and the δ s cannot be identified, as is well known in the discrete choice literature. So we calibrate these values in a separate second step. Economic theories typically give little guidance regarding how calibration should be carried out. Following conventions in the literature, we calibrate the

¹⁴ For a complete and detailed description of the model as well as the likelihood function, see Lahiri and Zhao (2015).

quantified expectations so that they have the same mean and variance as the actual values over our sample period. This is done by first standardizing the uncalibrated series, and then multiplying the standardized values by the standard deviation of the actuals, before adding the mean of the actuals. We want to emphasize that calibrating the series of estimates does not alter its temporal dynamics. In particular, the calibrated series and the uncalibrated series have the same correlation coefficient with the actual values. Calibration is simply a procedure to facilitate the comparison between the quantified series and the actual values. The calibrated series is globally unbiased by definition. One cannot determine the level of bias in the quantified series, regardless of what calibration procedure is used, or if calibration is performed at all.

Our final specification of the HOPIT model is based on preliminary analysis and tests. As Dasgupta and Lahiri (1992) and, more recently, Breitung and Schmeling (2013) have demonstrated, for the validity of the Carlson-Parkin procedure, it is important to allow for temporal and individual heterogeneity in the indifference thresholds and the variances to explain the breaks in the correlation between the quantitative and qualitative forecasts. In our specification, a survey respondent's location of residence, gender, age, and employment category are allowed to affect the respondent's indifference thresholds. These groups of independent variables may have different effect on the two unobserved thresholds of our HOPIT model. We group the responses into three categories, requiring two thresholds to be estimated. The variance is allowed to be time varying, but is restricted to be the same for all the cross-sectional units.¹⁵ However, due to the short time period over which our model is estimated, we do not worry about temporal variations in indifference thresholds.

¹⁵ We checked all these restrictions for each group of independent variables using standard likelihood ratio tests.

4. Empirical Results

4.1 Examining quantitative expectations

Given that the IESH directly asks for households' quantitative expectations, the natural starting point for anyone who intends to obtain an aggregate measure of inflation expectation is to extract the first few moments of individual quantitative responses. Since the responses are recorded as intervals, we simply take the midpoint of an interval when aggregating. For example, a response of 2 – 3% is taken as 2.5%. The <1% responses are treated as 0.5% and the >16% responses are treated as 16.5%.¹⁶

<< Figure 1 here >>

The mean of the individual expectations are compared with the actual rate of inflation in Figure 1. In addition to the three-month- and one-year-ahead expectations, we also plot the reported inflation perceptions in the same figure as a reference. The quantitative expectations are less variable and persistently biased in relation to the official rate. Interestingly, expectations underestimated the actuals during the sudden upsurge in inflation in 2008-2009, but then consistently overestimated since 2010. Thus, as is typically the case, expectations underestimated changes in the actual inflation rate. During this later period, the actual inflation rate fluctuated between 1% to 12%; but the expectations are nearly 4% higher on average. As Patra and Ray (2010) emphasized, inflation surprises can seep into household expectations that can linger on for a while, creating stark challenges for the monetary authority, particularly in an emerging economy like India. Such persistent heavy bias generated media skepticism in the usefulness of this new survey and spurred public discussions about its possible discontinuation. However, the surge in inflation

¹⁶These two choices are reasonable given the historical inflation rate in India since the 80's.

that India witnessed is a world-wide phenomenon, and similar biases have been observed in household surveys in a number of other countries, see Das et al. (2016) and Easaw et al. (2013).

Comparing the two series of expectations and the series of perceptions in Figure 1, we can see that they have almost identical dynamics, with pairwise correlations all exceeding 0.95. In particular, all three series have the same turning points in 2009Q1 and 2014Q3, suggesting that the expectations series have no additional foresight than the perceptions. When the actual inflation rate declined sharply in 2014Q1, both perceptions and expectations remained high until one year later. As already stated, in subsequent empirical exercises, we focus on three-month-ahead expectations given that the one-year-ahead series shows little difference. The similarity between the perceptions and the expectations suggests that in order to study how quickly households adjust to new information, it may be more efficient to study the dynamics of perceptions than expectations even in a rational expectations world. However, for our purpose of constructing better estimates of household expectations, neither series alone is sufficient: In the exercises to follow, we utilize both perceptions and expectations at the same time by looking into the subtle differences between the two, i.e., the expected direction of change in the inflation rate implied by them.

<< Figure 2 here >>

When we look at the cross-sectional distributions of the expectations, it becomes clear why the aggregate expectations are persistently high. We plot the distributions of the quantitative expectations quarter by quarter in Figure 2, with the vertical axis showing the percentage of responses. The actual inflation rate for a quarter is marked with a solid vertical line. The dashed vertical line shows the mean of the distribution for that quarter. Figure 2 clearly shows the source of the bias. At the beginning of the sample as well as towards the end of the sample, the distributions of inflation expectations are largely bell-shaped, with only small concentrations of

extreme responses (i.e., $<1\%$ and $>16\%$). However, between 2009Q3 and 2014Q3, we see a large number of responses concentrated in the $>16\%$ category. These extreme responses account for much of the bias we observe in the aggregate.

One possible way to address the problem caused by these outlying responses is trimming, i.e., to impose a “sanity” clause on the reality perceived by lay households. To explore whether trimming is an appropriate solution, we consider several alternative approaches. First, we consider the standard practice of trimming the top and the bottom 5% of the responses. Second, we consider trimming only the top 5% of the responses, since the issue we are trying to address is positive rather than negative bias. The third method removes extreme responses that lie beyond predefined thresholds: The upper threshold is defined as the third quartile plus 1.5 times the interquartile range. The lower threshold is the first quartile minus 1.5 times the interquartile range. In addition, we consider using the median instead of the mean when aggregating individual responses. We plot the results in Figure 3. For comparison, we also plot the actual inflation rate and the mean of the individual responses excluding “ $>16\%$.” It is obvious that except for the last option, none of the other trimming methods significantly reduces the bias. Taking the median instead of the mean even increases bias for the period between 2013 and 2014. It seems that a simple way to significantly reduce the amount of bias in aggregate expectations is to completely discard all the “ $> 16\%$ ” responses. But even this approach fails to bring the expectations in line with the actuals for the post-2014 period.

<< Figure 3 here >>

Despite its somewhat promising performance, discarding all the “ $> 16\%$ ” responses should not be the preferred aggregation method for a number of reasons. First, over the entire sample, there are 19% of the responses that fall into this category. It is difficult to argue that such a large

proportion of responses are simply outliers and should be discarded. Second, since 16% is the highest category, any respondent with even higher expectations is forced into this category. Considering this possibility, trimming these responses would only introduce additional distortions, rather than providing a more accurate measurement.¹⁷ Third, for many quarters in our sample, particularly during 2008-2010, households with the same observable characteristics did not respond in such extremes. So these high values must be triggered by some new economic changes to this select group. Finally, these extreme responses are associated with respondent characteristics that may reflect their personal experiences, and are therefore potentially informative. Das *et al.* (2016) explore the asymmetry and heterogeneity in these quantitative responses and find that a large number of respondents giving these extreme responses are from cities that experienced higher inflation locally, often due to fluctuations in food and energy prices. These respondents tend to be older, poorer, and of lower socio-economic status in general. Given the reasons above, we believe that rather than trying to reduce the bias in quantitative data by trimming away a large number of responses using some arbitrary rules, it is better to estimate household inflation expectations using qualitative data that can perform as a natural filter, cf. Proietti and Frale (2011).¹⁸

¹⁷ Since 2015Q1, the actual numeric responses from these respondents are recorded. Over the period from 2015Q1 to 2017Q2, the mean and median of the reported expectations are 31% and 25% respectively, both much higher than 16%. This evidence is similar to the University of Michigan's consumer sentiment survey over 1978 - 2014. The Michigan survey records one-year-ahead quantitative inflation expectations up to a rate of inflation 50%. Out of around 8800 responses above 16%, 4700 are above 20%; 1900 are above 30%; and 1400 are above 40%. Keep in mind that on average, the inflation rate in the US is much lower than that in India. Thus, the extreme responses found in IESH is not unusual even in established household surveys.

¹⁸ Kishor (2011) reports significantly positive data revisions in inflation rate based on Indian Wholesale Price Index during 1999-2009. Thus, the use of preliminary rather than the revised inflation data would not have helped to reconcile the overestimation of the actual inflation by the quantitative expectations.

4.2 Balance statistics and qualitative response categories

The most straightforward and popular way to summarize and quantify qualitative responses is to use the balance statistic. In order to calculate it, we need to group the qualitative responses into a few categories – generally three. The standard practice is to define the categories relative to the level of the target variable, i.e., an “up” response means the price level goes up and a “down” response means the price level goes down. However, in a country such as India, where the inflation rate has been persistently high, very few households expect the price level to decline. In our sample, especially before 2014, nearly 95% of the households expect the price level to go up each quarter. If we follow the standard practice and categorize the qualitative responses based on the price level, there would be little play in the resulting percentages. In fact, during several quarters between 2011 and 2013, fewer than 10 households out of a sample size of more than 4000 expect the price level to decline. As an alternative, we could categorize the qualitative responses with respect to the inflation rate, e.g., “up” responses capture all who expect the inflation rate to increase. According to this alternative definition, in addition to the responses “price increases less,” the last two categories “no change in price” and “decline in price” are also considered “down” responses. In general, the latter two responses may not necessarily imply a lower inflation rate. But in our context, when both actual and perceived inflation are persistently and significantly higher than zero, both these responses would certainly imply a decline from the current inflation rate. By categorizing the qualitative responses with respect to the rate of inflation, we are able to quantify households’ beliefs on how the inflation rate will change more informatively. During most of the quarters before 2014, around 70% of the households expect inflation rate to increase. Towards the end of our sample, this number declines to only 30%. Since 2015, nearly 40% the households expect the inflation rate to decline. These changes are consistent with the official inflation statistics.

<<Figure 4 here>>

Figure 4 shows the balance statistics from the reported qualitative responses. To facilitate comparison, we calibrate both sets of balance statistics so that they have the same mean and variance as the actual inflation rate.¹⁹ The correlation coefficient between the two balance statistics is 0.92. The correlations between the two balance statistics based on the price level and the inflation rate with the actuals are 0.75 and 0.74 respectively. The balance statistic based on the inflation rate is less volatile and tracks the actuals much better when inflation suddenly started to fall after 2012Q3. Compared to the quantitative series in Figure 3, this successful behavior of the balance statistic is quite remarkable and convincing due to its simplicity. The balance statistic based on the price level started its decline with a lag of two quarters in a choppy fashion, whereas the one based on the inflation rate started falling contemporaneously and smoothly. However, both statistics became more volatile post 2015 and neither tracked the actual rates particularly well.

While the differences between the two sets of balance statistics seem small, there is a theoretical reason why it is preferable to categorize the responses with respect to the inflation rate in the Indian situation. It is well-known that standard quantification methods are not very reliable when the percentage of responses is extremely high or low. For example, as discussed in Lahiri and Zhao (2015), the Carlson-Parkin method produces *lower* inflation estimates when *more* respondents believe that the price level is to increase, if the proportion exceeds a particular threshold.²⁰ While the HOPIT model does not suffer from this exact issue, its estimates tend to be

¹⁹ The procedure is the same as what used in our HOPIT model and is described in Section 3. Again, it is done simply to facilitate comparison across estimates and the official statistics. Neither the dynamics of the estimates nor the pairwise correlations is altered.

²⁰ This threshold is a function of the proportion of respondents who believe that the price level will stay the same. For example, when 10% of the respondents believe that the price level will stay the same, the threshold for observing such counterintuitive results is roughly 80%. See Figure 2 of Lahiri and Zhao (2015) and associated discussions.

less accurate when some categories contain very few observations. This is especially so when there are many parameters in the model because individual socio-economic characteristics appear as covariates in the specification. We can avoid such problems if qualitative responses are categorized with respect to the inflation rate, not the price level.

4.3 Consistency between qualitative and quantitative expectations

Reflecting the same underlying expectations, the qualitative and the quantitative data should have common information content. The potential for improving estimates of inflation expectations by using qualitative data lies in the differences between the two. To check the consistency between the two types of responses, we impute the qualitative response implied by each quantitative response, and compare the imputed directional (qualitative) forecasts with the reported qualitative responses. Consistent with the assumption in the quantification exercises discussed later on, we assume that households are unable to perceive minor changes in inflation. We set this so-called indifference (or imperceptibility) threshold to be 1%. Since the quantitative responses are recorded in multiples of 1%, this assumption seems natural in our context.²¹ More importantly, because the reported qualitative responses in the survey are recorded with reference to the current rate of inflation, we need a reasonable measure of it in order to convert the quantitative expectations to qualitative directional forecasts. The official inflation rate certainly fits this description. But the preliminary official data come with a lag and are subject to revision. Consequently, not all households are equally attentive to their announcements. We therefore use the revised official data.

²¹ Our estimates from the HOPIT model suggest that the thresholds are around 1% on average with very little variation, consistent with our assumption here.

Alternatively, given that households may form their expectations conditioned on their individual-specific perceptions, we also consider using these perceptions as the current rate.²²

<<Figure 5 here>>

We plot the balance statistics of the two sets of implied qualitative expectations in Figure 5. Comparing the two plots, we see that the balance statistics based on directional forecasts computed using perceptions are somewhat better aligned with the actual inflation rate, compared to those with the current official inflation rates as the base. This is especially true over the period of 2011 to 2015, when actual inflation rates are relatively stable. Like the behavior of the series of quantitative expectations over this period, the balance statistics with the actual inflation rates as the base failed to capture the significant drop in inflation. However, the turning point of the balance statistics with respect to inflation perceptions is well aligned with that of the actual inflation rates. As we have seen in Figure 1, both perceptions and expectations are similarly biased. Therefore, the direction of change implied by the expectations with reference to the actual inflation rates are similarly biased, but the direction of change implied by the expectations with respect to perceptions are not. Another rationale for the use of perceptions is that they may match the preliminary inflation figures better than the finally revised inflation values. Note that similar to what Figure 4 shows, towards the end of the sample period, both series show notable departures from the official statistics.

<<Figure 6 here>>

²² In the context of household inflation forecasts in the U.S., Lahiri and Zhao (2016) have documented the value of perceptions in explaining revisions in expectations.

To see how close the reported qualitative data and the imputed directional forecasts are, we report the Goodman-Kruskal's gamma coefficients in Figure 6. Based on the concordant and discordant pairs of observations, this statistic measures the degree of association between two ordinal variables. The gamma statistic is bounded between -1 and 1. When the value is close to 0, the two variables tend to be unrelated. The gamma value can be interpreted as the difference between the likelihood of two randomly chosen observations being of the same order and the likelihood of them being ordered differently. As shown in Figure 6, the reported qualitative responses and the implied directional expectations are very similar over the first half of our sample period. The two sets of qualitative data are positively associated in all periods, i.e., the gamma statistics are never below 0. The estimated standard errors for the gamma coefficients are small, with an average of 0.015 and a maximum of 0.04. That is, the gamma statistics are significantly different from either 1 or 0 at the conventional 5% level of significance. The correlation fell dramatically towards the end of our sample period as the reported qualitative responses and the directional forecasts derived from quantitative forecasts behaved quite differently with the sudden downward drift of inflation after 2013Q2 (see Figures 4 and 5).

4.4 Quantified inflation expectations

Based on our analysis above, we proceed to estimate household inflation expectations by quantifying two sets of qualitative data. The *reported* qualitative responses are the ones recorded by the survey. The *imputed* qualitative expectations are what the quantitative expectations with reference to perceptions imply. Using the HOPIT model, we obtain two sets of estimated (quantified) inflation expectations from the two sets of data. Again, both sets of estimates are calibrated the same way, so that both have the same mean and variance as the actual inflation rates during our sample period. Figure 7 compares them.

<<Figure 7 here>>

From late 2008 to early 2010, when the actual inflation rate declined slightly before increasing significantly, the estimates from the reported responses tracked the actuals much more closely than the estimates from the imputed responses did. The two sets of estimates subsequently moved in a similar fashion. Both series started to decline sharply in 2013Q3 in tandem with the actual inflation rate. Note that this behavior sharply contrasts with that of the quantitative expectations, which remained nearly constant for one additional year. Nevertheless, this is a clear example of how we are able to improve the estimates of inflation expectations by converting the quantitative expectations to a trichotomous ordered response variable. Comparing the quantitative expectations with the perceptions, we recover valuable information on the turning point. This difference in the timing of the turning point in the quantitative expectations and that of the quantified expectations also suggests an internal consistency in household expectations formation. Despite the level being much different from the actual inflation rate, the quantitative expectations and perceptions are formed consistently, in the sense that the difference between the two correctly tracks the movements of the actual inflation rates. Similar to the first part of the sample, during the periods after 2013Q3, the estimates based on the reported responses tracked the actuals more closely than those based on imputed responses did. This is in line with the consensus in the economics and psychology literature that directional questions in Consumer Tendency Surveys (CTS) may often be more suitable for households, since lay consumers are much less likely to give accurate numeric responses compared with professional forecasters.

<< Figure 8 here>>

With four sets of estimates²³ of household inflation expectations, there is a scope for further improvement through forecast combination. We explore this potential by combining them using a simple regression. First, we regress the actual inflation rate on the four sets of estimates. We find that the two series from the imputed data based on quantitative forecasts do not significantly add to the accuracy in the presence of the other two based on qualitative responses. The balance statistics and HOPIT model estimates based on the reported qualitative responses are then combined using the well-known Granger-Ramanathan forecast combination procedure. The results are reported in Figure 8. The balance statistics and the HOPIT estimates using the same qualitative responses have their own *pros* and *cons*. The balance is known to pick up the smoother cyclical features of the series, whereas the generalized Carlson-Parkin (CP) or HOPIT estimates pick up more short-run fluctuations.²⁴ Also, it is well-known that CP estimates tend to be very sensitive to changes in %Same when it is small and variable. As we can see in Figure 7, our HOPIT estimates shot up from 9% to nearly 15% as the inverse of %Same increased from 4% to 8.5% (see Fig. 9, lower panel). The balance was unaffected by this increase in %Same (Fig. 4). Thus, a combination of the two can potentially be more robust than any individual set of estimates over the business cycle. The in-sample RMSE of the combined estimates is 2.28, which is about the same as the best individual.²⁵ The weights of the two sets of estimates are insignificantly different from equal. So in practice, one could as well use equal weights for combination.

²³ We have four sets of estimates: two from purely qualitative data (the balance statistics and the HOPIT model estimates based on qualitative responses) and two based on quantitative expectations (balance statistics from implied qualitative responses and HOPIT estimates based qualitative responses imputed from numerical forecasts).

²⁴ See, for example, Dasgupta and Lahiri (1992), Proietti and Frale (2011), and Breitung and Schmeling (2013). Vermeulen (2014) shows that the balance statistic does well during stable periods, whereas the CP method works relatively better during volatile periods.

²⁵ Both the balance statistics and the HOPIT model based on reported qualitative responses show similar performance, with in-sample RMSE of 2.28 and 2.32, respectively. The difference between the two is not statistically significant.

In our application, both the balance statistics and the HOPIT model fit the actual values equally well. We, however, prefer a combined estimate because the balance statistic acts as a natural filtering device or a smoother, whereas the HOPIT model allows for important respondent-specific characteristics to affect the underlying model parameters, including the indifference thresholds and disagreement. Measures based on qualitative responses match the official inflation rates well even in periods of abrupt changes, suggesting that the Indian monetary authority is better off following the simple balance statistic than the quantitative expectations. The latter is useful in tracking changes in the cross-sectional distributions over time.

4.5 Disagreement in inflation expectations

Based on large quarterly samples of 4,000-5,000 households, the standard deviations (s.d.) of the cross-sectional distribution of the quantitative expectations are straightforward measures of the level of disagreement in household inflation expectations.²⁶ In addition, the HOPIT model produces estimates of the standard deviation of the residuals as a measure of forecast disagreement. More recently, Bachmann et al. (2013) argue that under certain conditions, estimates of cross-sectional dispersions of qualitative expectations, coded 1, 0, and -1, can be a useful proxy for uncertainty. Obviously, if one were to change the way the responses are coded, the standard deviation could change, so it can be freely calibrated.²⁷

<<Figure 9 here>>

²⁶ The cross-sectional dispersion of beliefs has long been recognized as an informative indicator. It was shown to have significant predictive power as early as Dasgupta and Lahiri (1993).

²⁷ The HOPIT model estimates, based on the same qualitative data, are also identified only up to a scale parameter. But the scale parameter is determined as the estimated expectations are calibrated against the actual inflation rates. Specifically, the scale parameter is the ratio of the standard deviation of the actuals to that of the uncalibrated expectations.

The s.d. of the quantitative forecasts and the Bachmann et al. (2013) measure (FDISP) are plotted in the top panel of Figure 9. These two series have a correlation of only 0.35, even though they look somewhat similar, especially over the latter half of the sample period. This is not entirely unexpected, since the qualitative responses tend to concentrate on the two extremes (i.e., not many households expect the inflation rate to stay the same) while the quantitative expectations are more evenly spread out across multiple bins. The FDISP and the HOPIT estimates together with the inverse of %Same are presented in the bottom panel of Figure 9. In the CTS literature, the latter has sometimes been used as a proxy for uncertainty in the balance statistic, see United Nations (2015). The FDISP and the HOPIT estimates are similar, with a correlation of 0.86, since both are based on the same qualitative data set. The HOPIT estimates by definition have less variability because some of the variations in expectations are due to the variations in the means over time and the respondent characteristics, which are accounted for by the independent variables in the model. This makes it an arguably more reliable measure.²⁸ Both series declined slowly from 2008 to 2013. Then, there was a large increase accompanied by a significant decline in the levels of the expectations (see Figure 1), suggesting that households were initially uncertain about the decline in inflation. However, as the decline in the actual inflation rate persisted, the disagreement implied by the standard deviation of the HOPIT residuals dissipated, while the FDISP measure continued to surge. For both the series, an increased level of disagreement can be observed at the beginning of the sample period, when the actual inflation rate increased suddenly. A similar finding is reported in Cavallo *et al.* (2016), where the authors document an asymmetric reaction to inflation signals using data from Argentina.

²⁸ The difference in variability is only conceptual because the FDISP can be freely scaled.

As shown in Figure 9, the time series of s.d. from the quantitative forecasts and the two from the qualitative forecasts (FDISP and HOPIT) are rather different, despite all three being based on the same set of households for the same target variable. This contrast serves as a reminder that the last two disagreement measures are based on a truncated version of the underlying quantitative variable. Hence the estimated cross-sectional variances, by definition, are expected to be smaller than the actual. The extent of underestimation will vary over time depending on the extent of truncation. This problem with FDISP as a measure of uncertainty can be easily seen. Since FDISP is defined as the square root of $\frac{Frac_{up} + Frac_{down} - (Frac_{up} - Frac_{down})^2}{2}$, or equivalently, the square root of $1 - Frac_{same} - (Frac_{up} - Frac_{down})^2$, it is inversely related to the balance statistic whenever the balance (i.e., $Frac_{up} - Frac_{down}$) is above zero, keeping the value of $Frac_{same}$ the same. This is likely to be the case in a persistently high inflation environment, especially when the balance statistic is defined with respect to the price level. In our data set of Indian inflation forecasts, when the balance statistic is defined with respect to the price level, $Frac_{up} - Frac_{down}$ is *always* above zero. As a result, the FDISP measure is nearly perfectly negatively correlated with the balance statistic with a correlation of -0.97. Even when we define the balance statistic with respect to the inflation rate, $Frac_{up} - Frac_{down}$ is above zero for all but a few quarters. The sample correlation between FDISP and the balance statistic is -0.91. In Figure 10, we plot FDISP against the balance statistics under the two definitions (based on prices and inflation) to make the point that one should be careful about making inference regarding cross-sectional variability or disagreement in a sample based on qualitative directional data. Given the balance statistic, FDISP in our sample would have very little additional information.

<<Figure 10 here>>

5. Conclusions

In this paper, we estimate the inflation expectations of urban households in India using a quarterly survey conducted by the Reserve Bank of India. We show that the quantitative responses from the survey are significantly biased and the direction of bias depends on the stage of the inflation cycle. We use several trimming methods to reduce the bias, but find that trimming does not solve the problem. We therefore turn to the qualitative responses with the hope that these may filter the aberrant forecasts naturally. Given the unique structure of the survey, we are able to compare the quantitative responses with the qualitative responses. Furthermore, we show that the qualitative expectations implied by the quantitative responses are not subject to the same amount of bias as the quantitative expectations, provided we derive the qualitative responses relative to the perceived current inflation rates, as opposed to the actual inflation rates.

We proceed by quantifying the qualitative expectations using a flexible HOPIT model that yields estimates of aggregate inflation expectations and the associated disagreement, while controlling for survey respondent's location of residence, age, gender, and employment category. We compare the estimates obtained using the reported qualitative responses and the imputed qualitative expectations implied by the quantitative expectations. We find that both sets of estimates track the actual inflation rate better than the pure quantitative expectations. In particular, the turning points of both sets of estimated expectations match that of the actual values, while the quantitative expectations have a significant lag of more than two quarters. This illustrates the superiority of the qualitative responses during this volatile inflation regime.

In addition, we examine the HOPIT model's estimates of disagreement in inflation expectations and the FDISP – the standard deviation of the three-category qualitative responses – recently proposed by Bachmann et al. (2013). These two disagreement measures do not match well

with the estimated standard deviations of the cross-sectional distributions of quantitative forecasts available in the survey based on over 4,000 households. In our data set, the correlation between the balance statistic and the FDISP measure of disagreement based on the qualitative indicators is almost perfectly negative, making the later a dubious proxy for the true forecast disagreement or uncertainty.

We also conclude that the proposed HOPIT model based on qualitative responses when directional forecasts are evaluated with respect to the inflation rates (not price levels) is suitable to extract the dynamics of inflation expectations over this volatile inflation regime in India. These estimates are significantly better than the simple average or median of the quantitative responses. Our approach to measuring inflation expectations should also be of value to many other emerging economies with high and highly variable inflation rates. When only quantitative survey responses are available, using imputed qualitative responses with the HOPIT model may be a second-best alternative. In most countries, household expectations of inflation play a central role in the conduct of monetary policy. This paper presents evidence that measures based on qualitative expectations from the RBI's IESH survey track the actual inflation rate well enough for Indian policy-makers to take them seriously for setting monetary targets.

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Figure 1. Quantitative Perceptions/Expectations and Actual Inflation Rates

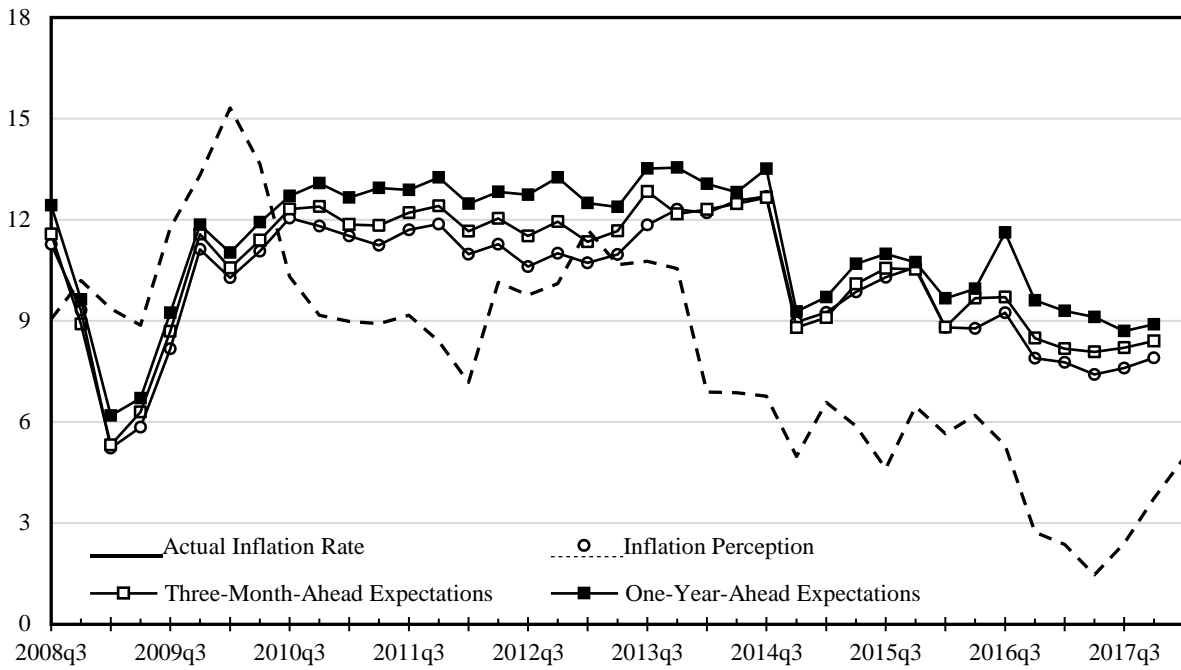
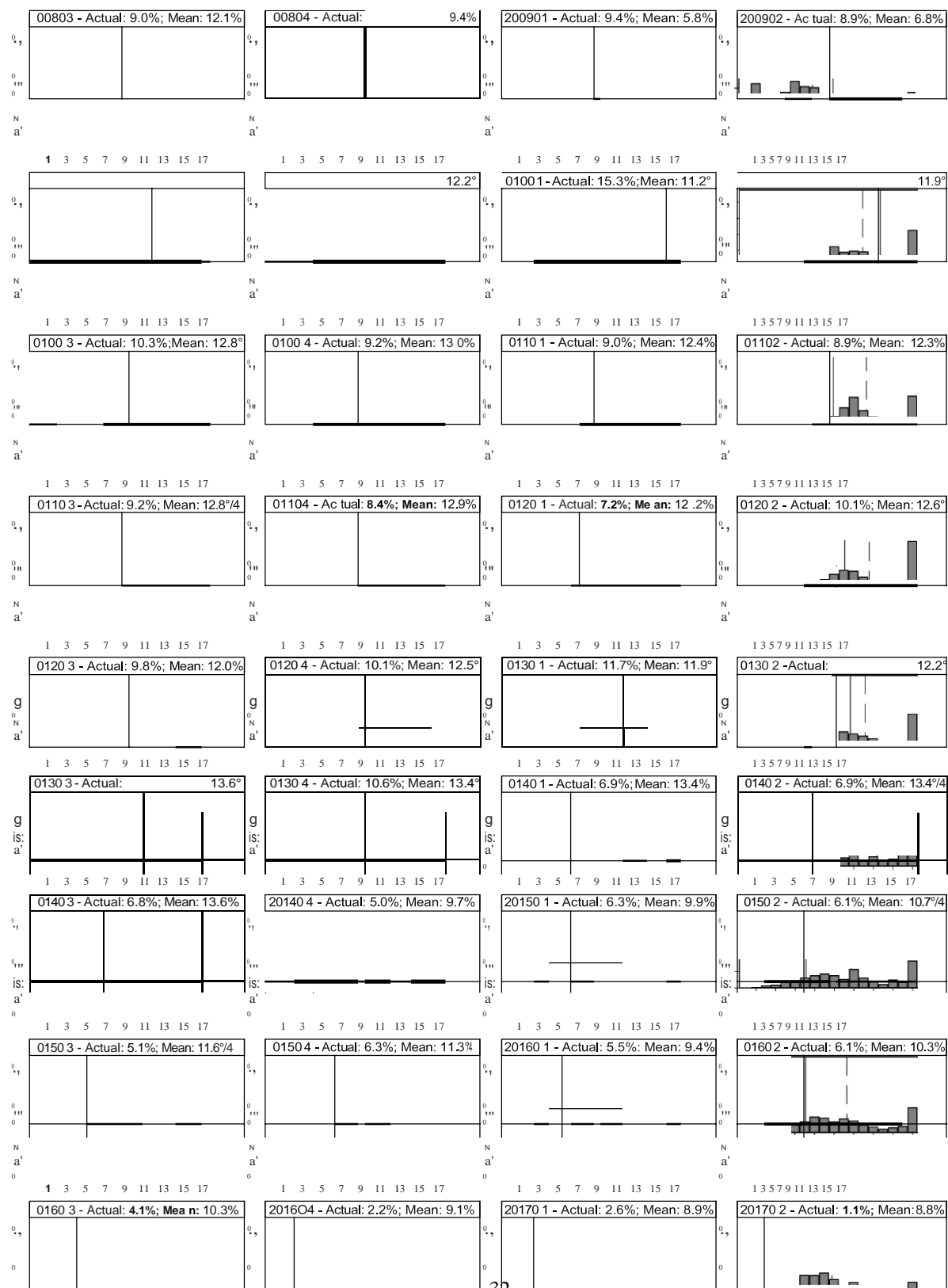


Figure 2. Cross-Sectional Distribution of Quantitative Inflation Expectations

The actual inflation rate for each quarter is marked with a solid vertical line. The dashed vertical line shows the mean of the distribution for that quarter.



$$\begin{array}{c} \text{''' } \\ 0 \\ \text{N} \\ \text{a'} \end{array}$$

1 3 5 7 9 11 13 15 17

$$\begin{array}{c} \text{''' } \\ 0 \\ \text{N} \\ \text{a'} \end{array}$$

1 3 5 7 9 11 13 15 17

$$\begin{array}{c} \text{''' } \\ 0 \\ \text{N} \\ \text{a'} \end{array}$$

1 3 5 7 9 11 13 15 17

$$\begin{array}{c} \text{''' } \\ 0 \\ \text{N} \\ \text{a'} \end{array}$$

1 3 5 7 9 11 13 15 17

Figure 3. Aggregate Quantitative Expectations with Alternative Trimming Methods

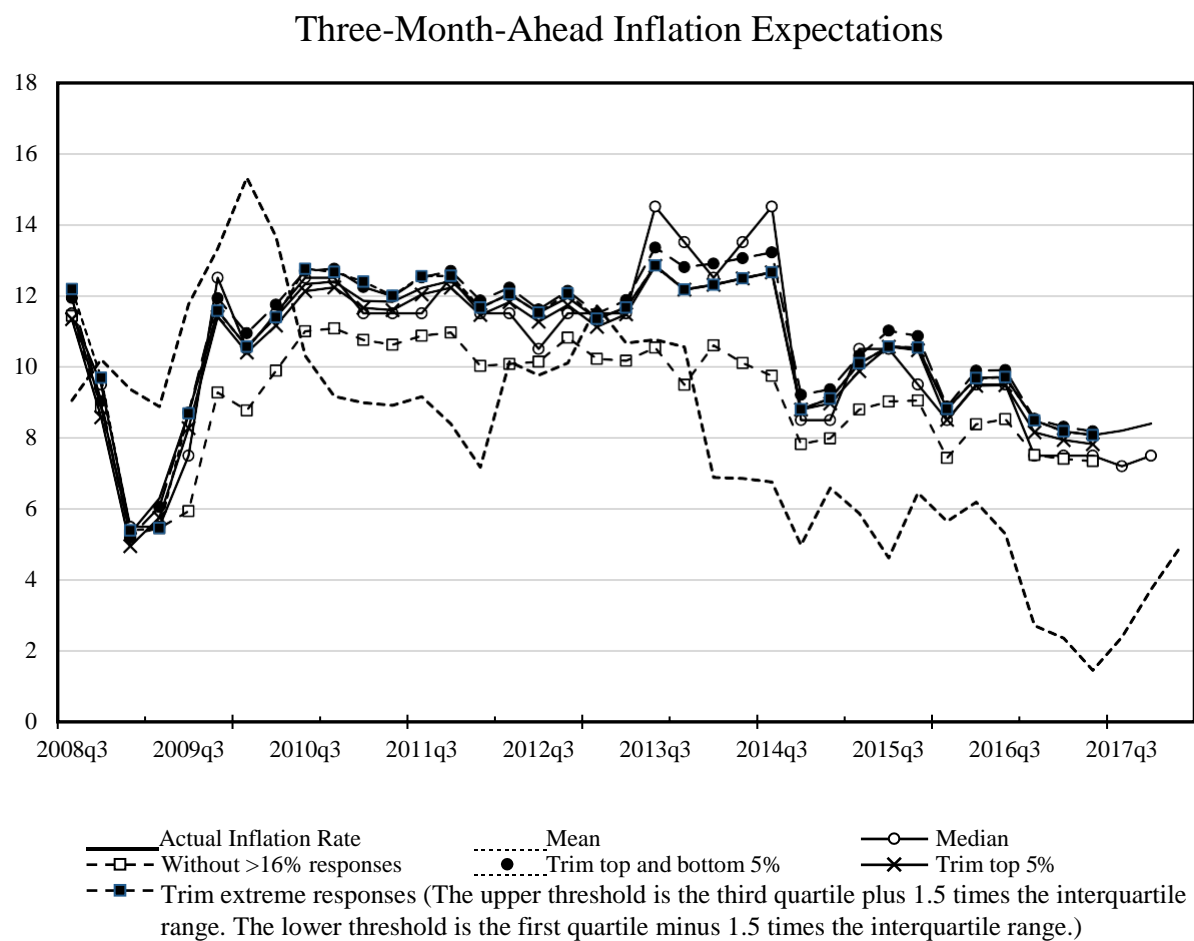


Figure 4. Balance Statistics from Reported Qualitative Responses

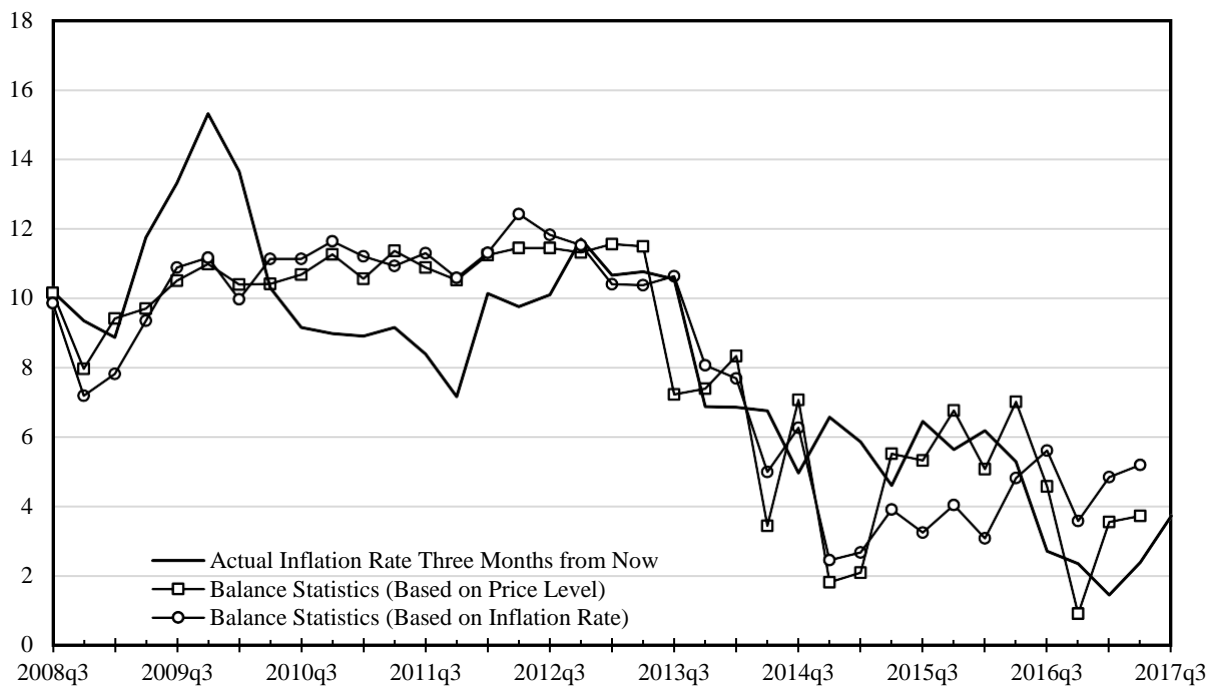


Figure 5. Balance Statistics Implied by Quantitative Price Expectations

Figure 5 shows the two balance statistics calculated using the directional forecasts implied by the quantitative price expectations, where the changes are calculated with respect to the current actual and perceived inflation rates.

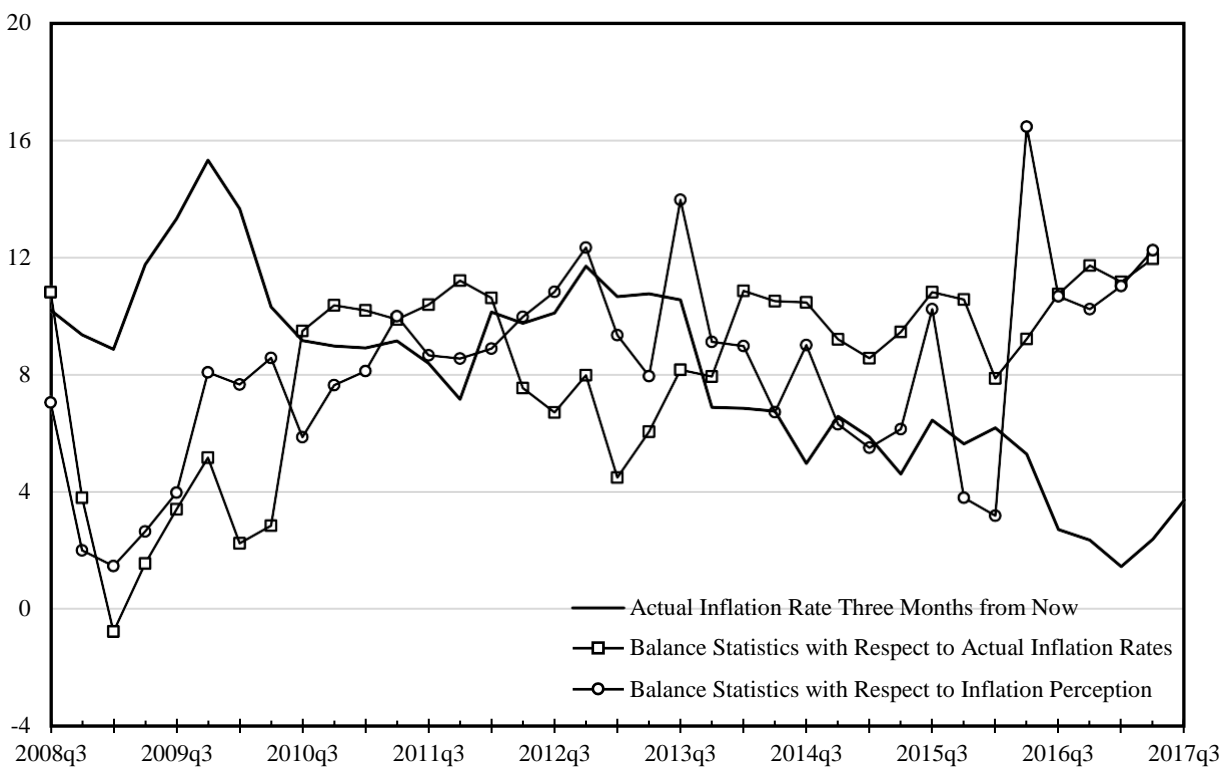


Figure 6. Association between Reported and Implied Qualitative Expectations

This figure shows the Goodman-Kruskal's gamma coefficients between the reported and the implied qualitative expectations (derived using inflation perceptions). The gamma coefficients are calculated separately for each quarter. The estimated standard errors for the gamma coefficients are small, with an average of 0.015 and a maximum of 0.04. So we omit the confidence bands from the figure.

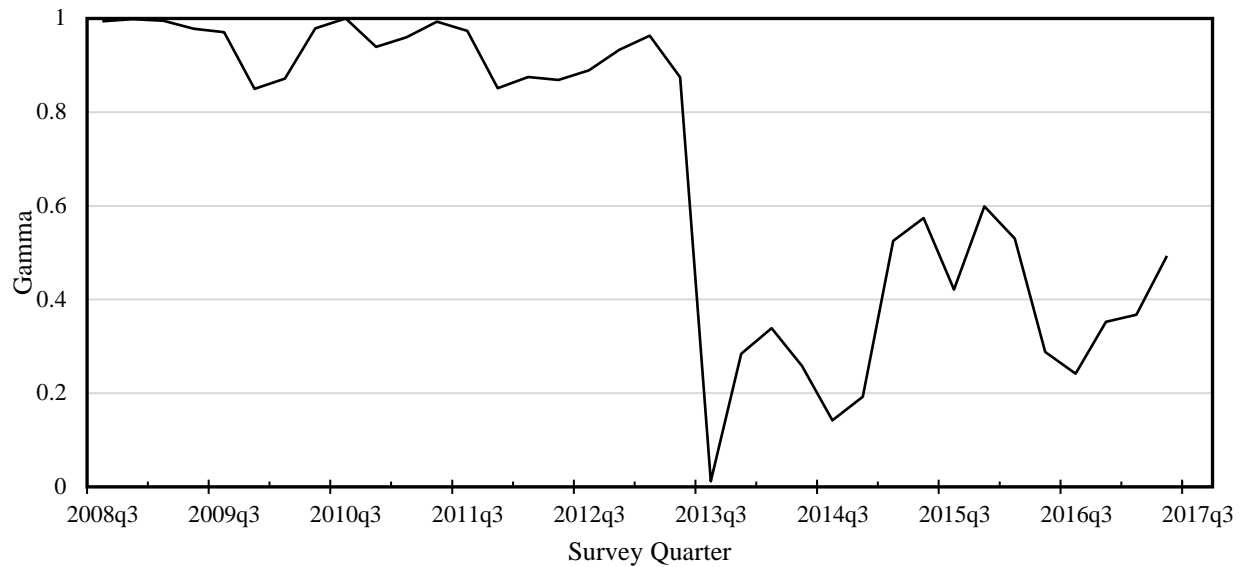


Figure 7. Alternative Estimates of Inflation Expectations

Figure 7 compares alternative estimates of inflation expectations and actual inflation rates: quantified expectations based on reported qualitative responses, and quantified expectations based on imputed qualitative responses (derived using inflation perceptions, not actual inflation rates).

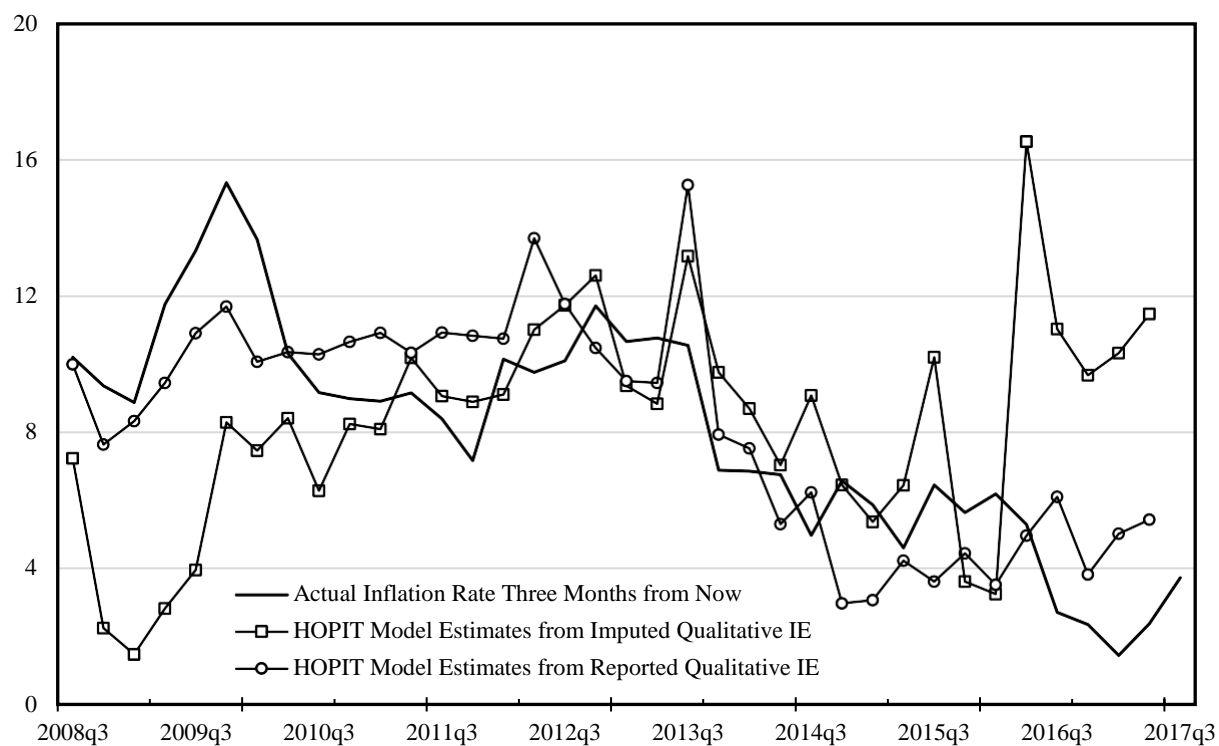


Figure 8. Combining Balance Statistics and HOPIT Model Estimates

This figure shows the estimates of household inflation expectations obtained by combining balance statistics and HOPIT model estimates, where both sets of estimates are based on reported qualitative responses.

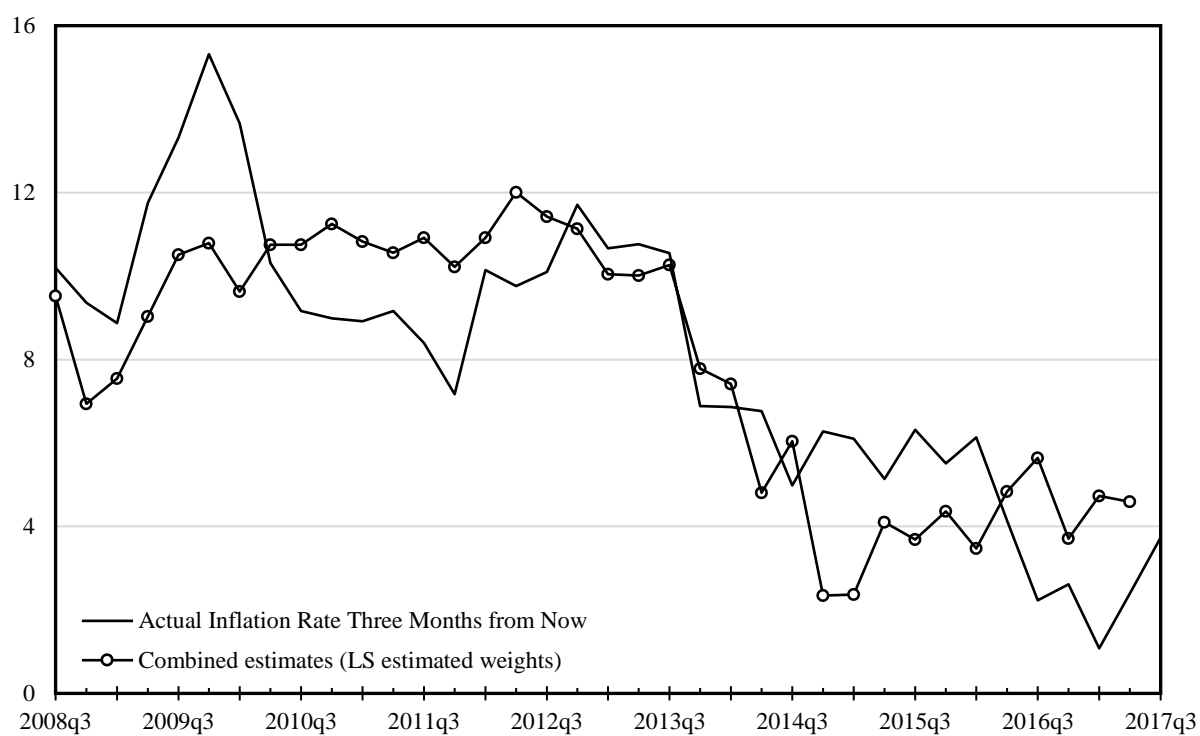


Figure 9. Disagreement in Household Inflation Expectations

The top plot compares the s.d. of cross-sectional distribution of quantitative expectations with the FDISP. The bottom plot compares HOPIT model estimates with the FDISP and the inverse of the percentage of “same” responses (%Same).

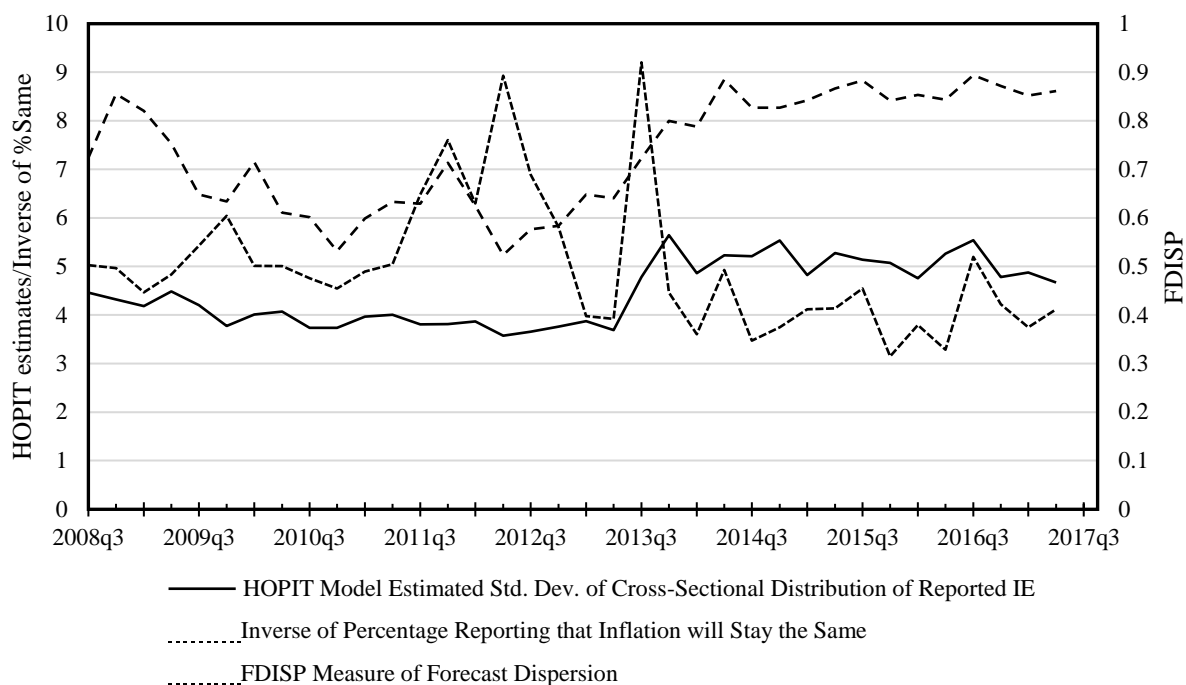
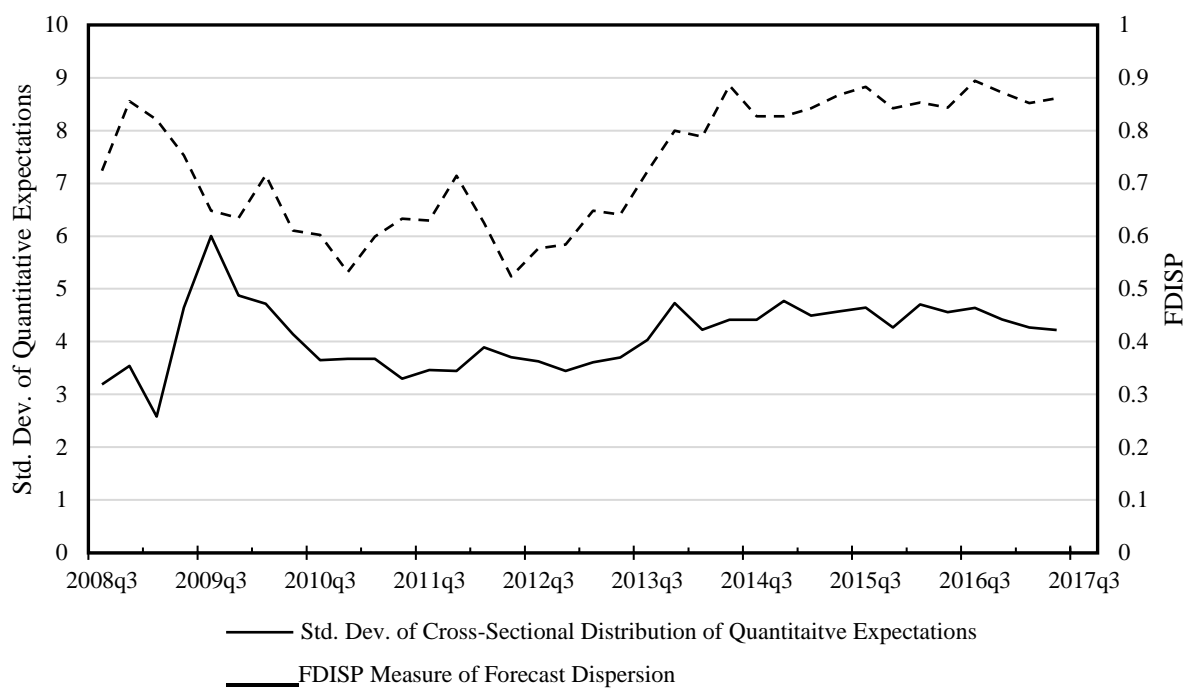


Figure 10. FDISP vs. Balance Statistics

Figure 10 compares the FDISP measure with the balance statistics computed using the same response shares. In the top plot, the response shares are based on responses categorized with respect to the price level, whereas in the lower plot, the responses are categorized with respect to the inflation rate.

