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Uncertainty and Disagreement of Inflation Expectations: Evidence from Household-Level Qualitative Survey Responses

By Yongchen Zhao

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Yongchen Zhao†

Department of Economics, Towson University

Abstract

We propose a procedure that jointly estimates expectation, uncertainty, and disagreement using a flexible hierarchical ordered response model and individual-level qualitative data. Based on the Michigan survey of US consumers, our results reveal how their inflation expectations and the associated uncertainty are affected by various factors, including their perceptions of economic conditions, recollections of relevant news reports, and sociodemographic characteristics. An examination of the dynamics of inflation uncertainty and disagreement produces evidence in support of using the latter as a proxy of the former. However, our results also highlight important episodes (such as the start of the COVID pandemic) in which the two series diverge.

Keywords: Joint estimation; Quantification; Household demographics; Subjective news shocks; Hierarchical ordered response model;

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† 8000 York Road, Towson, MD 21252; yzhao@towson.edu.

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1. Introduction

Inflation expectations are of critical importance in households' decision-making. Having potentially great impact on the future course of the economy, they are always under intense scrutiny of researchers and policy makers. Just as important are the uncertainty associated with these expectations, with relevant work dating back at least to Zarnowitz and Lambros (1987). However, despite the common knowledge that people's expectations differ, systematic studies on the measurement and properties of this disagreement started more recently and focused more on professional forecasters. Existing literature contains several measures of uncertainty and disagreement, with most constructed using density forecasts or forecasts reported as histograms.[1] While it is common practice today for surveys to solicit forecast densities or histograms from professional forecasters, asking households for the same remains uncommon. It is well known that such forecasts are more difficult (though not impossible) to elicit from laypersons than professionals. As a result, much data from households exist in the form of qualitative survey responses. This lack of quantitative data makes measuring uncertainty and disagreement more challenging when it comes to household expectations. The prevailing practice is to use the dispersion of the qualitative data, i.e., a measure of disagreement, as a proxy of uncertainty. While

[1] We postpone discussions of specific references to the next section, which is dedicated to a brief review of the literature related to our work.

existing measures of dispersion are usually easy to calculate and only require aggregate data, their use precludes the separation of uncertainty and disagreement, and assumes that the latter is a reasonable proxy of the former. Despite this being a popular practice, its validity has been a subject of frequent debate.

We address this challenge by proposing a procedure that jointly estimates expectation, uncertainty, and disagreement, while only requiring qualitative data on the micro level. As a result, the procedure is widely applicable and is not subjected to any potential issues associated with using disagreement to proxy uncertainty. We achieve this desirable outcome using a flexible hierarchical ordered response model that takes in explanatory variables (such as respondent demographics) in addition to the qualitative expectations. Our approach is rooted in the popular statistical framework for quantifying qualitative surveys. The same framework has already been successfully used for the measurement of disagreement using aggregate data. However, to our knowledge, we are the first to extend it for the joint estimation of both uncertainty and disagreement using micro data.

We illustrate the use of the procedure with empirical exercises focusing on US households. Our data set, from the Michigan survey, contains both quantitative and qualitative data on inflation expectations. However, since the main advantage of our procedure is that it does not require quantitative data, we shall act as if quantitative data are unavailable, and use only the qualitative survey responses to measure the disagreement and uncertainty of US household inflation expectations. The quantitative data from the survey are then used solely for comparison purposes. We believe our results highlight the usefulness of the proposed measurements, which will hopefully be applied in the future to the study of target variables for which quantitative data do not yet exist.

More specifically, we first report our estimates of expectation, uncertainty, and disagreement based on qualitative data, and discuss the determinants of individual-level expectation and uncertainty. Then, we compare our estimates with several existing measures of dispersion of qualitative data. In addition, we examine the dynamics of inflation uncertainty and disagreement. Finally, we provide some evidence based on micro data, which confirms existing reports based on aggregate data that higher inflation uncertainty makes consumers more hesitant towards durable goods purchase. Our results support the use of existing measures of dispersion as proxies of uncertainty when individual data are unavailable. However, we also highlight important episodes (such as the start of the COVID pandemic) in which disagreement and uncertainty diverge.

This work builds on and contributes to three strings of literature. First and foremost, this work contributes to the literature on the measurement and properties of uncertainty and disagreement, especially those captured by qualitative survey responses. We offer a new alternative to existing measures of disagreement, while our results provide up-to-date information on how uncertainty and disagreement evolved as the US economy headed into the COVID pandemic. Furthermore, our work contributes to the literature on the quantification of qualitative survey responses. Our model is a direct extension of Lahiri and Zhao (2015), which, in turn, extends earlier work on the probability approach to quantification. Our work contributes to this literature by providing a unified approach to the quantification of not only the expectation but also the associated uncertainty and disagreement. In particular, our approach leverages survey information normally unused by many existing quantification methods, such as survey respondents' perceptions and demographic characteristics. Finally, we contribute to the literature concerning household expectations and their formation. We base our model of inflation expectation, uncertainty, and disagreement on results reported in this literature. Our results provide further confirmations of existing observations on the role of certain factors in the expectation formation process. More importantly, our results also show the effect of these factors on uncertainty and disagreement.

The rest of the paper is organized as follows. The next section presents a quick overview of selected contributions to related literature. In the first part of Section 3, we briefly introduce six existing measures of dispersion of qualitative data. We then detail our approach in the second part of the section. Section 4 describes our data set. The empirical results are presented and discussed in Section 5. We make a few concluding remarks in Section 6.

2. A Brief Review of Recent Literature

The primary objective of this work is to provide a procedure that allows researchers to obtain, from a unified probabilistic framework, separate estimates of expectations, uncertainty, and disagreement, all while using nothing more than qualitative survey data. Given this aim, the contributions that most closely relate to our work include Lahiri and Zhao (2015) and Mokinski *et al.* (2015). The former, extending earlier work on quantification such as Mitchell *et al.* (2007),[2] concentrated on the estimation of expectations. Although not working specifically on disagreement and uncertainty, Lahiri and Zhao (2015) established the usefulness of the discrete choice model in our context. The latter paper was built on the same probability approach to quantification and it focused specifically on measuring disagreement. However, Mokinski *et al.* (2015) used only the aggregate data on response shares derived from the individual qualitative responses and not the

[2] See Lahiri and Zhao (2015) for a thorough review of the quantification literature.

individual data directly (nor any of the additional individual specific variables from the survey, such as respondent demographics).

Using data on inflation expectations, our work naturally relates to that of many researchers, who, over the years, studied inflation expectations and highlighted the important role expectations play in driving economic activities and economic policies. For example, Carvalho and Nechio (2014) examined the same Michigan survey data that we use below on household inflation expectations (as well as other target variables) and documented some important deviations from widely-accepted theoretical results that monetary policy makers rely on. Their work highlighted the continuing need for more research in this area. Similarly, much work was done in the literature on inflation uncertainty. For example, Giordani and Söderlind (2003) examined inflation forecast uncertainty using professional forecasts and compared the survey measure of uncertainty with measures derived using time series models. Clements (2014) addressed the important conceptual distinction between ex ante and ex post uncertainty and discussed their respective measurements. In a recent contribution on the issue of measurement, Bachmann et al. (2013) advocated the use of the standard deviation of specifically coded qualitative data as a proxy of uncertainty. Binder (2017) proposed a measure of uncertainty based on the observation that people tend to round their numerical answers when they feel uncertain.

Though relatively fewer in quantity, a significant number of papers considered both disagreement and uncertainty, with many paying special attention to their measurement. Among this work, most use density forecasts or histograms. For example, Boero *et al.* (2008) used professional forecasts, and Bruin *et al.* (2011) used similarly structured data from consumers to measure inflation uncertainty. Krüger and Nolte (2016) also worked with professional forecasts and compared disagreement and uncertainty. Lahiri and Liu (2006) summarized the literature on inflation uncertainty and its measurement using density forecasts. Rich and Tracy (2010) took advantage of matched point and density forecasts and found that increases in expected inflation do not always occur during periods of elevated uncertainty. One common practice, especially in cases where data hardly permit otherwise, is to use disagreement to proxy uncertainty. For example, Bomberger (1996) proposed to use the disagreement observed in survey forecasts as a proxy of the uncertainty of the target variable. But whether disagreement is a good proxy of uncertainty in general remains a subject of debate, e.g., Giordani and Söderlind (2003) and Glas and Hartmann (2016). In particular, Lahiri and Sheng (2010) argued that the validity of this practice remains largely an empirical matter by showing, through forecast error decomposition, that aggregate forecast uncertainty embodies both disagreement and perceived variability of future aggregate shocks that vary depending on the specific forecasting environment. In a recent contribution, Rich and Tracy (2021) provided further evidence based on professional forecasts from the European Central Bank's survey that disagreement is not a reliable proxy for uncertainty.

Also related to our work is a string of literature that primarily focuses on disagreement. For example, in an early contribution, Mankiw *et al.* (2003) provided evidence that emphasizes the possibility of disagreement about inflation expectations being an important driver of macroeconomic dynamics. Lahiri and Sheng (2008) attempted to explain the disagreement of professional forecasters and its evolution across horizons using a panel of fixed-target multi-horizon forecasts. More recently, Andrade *et al.* (2016) considered the disagreement among professional forecasters and documented several important characteristics of disagreement across forecast horizons. Łyziak and Sheng (2018) explored potential sources of consumers' disagreement about inflation expectations. Using data from the Central Bank of Brazil, Montes *et al*. (2016, 2018) examined the impact of central bank communication and fiscal credibility on disagreement. Falck *et al*. (2021) discussed the interaction between disagreement and the efficacy of monetary policy.

In addition, when building our model of inflation expectations using additional variables about survey respondents' attitudes and characteristics, we draw upon many of the important results reported by earlier researchers, including Bruin *et al.* (2010), Dräger and Lamla (2012), Carvalho and Nechio (2014), Dräger *et al.* (2016), and Lahiri and Zhao (2016).

3. Measuring Uncertainty and Disagreement

3.1 Measuring the dispersion of qualitative survey responses using aggregate data

Let y^*_{it+h} be the latent expectation of individual i at time t about the target variable y_{t+h}, where both y^* and y are continuous and h denotes the forecast horizon.[3] Consider a survey question asking for the direction of change of y_{t+h}. The three possible responses are "go up," "stay the same," and "go down," coded 1 to 3, respectively. In the literature on quantifying qualitative survey responses, a standard assumption is that people cannot accurately perceive very small changes in y. Under this assumption, we can express individual i's qualitative response as $y_{it} = \sum_{j=1}^{J}[j \times \mathcal{I}\{\delta_{itj-1} < y^*_{it} \leq \delta_{itj}\}]$, where $J = 3$ is the number of possible responses, δ_{itj} is the threshold parameter associated with response j, and $\mathcal{I}(\cdot)$ is the indicator function. For all i and t, $\delta_{it0} = -\infty$ and $\delta_{itJ} = \infty$. The δs are also referred to in various literatures as the "indifference limen," the "range of imperceptibility," or the "just-noticeable-difference" parameters. After the

[3] In general, the y^*_{it}s do not have to equal the quantitative survey responses. Unless forced to be by survey design, the qualitative and the quantitative responses may not even be consistent, i.e., an individual may report a qualitative response of "go down" while giving a quantitative response that is positive, see Das *et al.* (2019) for a recent example.

individual responses (the y_{it}s) are aggregated, the standard practice of survey administrators is to report the share of each possible response. We use p_{jt} to denote the proportion of response $j \in \{1,2,3\}$ observed in time period t, with $\sum_j p_{jt} = 1\ \forall t$. In addition, let $q_{jt} = \sum_{s=1}^{j} p_{st}$ be the corresponding cumulative response shares, with $q_{1t} = p_{1t}$ and $q_{Jt} = 1$.

Below, we introduce six existing measures of dispersion that have often been used in the literature. We will use them as references and compare our measures against them in the next section. Since all of them rely only on the aggregate data, i.e., the p_{jt}s and the q_{jt}s, they cannot be used to measure disagreement and uncertainty separately. Therefore, we will simply refer to them as measures of dispersion. In different contexts, they may be used as simple measures of disagreement, or as proxies of uncertainty. For brevity, we only include the definitions of these measures here. Further details, including examples of recent applications of these measures, are available in Mokinski *et al.* (2015) and in references therein.

The first measure, IQV, or the Index of Qualitative Variations, was proposed by Gibbs and Poston Jr (1975). It is defined as

$$IQV_t = \frac{J}{J-1}\left(1 - \sum_j p_{jt}^2\right).$$

The next two measures both use the following normalized measure of concentration of ordinal data:

$$l_t^2 = \frac{4}{J-1}\sum_{s=1}^{J-1}\left(q_{st} - \frac{1}{2}\right)^2.$$

Blair and Lacy (2000) advocated the use of $1 - l_t^2$ and Kvålseth (1995) $1 - l_t$. We refer to the former as BL and the latter COV (coefficient of ordinal variation). The fourth measure, REA, is proposed by Reardon (2009):

$$REA_t = (J-1)^{-1} \sum_{s=1}^{J-1} [q_{st}\, log_2\, q_{st}^{-1} + (1-q_{st})\, log_2 (1-q_{st})^{-1}].$$

The fifth measure, which we call BES, is proposed by Bachmann *et al.* (2013):

$$BES_t = \sqrt{p_{3t} + p_{1t} - (p_{3t} - p_{1t})^2}.$$

While its calculation requires no more than the response shares, the measure actual equals the standard deviation of the individual responses if they are coded as -1, 0, and 1, respectively for $j = 1$, 2, and 3. All five measures above are scale independent. They always fall between 0 and 1, with higher values indicating higher levels of dispersion.

The last measure we use as a reference is proposed by Mokinski *et al.* (2015) and is subsequently referred to as MSY. The authors in fact proposed several variants of the measure. We use the one that they denoted in their work as "t_4, AO." This variant most closely resembles our own in terms of methodology. It is the most accurate one based on the same short-run inflation expectations data that we also use (see their Table II). With $J = 3$, the MSY is defined as

$$MSY_t = 2\tau_t [F^{-1}(1-p_{3t}) - F^{-1}(p_{1t})]^{-1},$$

where $F(\cdot)$ is the cumulative distribution function of the t-distribution with 4 degrees of freedom and τ_t is the smoothed state estimates from a state-space model. The state equation sets τ_t as a random walk, and the observation equation is $A_t = \tau_t x_t + u_t$, where u_t is the usual error term and the aggregate expectation $x_t = [F^{-1}(p_{1t}) + F^{-1}(1-p_{3t})]/[F^{-1}(p_{1t}) - F^{-1}(1-p_{3t})]$. The state-space model calibrates the aggregate expectations against A_t, the average monthly inflation rate of the last 12 months (see Atkeson and Ohanian (2001)).

3.2 Joint estimation of expectation, uncertainty, and disagreement using individual data

Our measures arise from the ordered choice model framework of Lahiri and Zhao (2015). Let

$$y_{it}^{*} = y_{t}^{*} + \boldsymbol{X}_{it}\beta_{0} + \varepsilon_{it}, \tag{1}$$

where y_t^* is the latent aggregate expectation, the term $\boldsymbol{X}_{it}\beta_0$ captures individual heterogeneity in the expectations, and ε_{it} is a heteroskedastic error term. Recall that, while we do not directly observe y_{it}^*, we do observe a qualitative response $y_{it} = \sum_{j=1}^{J}[j \times \mathcal{I}\{\delta_{itj-1} < y_{it}^* \leq \delta_{itj}\}]$. We assume that δ_{itj} is a function of individual-specific sociodemographic characteristics $\boldsymbol{W}_{it}$, which capture the cross-sectional heterogeneity in the thresholds. Furthermore, let $f_{it}(\cdot)$ be the latent density forecast of individual i with mean y_{it}^* and standard deviation σ_{it}, where σ_{it} varies over time and depends on individual-specific factors $\boldsymbol{Z}_{it}$. (The three sets of individual characteristics $\boldsymbol{W}_{it}$, $\boldsymbol{X}_{it}$, and $\boldsymbol{Z}_{it}$ may have elements in common.) The aggregate density forecast, which is usually taken as the average of individual densities, is then $f_t(y) \equiv n_t^{-1}\sum_{i=1}^{n_t} f_{it}(y)$, where n_t is the number of individuals responding to month t's survey.

To estimate y_{it}^* and σ_{it} using data on y_{it} and $\boldsymbol{W}_{it}$, $\boldsymbol{X}_{it}$, and $\boldsymbol{Z}_{it}$, we use the hierarchical ordered choice model (henceforth the HOPIT model), which amounts to maximizing the following likelihood function:

$$\begin{aligned}\mathcal{L} = &\sum_{t=1}^{T}\sum_{i=1}^{n_t}\left\{\mathcal{I}\{y_{it} = 1\} \cdot \ln\left[\Phi\left(\frac{\delta_{it1} - y_t^* - \boldsymbol{X}_{it}\beta_0}{\sigma_{it}}\right)\right]\right\} \\ &+ \sum_{t=1}^{T}\sum_{i=1}^{n_t}\left\{\mathcal{I}\{y_{it} = 2\} \cdot \ln\left[\Phi\left(\frac{\delta_{it2} - y_t^* - \boldsymbol{X}_{it}\beta_0}{\sigma_{it}}\right) - \Phi\left(\frac{\delta_{it1} - y_t^* - \boldsymbol{X}_{it}\beta_0}{\sigma_{it}}\right)\right]\right\}\end{aligned} \tag{2}$$

$$+\sum_{t=1}^{T}\sum_{i=1}^{n_t}\left\{\mathcal{I}\{y_{it}=3\}\cdot\ln\left[1-\Phi\left(\frac{\delta_{it2}-y_t^*-\boldsymbol{X}_{it}\beta_0}{\sigma_{it}}\right)\right]\right\},$$

where $\Phi(\cdot)$ is the normal CDF and T is the total number of time periods in the data set.[4] To ensure that the δs are properly ordered and that σ_{it} is positive, we use the following specification, where $\delta_{itj} < \delta_{itj+1}\ \forall\ j \in \{1,2,3\}$ and $\delta_{it1} < 0$:

$$\delta_{it1} = -\exp(\boldsymbol{W}_{it}\beta_1), \tag{3}$$

$$\delta_{it2} = \delta_{it1} + \exp(\boldsymbol{W}_{it}\beta_2), \tag{4}$$

$$\sigma_{it} = \exp(\sigma_t + \boldsymbol{Z}_{it}\beta_3). \tag{5}$$

As is the case in the estimation of standard ordered probit models, y_{it}^* and σ_{it} are only identified up to scale. Additional information or assumption is needed in order to determine the scale of these series. There are several popular alternatives in the quantification literature. Since we intend to compare our disagreement and uncertainty estimates with primarily the MSY measure of Mokinski et al. (2015), we use the same state-space model as they did.[5]

Using the model's estimates of individual and aggregate forecast densities, we proceed to calculate individual and aggregate expectation and uncertainty, as well as disagreement (which exists only at the aggregate level). The aggregate expectation is simply the average of the y_{it}^*s. We follow the standard practice in the density forecast literature and define individual uncertainty as the dispersion of f_{it}, which we measure using σ_{it}. Disagreement among individuals can be

[4] As shown in Lahiri and Zhao (2015) and Mokinski et al. (2015), while alternatives exist, there is no conclusive evidence against the normality assumption.

[5] Details are in the previous subsection. Alternative reference series are examined in the next section as a robustness check.

measured using the cross-sectional dispersion of y_{it}^*, denoted as $d_t \equiv \left[n_t^{-1} \sum_{i=1}^{n_t} \left(y_{it}^* - n_t^{-1} \sum_{i=1}^{n_t} y_{it}^*\right)^2\right]^{\frac{1}{2}}$. Measuring aggregate uncertainty is the most challenging task. One natural choice is to use the standard deviation of the aggregate forecast density $\sigma_t \equiv \left(n_t^{-1} \sum_{i=1}^{n_t} \sigma_{it}^2 + d_t^2\right)^{1/2}$ in a way analogous to using σ_{it} to measure individual uncertainty. In situations where the individual uncertainty is unobservable, the only option is to use the disagreement d_t as a proxy. However, this is sometimes considered a poor choice.[6] Since our model allows us to readily estimate both components of σ_t, we shall use the square root of the average of individual uncertainty, $\left(n_t^{-1} \sum_{i=1}^{n_t} \sigma_{it}^2\right)^{1/2}$, as a measure of aggregate uncertainty. This way, the sum of squared uncertainty and disagreement equals the variance of the aggregate forecast density. And the composition of this variance is reflected by the dynamic relationship between our measures of uncertainty and disagreement. Note that since we work exclusively with subjective expectations of households, our measure of uncertainty should be interpreted accordingly: It captures the *ex ante* uncertainty of the expectations, not the *ex post* uncertainty, nor the uncertainty of the target variable. A more detailed discussion of the differences can be found in Clements (2014).

4. Data

In our empirical exercises, we use data from the University of Michigan's Survey of Consumers. It is one of the most highly respected household surveys in the US. The well-known Index of Consumer Sentiment is based on this survey. Each month, the survey draws a representative sample of households from around the country. Initially, the sample size was around 1000. It decreased to

[6] Boero *et al.* (2008) discussed this issue in more details. Rich and Tracy (2010) found little evidence that disagreement is a good proxy for uncertainty. In the next section, we also look into this issue.

about 700 in the early 80s and then again decreased to about 500 by the late 80s. The survey contains a large number of questions. Of primary importance are the ones concerning respondents' one-year-ahead inflation expectations:[7]

- A12. During the next 12 months, do you think that prices in general will go up, go down, or stay where they are now?
- A12a. (If the response to A12 is "stay the same.") Do you mean that prices will go up at the same rate as now, or that prices in general will not go up during the next 12 months?
- A12b. By about what percent do you expect prices to go (up/down) on the average, during the next 12 months?
- A12c. How many cents on the dollar do you expect prices to go (up/down) on the average, during the next 12 months?

As the questions suggest, each survey respondent is asked for their expected direction of change (i.e., the qualitative response) before the magnitude of the change (i.e., the quantitative response).[8] This specific design aspect of the survey ensures that the resulting data have three important properties. First, the qualitative responses arise from survey respondents thinking about the target purely qualitatively. In other words, the qualitative responses are not derived by artificially taking

[7] Respondents who did not respond to these questions are discarded from our data set.

[8] Note that the quantitative responses are expected rates of inflation (i.e., *how much* prices go up or down) while the qualitative responses should be stated with respect to prices and not inflation (i.e., *whether* prices go up or down). For ease of exposition, we may subsequently refer to both as data on "inflation expectations" when there is no risk for confusion.

the sign of some quantitative responses.[9] Second, the probing question A12a acts as a natural "quality check" on the data, helping to clear up possible misunderstandings regarding the differences between price level and inflation. About 11% of the responses fall into this category.[10] Third, by adapting the wording of question A12b to the responses given to the first two questions, the survey makes sure that the quantitative data are consistent in sign with the qualitative data. Specifically, there is no risk of a respondent reporting a belief that prices will "go up" and then reporting a negative inflation expectation.

Our data set also includes the responses to several other questions. Together, they allow us to determine each survey respondent's age, gender, household income (in quintiles), level of education, region of residence (northeast, north central, south, or west), as well as the respondent's perceptions on their personal financial situation and the overall business conditions now compared to one year ago (better, same, or worse). We also have data on whether the respondent heard any news recently, and if any, the general topic of what the respondent heard. This information on the recollection of recent news is then used to put survey respondents into one of four possible groups: those who heard no news; those who heard only good news; those who heard only bad news; and those who heard both good news and bad news. We then create dummy variables accordingly and

[9] While an exploration of the specific psychological effect involved in the process is beyond the scope of this paper, one may reasonably argue that respondents could think/behave/respond differently when faced with qualitative vs. quantitative questions.

[10] These "go up at the same rate" responses are merged with the "go up" responses since both simply mean that "prices go up." Note that we do not in general know what rate a respondent has in mind when reporting an expectation that prices "go up at the same rate." But we believe it is reasonable to assume that this rate is individual specific and unobservable (as long as we do not have a panel and we act as if quantitative data do not exist).

use them in subsequent analyses. In addition to this set of dummies, which are created based on the recollection of news *in general*, we create two other sets of dummies for, respectively, news that is specifically related to unemployment and inflation. As stated in the previous section, our model uses three sets of independent variables $\boldsymbol{W}$, $\boldsymbol{X}$, and $\boldsymbol{Z}$. Based on evidence in the existing literature on household expectations and consumer sentiment in general, we postulate that all of the variables above may affect one's expectation and the associated uncertainty, and thus belong to $\boldsymbol{X}$ and $\boldsymbol{Z}$, while only the sociodemographic characteristics affect the thresholds, and thus belong to $\boldsymbol{W}$. Our data set also contains the point forecasts of inflation from the US Survey of Professional Forecasters (SPF) as alternative calibration targets for robustness checks. Our empirical results below are based on 294,055 individual survey responses from 466 months – March 1982 to December 2020.[11]

It is worth stressing that the news variables here are not objective measures of news coverage. The survey contains neither information on the actual content of the news reports (other than the general topic as perceived by the survey respondent) nor the intensity of the reporting. Both factors impact household inflation expectation and disagreement according to Lamla and Maag (2012). Using household inflation expectation data from Colombia, Anzoátegui-Zapata and Galvis-Ciro (2020) found that decreases in disagreement are often accompanied by increases in information demand (measured using Google Trend search volume data). In our setup, the news variables directly affect both expectations and uncertainty. Although we do not estimate an equation that

[11] Earlier data are discarded since it was unclear whether a qualitative response of "same" meant the price will stay the same (i.e., zero inflation) or the inflation rate will stay the same. Our conclusions stay the same even if they are retained.

links news and disagreement specifically, they are not independent, since we measure disagreement using the standard deviation of individual-level expectations.

[Figure 1 here]

The mean and the standard deviation of the quantitative responses, along with the actual inflation rate, are shown in Figure 1.[12] The mean of the expectations sometimes leads the actual values, especially around major turning points. However, it often far exceeds the actuals, and the two series do not always move together, especially since 2010. The individual-level quantitative responses frequently fall outside of what may be considered a "reasonable" range given the actual inflation rates from the recent past. For example, since 2010, more than 15% of the quantitative responses exceed 5% in magnitude, among which over 20% are at least twice as big, while the actual inflation rates over the same period average to a mere 1.7%. As noted in Boero *et al.* (2008), even for professional forecasters, their point forecasts are sometimes different from the mean of their density forecasts. Bruin *et al.* (2011) documented similar differences in household expectations. At the aggregate level, inflation expectations based on quantitative survey responses often display a significant bias. According to Lahiri and Zhao (2015) and Das *et al.* (2019), the qualitative responses may prove to be a better data source than their quantitative counterpart for the purpose of measuring household inflation expectations. Therefore, we do not consider the quantitative responses the "authoritative answers," of which the qualitative responses are mere approximations. Instead, both are imperfect reflections of the latent "true" expectation. While we do consider the mean and the standard deviation of the quantitative responses useful reference series in our exercises below, we make no attempt to force our measures of expectation, uncertainty,

[12] Shaded areas represent recessions as declared by the NBER. The same applies to all subsequent figures.

and disagreement to match them. Our measurement procedure is equally applicable regardless of whether quantitative data are available. Regardless of the assessment of their quality, since the Michigan survey does not collect quantitative expectations as densities or histograms, one cannot simultaneously obtain measures of disagreement and uncertainty directly from the quantitative data.

[Figure 2 and 3 here]

Figure 2 shows the shares of the qualitative responses to the inflation expectation question A12. Derived using only these response shares, the five scale-independent measures of dispersion presented in the previous section, IQV, BL, COV, REA, and BES, are plotted in Figure 3. The pairwise correlations of these measures, the response shares, and the mean and standard deviation of the quantitative expectations are reported in Table 1. It is clear from Figure 3 that all five measures are extremely similar. Since they are scale independent, the fact that one measure is systematically higher or lower than another is of no importance. As shown in Table 1, these measures are strongly correlated – even the lowest pairwise correlation, between BES and IQV, is above 0.95. In the vast majority of the months, the “up” responses are clearly in the majority. As a result, the dispersion measures all have strong negative correlations with the share of the “up” responses (below -0.9) and, at the same time, strong positive correlations with the other two response shares (mostly 0.9 or above). It is worth noting that neither the response shares nor the dispersion measures have correlations with the standard deviation of the quantitative responses that are nearly as strong, with most pairwise correlations around 0.5. This further confirms our earlier observation that the two types of responses, while reflecting the same underlying expectations, do not match precisely.

[Table 1 here]

5. Empirical Results

5.1 Factors affecting expectations and uncertainty

The estimated coefficients of the four equations of the HOPIT model are reported in Table 2. Generally speaking, in terms of how inflation expectations are affected by the factors included in the model, we do not observe any significant deviations from the findings in the literature (see Lahiri and Zhao (2016), among others). Survey respondents expect higher (lower) levels of inflation when their personal financial situation and the overall business condition have been deteriorating (improving) over the past year. Younger respondents, females, and those with lower levels of income and education typically have higher inflation expectations than those who are older, male, better educated, and more affluent do. In addition, survey respondents' recollections of recent news stories have significant impact on their inflation expectations. Our baseline is the group of respondents who report no recollection of any news, good or bad. Bad news, regardless of whether it is specifically about inflation, tends to induce higher inflation expectations, while good news does not always alleviate inflation concerns, except when the news is specifically about inflation. Bad news on unemployment is associated with lower levels of inflation expectations. All else controlled for, the region of residence does not have statistically significant effect on expectations.

[Table 2 here]

Using a household survey from the New York Fed as well as the Michigan survey, Binder (2017) proposed a novel measure of uncertainty based on rounding of quantitative expectations and documented how uncertainty varies by demographic groups. Our results are broadly in line. Most of the factors affecting the levels of inflation expectations also have significant impact on inflation uncertainty. Changes in the survey respondents' perceptions on their personal financial situations and the overall business condition generally lead to higher levels of uncertainty, regardless of whether the situations are improving. In terms of demographic characteristics, income, age, and education level affect uncertainty the same way as they affect expectations: The poor, the young, and the less well-educated feel more uncertain about future inflation. However, while females generally have higher expectations than males, they are more certain about their beliefs.

This last point may appear in contrast to the findings of Binder (2017), where the author found that females have higher uncertainty.[13] However, our results are not inconsistent with those of Binder (2017). While the differences may be attributed to the specific details of our respective empirical strategies, we believe the nature of qualitative data may also be a relevant factor: It is easy to conceive a respondent who feels certain that prices are going up, but uncertain as to the specific magnitude. Since Binder (2017) and Binder and Rodrigue (2018) both use quantitative data, our findings in fact are not contradictory. This apparent divergence in findings highlights the additional information present in the quantitative expectations that is absent from the qualitative data. To reiterate our earlier point on our contributions, the procedure proposed in this work is meant as an alternative and complement to existing measures. It is not meant as a replacement especially in situations where quantitative data are indeed available and of reasonable quality.

[13] Females are found to report round numbers like 5% and 10% more frequently. They are also more likely to respond with "don't know," which Binder (2017) takes as a signal of uncertainty. Furthermore, in a related study, Binder and Rodrigue (2018) found that females are more responsive to information treatment, indicating that their prior uncertainty is higher. Note that we discarded the "don't know" responses, as they do not naturally arise from our statistical framework, which assumes the existence of a latent density forecast.

Our results suggest that, in addition to respondent demographics, their recollections of recent news reports affect uncertainty. Similar to how they respond to changing financial and business conditions, people feel increasingly uncertain as they hear more news reports in general, regardless of whether the reports are good news or bad.[14] The only exception is bad news about unemployment – it leads to lower levels of expectations as well as uncertainty, which may be explained by consumers' confidence in the tradeoff relationship between inflation and unemployment (see Dräger *et al.* (2016) for additional discussions). Since the self-reported recollections of recent news are entirely subjective, they do not necessarily reflect actual news coverage. People may pay attention to only the news that interests them, and even this news may be misinterpreted or recalled incorrectly. It is also likely that what a survey respondent reports as recent news is actually from a much more distant past.[15] Dräger *et al.* (2016) also highlighted the role of central bank communications in the process of household expectation formation. The results here indicate that how such communications are interpreted and retained is perhaps as important as their contents and timeliness.

From the estimates of the two threshold equations, we observe that respondents who are older, male, or well-educated tend to have their lower threshold closer to zero, that is, they are

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[14] Some may consider this result counterintuitive, but it may not be. Note that our data do not allow us to observe the level of consistency of news reports. For example, one report may predict a mild increase in inflation while another predicting a significant increase. It is possible that uncertainty increases as people hear more (and different) news reports.

[15] This "information stickiness" has been well documented in the literature. There are also proposals of uncertainty measures based on an objective summary of recent news reports, cf. Baker *et al.* (2016). Our measures are obviously different as they are based on survey responses that are entirely subjective – consistency with any official statistic or objective measures of economic activity is not a primary concern.

more likely to give the “go down” response rather than the “stay the same” response when their expectations are low and close to zero. The same applies to those with higher levels of income. As for the distance between the two thresholds, i.e., the range of imperceptibility, the estimates suggest that male respondents with high income and education levels tend to have the smallest range. Note that this range is not the same as the uncertainty we are measuring: While respondents are “uncertain” about the *direction of change* as their expectations fall into this range, they can be very certain – or not certain at all – that their expectations do indeed fall into this range. In other words, the range of imperceptibility reflects nothing more than a decision rule used by individuals to convert their density forecast to a directional one – and the same decision rule can be used regardless of the variance of the forecast itself. Of course, this is not to say that these threshold parameters are of no importance. Assumptions on their properties (e.g., variability over time and across individuals) directly affect the specification and thus the estimates of the model.

5.2 Comparison with existing measures of dispersion

Now that we have examined expectations and uncertainty at the individual level, we turn to the aggregate measures. Following the standard practice in this literature, we use the correlation coefficient as the primary numerical tool when comparing our measures with the reference series. Table 3 shows the correlations between various measures of interest. While estimating inflation expectations is not our primary focus, we include this measure in our comparison wherever possible without sacrificing brevity. From Table 3, we observe that all six existing measures of dispersion are positively correlated with our measures of disagreement and uncertainty, with pairwise correlations generally around 0.5. As expected, our measures are highly correlated with that of Mokinski *et al.* (2015). From Panel B of the table, we observe moderately strong correlations between our measures and both the mean and the median of the quantitative expectations. The same can be observed between our uncertainty and disagreement measures and the standard deviation of the quantitative expectations. Panel C of Table 3 shows that disagreement and uncertainty are highly correlated, and that both of them are positively correlated with expectations.[16] This result is consistent with the result in Table 1 that the mean and the standard deviation of the quantitative expectations are positively correlated. However, we caution against overinterpreting the magnitude of the pairwise correlations reported in Panel C, as they may be influenced by the calibration procedure in which the same set of estimates from the state-space model are used to calibrate both the expectation and the uncertainty at the individual level.

[Table 3 here]

To compare the results obtained from the two types of survey responses, we regressed the standard deviation of the quantitative expectations on each of the measures derived using the qualitative data. The five scale-independent measures each accounts for somewhere around 22% to 37% of the variations in the standard deviation, while the number for MSY is a much higher 55%. Our measure of uncertainty alone accounts for 48% of the variations and our measure of disagreement about 34%. Together, the two measures account for 54% of the total variations in the standard deviation of the quantitative expectations. These observations are consistent with our definitions of uncertainty and disagreement, and are in line with the fact that existing measures, MSY included, capture the total amount of dispersion in the qualitative data, without separating uncertainty and disagreement. The evidence suggests that our measures of uncertainty and

[16] Bachmann *et al.* (2013) also noted a high level of correlation (about 0.7) between disagreement and uncertainty using qualitative responses from a set of business climate surveys.

disagreement are at least as good as existing measures, and they also do well in terms of consistency with cross-sectional variations in the quantitative expectations.

[Figures 4, 5, and 6 here]

Figure 4 compares the quantified expectations, the mean of the quantitative expectations, and the actual inflation rate. The quantified expectations exhibit less bias than the quantitative expectations, while the dynamics of the two series are largely similar. Like the quantitative expectations, the quantified expectations also have significant predictive power especially around major turning points in the actual values, such as in early 2008 and mid 2009. Figure 5 plots the standard deviation of the quantitative responses and the standard deviation of the aggregate forecast density implied by the qualitative data, i.e., the square root of the sum of the squared uncertainty and disagreement. As discussed above, both series largely co-move with the mean of their respective distributions, while peaking around the same points (usually during recessions). It is not surprising to see the gaps between the two series in the early 80s and the 2010s, given the prevalence of extremely high quantitative expectations and their general tendency towards overestimation. Finally, we compare our estimates of disagreement and the MSY in Figure 6. Since the MSY reflects in essence the sum of uncertainty and disagreement, the two series do not overlap entirely. But both measures capture the essential features of the underlying data, with important peaks and turning points reached at around the same time. Looking across the three figures and comparing all the measures, we observe that disagreement tends to spike around sharp changes in expectations and the actual rate.[17] However, as discussed below, there are important differences in the dynamics of disagreement and uncertainty.

[17] See also Mankiw *et al.* (2003), who made some similar observations based on a number of different surveys.

To further validate our procedure and make sure that the similarities between our measures and existing ones did not simply arise by chance, we examined various aspects of our model. To begin with, we considered alternative specifications by adding/dropping variables to/from the model and relaxing the normality assumption. Most of the variables we omitted are not statistically significant, while some contain a large amount of missing data.[18] We also estimated the model under more stringent assumptions on the thresholds including ones that require them to be symmetric around zero and/or time-invariant. In addition, we estimated our model using multiple subsamples to account for potential parameter instability, considering both subsamples covering a five-year-period each and subsamples delineated by business cycle peaks and troughs. Our main conclusions on the properties of expectation, uncertainty, and disagreement stay the same.

[Table 4 here]

In addition, we considered alternative reference series (A_t) for the calibration procedure. They include the actual inflation rate (moving average over the past five years), consensus forecasts of inflation from the SPF (moving average over the past year), as well as the mean of the quantitative survey responses. Note that the actual values of inflation rate are not required by our measures, although they certainly can be used. The framework suggested here would work flawlessly even when the qualitative expectations are about variables for which no official statistic exists (e.g., market volatility or future policy direction). Table 4 shows the correlations between existing measures of dispersion and our measures of disagreement and uncertainty derived using each of these reference series. Regardless of the choice of reference series, the correlation between

[18] For example, the survey also contains questions on respondents' marital status, home, and vehicle ownership, which contain up to 30% missing data. Stewart (2004) provided an estimator that allows for a flexible semiparametric distribution function.

our measures and existing scale-independent measures remain around 0.5 or higher. As expected, since different reference series are used, the correlations with MSY are lower than those reported in Table 3. It is also worth noting that regardless of which reference series is preferred, our observations on the relationship between expectations, uncertainty, and disagreement would remain unchanged since the same set of scaling factors are used by all three measures.

5.3 Relationship between uncertainty and disagreement

Prior research involving both uncertainty and disagreement mostly focused on professional forecasters and used their density forecasts to derive the two measures. It is well documented that the two do not always move in concordance despite their similarities. For example, using data on inflation expectations from the ECB's survey of professional forecasters, Glas and Hartmann (2016) found that during periods with expansionary monetary policy, uncertainty often exceeds disagreement, while the level of disagreement is largely unaffected.[19] Binder (2017) also compared uncertainty and disagreement and noted that while they are correlated, important differences exist.[20] Jointly estimating both of them from qualitative survey responses, we are uniquely well positioned to study their relationship when household expectations are concerned. Recall that our measures of disagreement and uncertainty squared add up to the variance of the aggregate forecast density, which is the target of existing measures of dispersion (often a proxy for uncertainty). To reveal the relationship between uncertainty and disagreement, we focus on their relative weights in this variance decomposition, i.e., the ratio of uncertainty to disagreement. More specifically, we

[19] See also Boero *et al.* (2008) and Krüger and Nolte (2016).

[20] In particular, Binder (2017) documented a weaker correlation after the Volcker disinflation.

examine the dynamics of this ratio and document how it changes as the actual inflation rate and the mean and standard deviation of the aggregate forecast density change.

[Table 5 and Figure 7 here]

Table 5 shows the correlations between our measures of expectation, uncertainty, disagreement, and the aforementioned variables. Figure 7 plots the ratio of uncertainty to disagreement and the average actual rate of inflation over the previous year. Same as previously documented, inflation uncertainty and disagreement generally increase together with recent actual rate and its expectation. As a result, the variance of the aggregate forecast density also increases with recent actuals and expectations. However, the relative weights of uncertainty and disagreement do not remain constant. For most periods in our sample, uncertainty is about two to three times bigger than disagreement. But the weight of uncertainty increases sharply around periods immediately preceding significant changes in inflation, such as the months before its turning points and early months of recessions. After a major turning point, as the trend of actual inflation starts to form, the weight of uncertainty reduces. This can be clearly seen around, for example, the early 90s and the late 2000s. Such a dynamic relationship is consistent with our intuitive understanding of uncertainty and disagreement: For example, despite not knowing the exact state of the economy, consumers do sense the deteriorating conditions as they approach a recession, and they become increasingly in agreement about a shared sense of heightened uncertainty. One prominent example is how both series reacted to the start of the COVID pandemic. Comparing Figure 6 and Figure 7, we observe a notable increase in uncertainty and a similarly major reduction in disagreement around the start of the pandemic, while the actual inflation rate had yet to change in any significant way. This shows how both measures contain information not found in expectations and actual values, present or past. Our observations also help us to address the suitability of disagreement as a proxy for uncertainty. It is clear that uncertainty and disagreement have an overall strong positive correlation. We believe that in many cases, especially when individual data are unavailable, disagreement may serve as a valid proxy of uncertainty, at least when household inflation expectations are concerned. However, we do want to stress the need and the benefit of separately identifying the two, as each provides a unique source of information not otherwise available.

5.4 Expectation, uncertainty, and consumption tendency

The relationships among inflation expectation, uncertainty, and consumption have been extensively studied. Recent empirical evidence based on the Michigan survey can be found in Binder (2017), where the author showed a significant negative relationship between inflation uncertainty and durable goods buying attitude (i.e., a qualitative response to the question whether it's a good time to purchase large household items). Since our measure of uncertainty is strongly correlated with all existing measures, we do not expect our result to be significantly different. We nevertheless subject our measures to this test and provide the most update-to-date evidence.

First, we compare our measure of uncertainty and that of Binder (2017).[21] What makes this comparison potentially interesting is the fact that the Binder (2017) measure is based on how respondents round their quantitative responses, instead of simple descriptive statistics often used to summarize quantitative data. The resulting uncertainty measure is an index that takes values from 0 to 100, with higher values indicating a higher level of uncertainty. Although as we pointed out in Subsection 5.1 above, the uncertainty about the direction of change of the general price level

[21] For this comparison, we use the updated data on the "short horizon inflation uncertainty index" that are publicly available from https://sites.google.com/site/inflationuncertainty/home.

(i.e., what the qualitative data capture) have slightly different interpretations than the uncertainty about the magnitude of the change (i.e., quantitative data), both uncertainty measures should capture the same underlying sentiment. As shown in Figure 8, indeed the two series have largely similar dynamics with a correlation of 0.52.

[Figure 8 here]

We now proceed with an ordered probit regression of individual durable goods buying attitudes on our estimate of individual-specific inflation expectation and uncertainty, the set of demographic variables used in the previous section, and a set of additional controls. The latter includes the survey respondents' expectations on their personal financial situations, household income, interest rate, unemployment rate, and their opinions on government policy. As expected, our results are qualitatively the same as those in Binder (2017) despite us using very different approaches to the measurement of uncertainty: Inflation expectation is statistically insignificant with a coefficient of 0.008 and a p-value of 0.242, but inflation uncertainty has a negative and statistically significant coefficient of -0.649, with a p-value less than 0.001.[22]

6. Concluding Remarks

This paper contributes to the important literature on the measurement and properties of uncertainty and disagreement. It proposes the first unified approach to their joint estimation using qualitative survey responses, thereby eliminating the need for using disagreement as a proxy of uncertainty when individual-level data are available. Since density or histogram forecasts are not needed, this

[22] The p-values are based on robust, time-clustered standard errors.

approach is widely applicable to a large number of variables for which reliable estimates of uncertainty are not previously available.

In our empirical exercises, we estimate and examine the uncertainty and disagreement associated with US households' inflation expectations. At the individual level, our model establishes direct links between expectation, uncertainty, and households' perceptions of economic conditions, recollections of recent news reports, and sociodemographic characteristics. Our results from the micro data largely confirm existing reports on these links that are based on aggregate data.

Taking advantage of our ability to separate uncertainty from disagreement, we carefully compare our measures and existing proxies of uncertainty constructed using aggregate response shares. Both our estimates and existing measures of dispersion adequately capture the overall variations in the data. We find that uncertainty and disagreement associated with US household inflation expectations have a strong positive correlation. Therefore, measures of disagreement may be used to proxy uncertainty when separate identification of the two is not feasible (e.g., where only aggregate data are available).

However, we observe important differences in the dynamics of uncertainty and disagreement that are consistent with the intuitive understandings of the two concepts. In particular, we find episodes in which households become increasingly in agreement of elevated levels of uncertainty. This is especially common during periods preceding major regime changes in inflation and significant events such as the COVID pandemic. These observations highlight the benefits of our approach and the limitations of using disagreement as a proxy of uncertainty.

In addition, our results suggest a need for further studies, both theoretical and empirical, on the links between disagreement, economic agents' behavior, and their impact on aggregate economic activities. We also hope that this work sparks future research on the uncertainty and disagreement of previously little studied variables, especially the ones without corresponding official statistics, such as household opinions on the effectiveness of government policies and central bank communications.

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Table 1. Correlations between selected measures of dispersion, the percentage shares of the qualitative responses, and the mean and standard deviation of the quantitative expectations

Correlation	IQV	BL	COV	REA	BES	MSY	PctUp	PctDown	PctSame	Mean
BL	0.99									
COV	0.97	1.00								
REA	0.98	1.00	0.99							
BES	0.95	0.99	0.98	0.99						
MSY	0.52	0.58	0.60	0.59	0.61					
PctUp	-0.99	-0.98	-0.98	-0.97	-0.94	-0.53				
PctDown	0.78	0.87	0.90	0.88	0.90	0.67	-0.81			
PctSame	0.96	0.91	0.89	0.89	0.84	0.40	-0.96	0.63		
QuantMean	-0.58	-0.55	-0.55	-0.54	-0.51	0.06	0.58	-0.43	-0.58	
QuantSD	0.47	0.54	0.56	0.55	0.57	0.74	-0.48	0.63	0.35	0.31

BL, COV, REA, BES, and MSY are the dispersion measures defined in the text. PctUp, PctDown, PctSame are the response shares (in percentage) of the “up,” “same,” and “down” responses. QuantMean and QuantSD are the mean and standard deviations of the quantitative responses.

Table 2. Estimated coefficients of the HOPIT model

Variable	Expectation Eq. (1)	Uncertainty Eq. (5)	Delta1 Eq. (3)	Delta2 Eq. (4)
Personal financial situation now compared with one year ago				
Better now	-0.0391***	0.0279**		
Same	(base)	(base)		
Worse now	0.1336***	0.0569***		
Overall business condition now compared with one year ago				
Better now	-0.0183	0.0222		
About the same	(base)	(base)		
Worse now	0.1981***	0.1334***		
Age				
Younger than 30	(base)	(base)	(base)	(base)
30 to 50	0.0282	-0.021	0.0335	0.0908***
51 to 65	-0.6029***	-0.2336***	0.1879***	-0.1160***
Older than 65	-0.8574***	-0.1920***	0.4212***	-0.042
Sex				
Male	(base)	(base)	(base)	(base)
Female	0.2769***	-0.0912***	-0.3332***	-0.0368*
Education				
Grade 0-12 no hs diploma	0.4798***	0.1475***	-0.3145***	0.1315***
Grade 0-12 w/hs diploma	0.3093***	0.0934***	-0.1163***	0.1389***
Grade 13-17 no col degree	0.0504	0.0203	-0.0609*	0.0019
Grade 13-17 w/ col degree	(base)	(base)	(base)	(base)
Region				
West	-0.0675	0.0025	0.0876**	-0.031
North Central	-0.0413	-0.0534**	0.0341	0.0147
Northeast	(base)	(base)	(base)	(base)
South	-0.031	-0.0197	0.0269	-0.0057
Income				
Bottom 20%	(base)	(base)	(base)	(base)
21-40%	-0.1577*	-0.0960***	0.0909*	0.0119
41-60%	-0.2195**	-0.1176***	0.1424***	0.042
61-80%	-0.2309**	-0.0848***	0.2156***	0.0977***
Top 20%	-0.2739***	-0.0786**	0.2395***	0.1275***
Heard good news only	-0.0216	0.0443***		
Heard bad news only	0.1953***	0.1048***		
Heard both good and bad news	0.1720***	0.1001***		
Heard good news on unemployment	-0.0172	-0.0175		
Heard bad news on unemployment	-0.0879***	-0.0427***		
Heard good news on inflation	-0.0927**	0.0637*		
Heard bad news on inflation	0.2343***	0.0256		

This table shows the estimated coefficients of the four equations in the HOPIT model. Each column corresponds to one equation, as indicated in the column heading. Coefficients of the time dummies are omitted. One to three stars after the coefficients indicate statistical significance at the 10%, 5%, and 1% level respectively.

Table 3. Correlations between various reference series and HOPIT model estimated aggregate expectations, uncertainty, and disagreement

Variable	Panel A					
	IQV	BL	COV	REA	BES	MSY
Expectation	-0.062	-0.025	-0.036	-0.010	0.026	0.663
Disagreement	0.491	0.485	0.478	0.477	0.462	0.844
Uncertainty	0.487	0.529	0.531	0.534	0.547	0.952

Variable	Panel B				Panel C	
	Mean	Median	Std. Dev.		Expectation	Disagreement
Expectation	0.570	0.576	0.496		-	-
Disagreement	0.105	0.144	0.580		0.687	-
Uncertainty	0.142	0.216	0.703		0.771	0.935

In Panel A (top), we report the correlations between our measures of expectation, disagreement, and uncertainty, and the six existing measures of dispersion of qualitative data. In Panel B (bottom left), we report the correlations between our measures and the mean, median, and standard deviation of the quantitative expectations. In Panel C (bottom right), we report the correlations between our three measures (lower triangle only).

Table 4. Correlations between existing measures of dispersion and measures of disagreement and uncertainty obtained using different reference series.

Reference series	**IQV**	**BL**	**COV**	**REA**	**BES**	**MSY**
Correlation with disagreement						
Actual inflation rate, average over the past 5 years	0.55	0.51	0.49	0.50	0.47	0.61
SPF consensus forecast, average over the past year	0.57	0.53	0.51	0.52	0.49	0.64
Quantitative survey responses, mean	0.55	0.51	0.50	0.49	0.45	0.30
Correlation with uncertainty						
Actual inflation rate, average over the past 5 years	0.58	0.57	0.56	0.57	0.56	0.75
SPF consensus forecast, average over the past year	0.59	0.60	0.58	0.60	0.60	0.80
Quantitative survey responses, mean	0.62	0.68	0.69	0.70	0.72	0.67

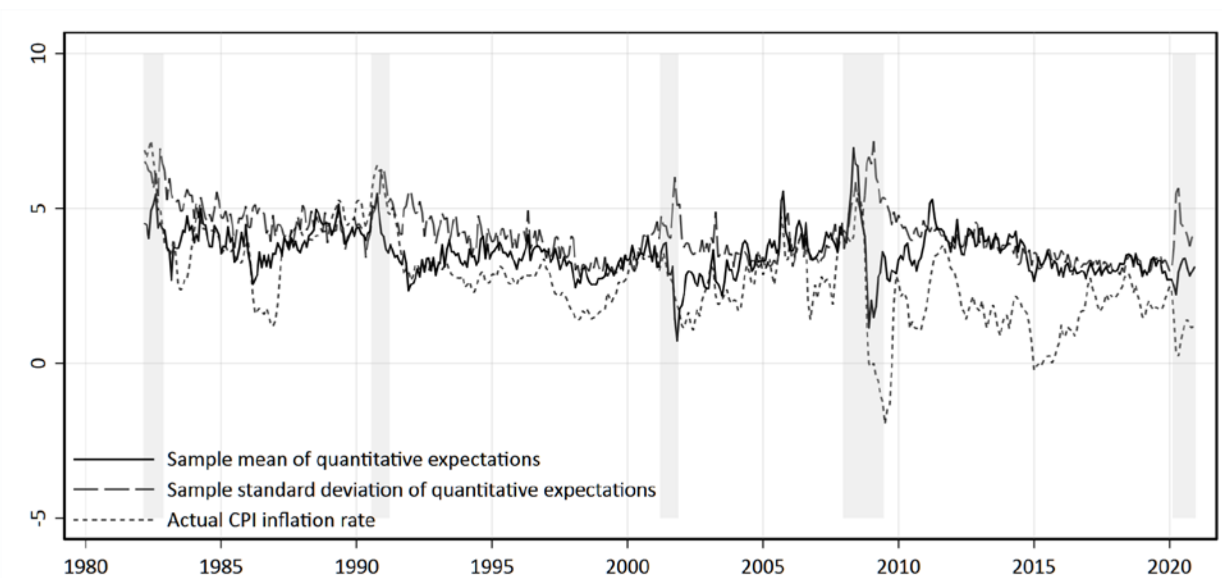
This table shows the correlations between existing measures of dispersion and our measure of disagreement (upper panel) and uncertainty (lower panel), where our measures are based on the same HOPIT model previously reported, but with scales determined using different reference series.

Table 5. Correlations between measures of expectation, uncertainty, disagreement, standard deviation of aggregate forecast density, and recent actual inflation rate

Variable/Correlations	Recent actual inflation	Uncertainty to disagreement ratio	Std. dev. of aggregate forecast density
Uncertainty to disagreement ratio	0.356	1.000	0.281
Std. dev. of aggregate forecast density	0.838	0.281	1.000
Quantified expectations	0.907	0.397	0.767
Disagreement	0.771	0.003	0.948
Uncertainty	0.840	0.314	0.999

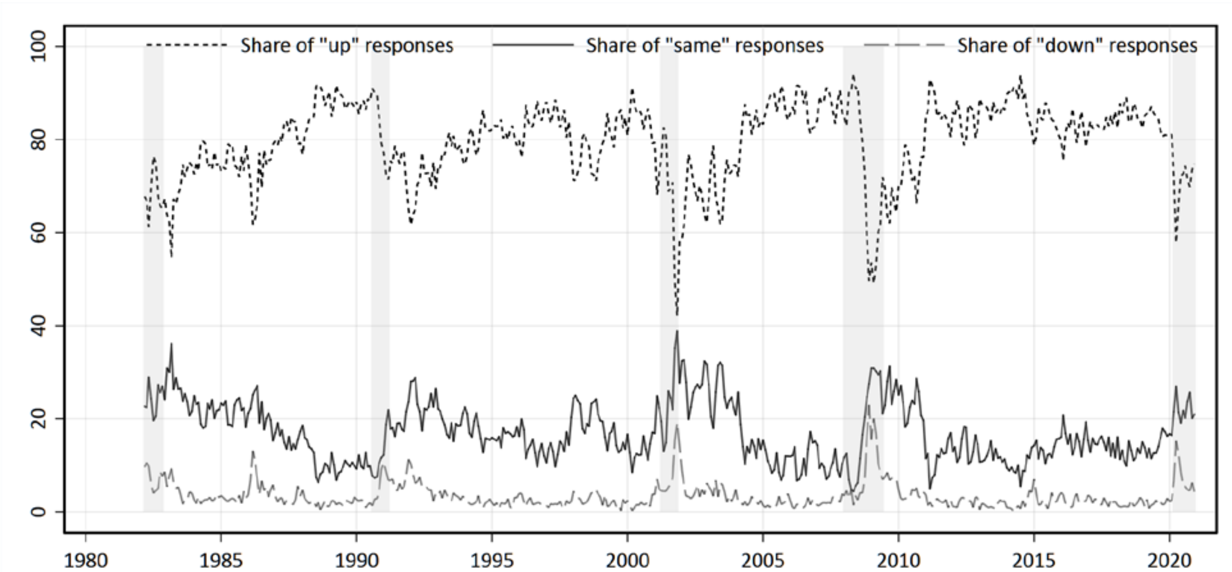
This table shows the correlations between measures of expectation, uncertainty, disagreement, standard deviation of aggregate forecast density, and recent actual inflation rate. Both uncertainty and disagreement, as well as quantified expectations are our estimates based on the HOPIT model.

Figure 1. Mean and standard deviation of quantitative expectations and the actual inflation rate



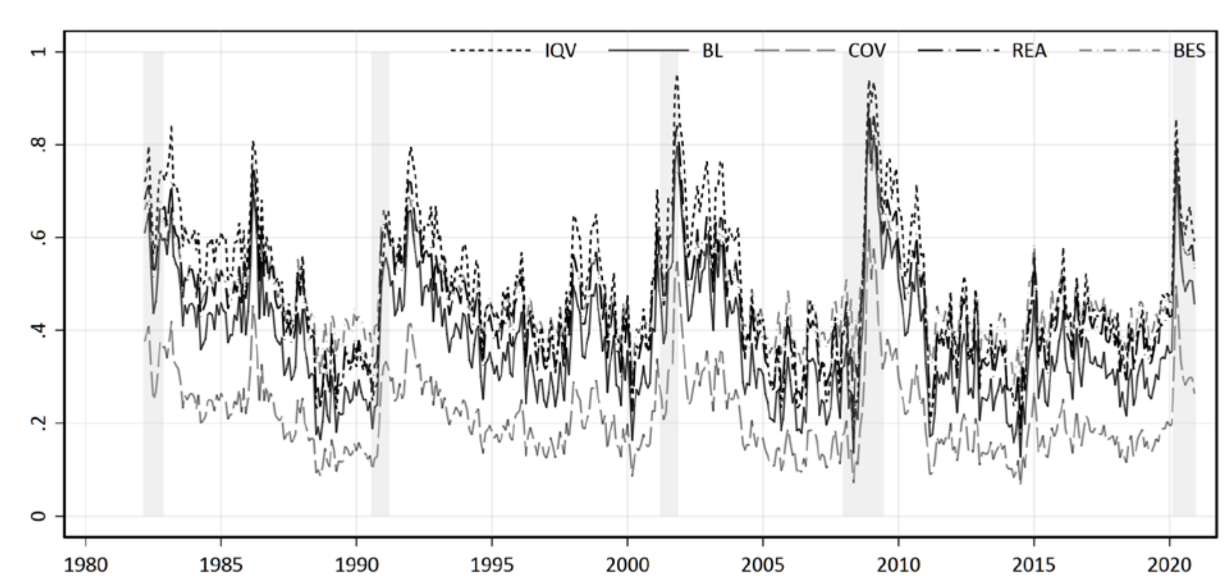
This figure compares the sample mean and the sample standard deviation of the quantitative expectations as well as the actual CPI inflation rate.

Figure 2. Shares of qualitative responses to the inflation expectation question (percentages)



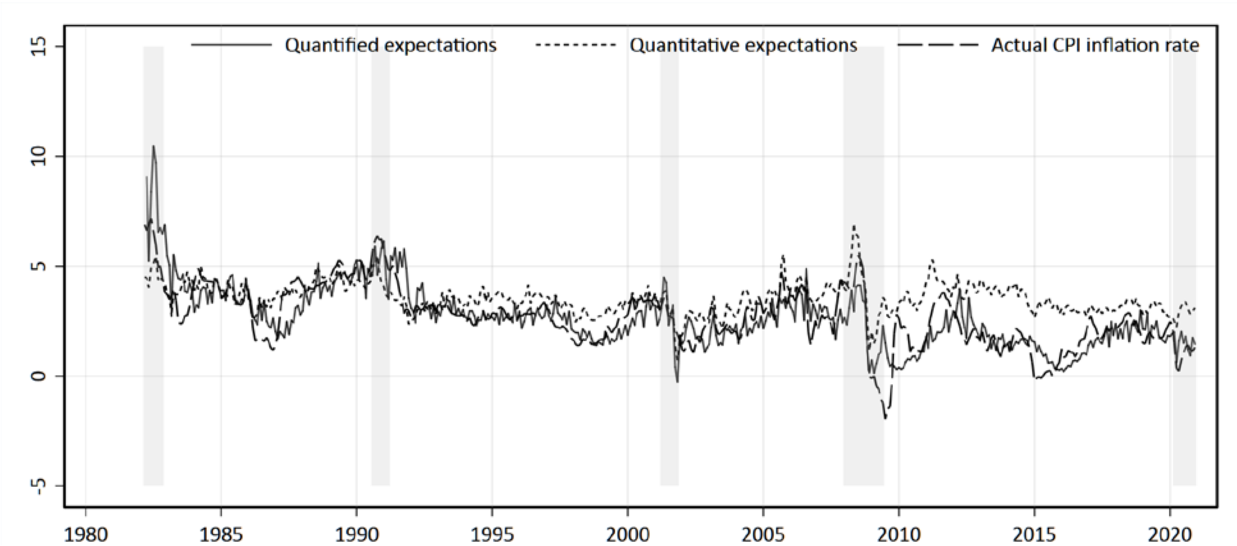
This figure shows the evolution of the response shares of the qualitative responses over time. The response shares are expressed as percentage of total non-missing responses. The response shares of the three responses, "up," "same," and "down," add to 100%.

Figure 3. Measures of dispersion derived from aggregate response share data



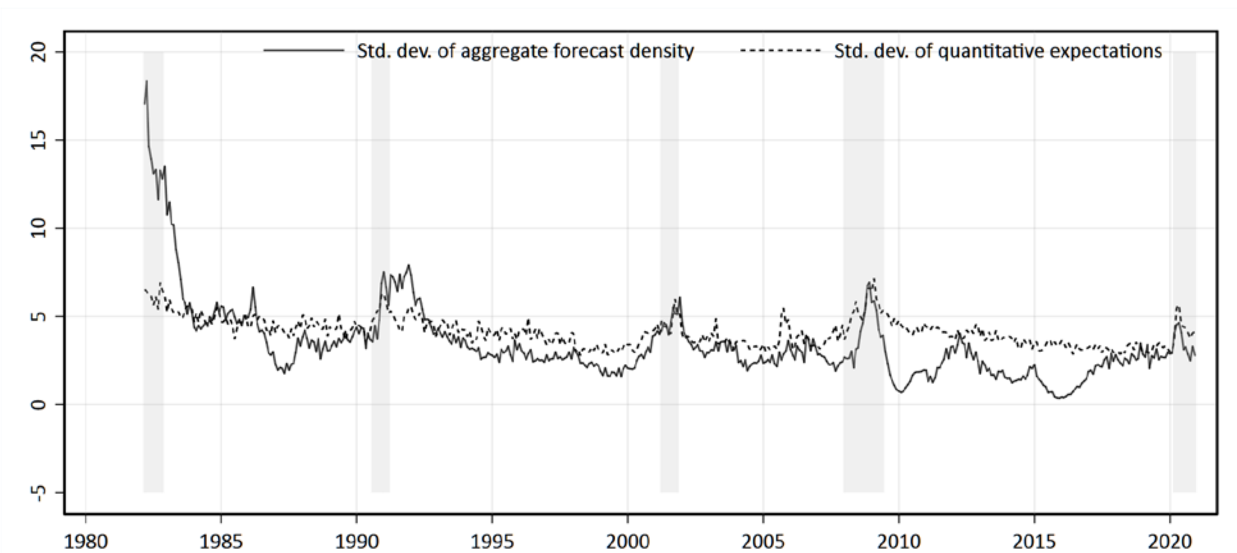
This figure highlights the co-movement of existing measures of dispersion of qualitative data. All the measures depicted in the figure are derived from the response shares data (shown in Figure 2) that are time series aggregated from individual responses.

Figure 4. Quantified expectations vs. mean of quantitative expectations



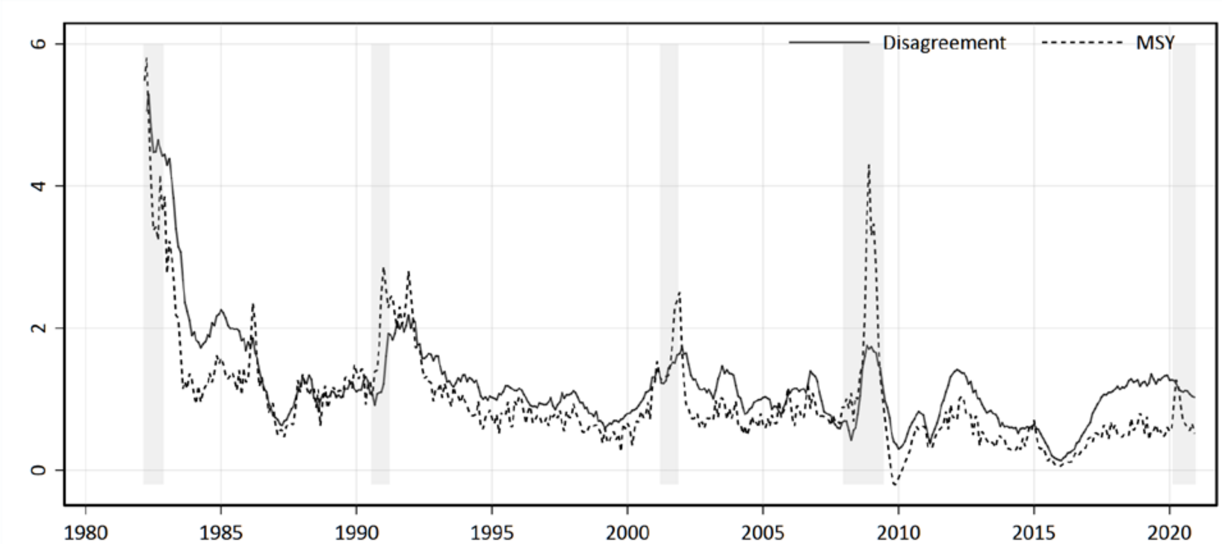
This figure compares the quantified expectations (our estimates) and the sample mean of the quantitative expectations as well as the actual CPI inflation rate.

Figure 5. Standard deviation of aggregate forecast density implied by qualitative responses vs. standard deviation of quantitative expectations



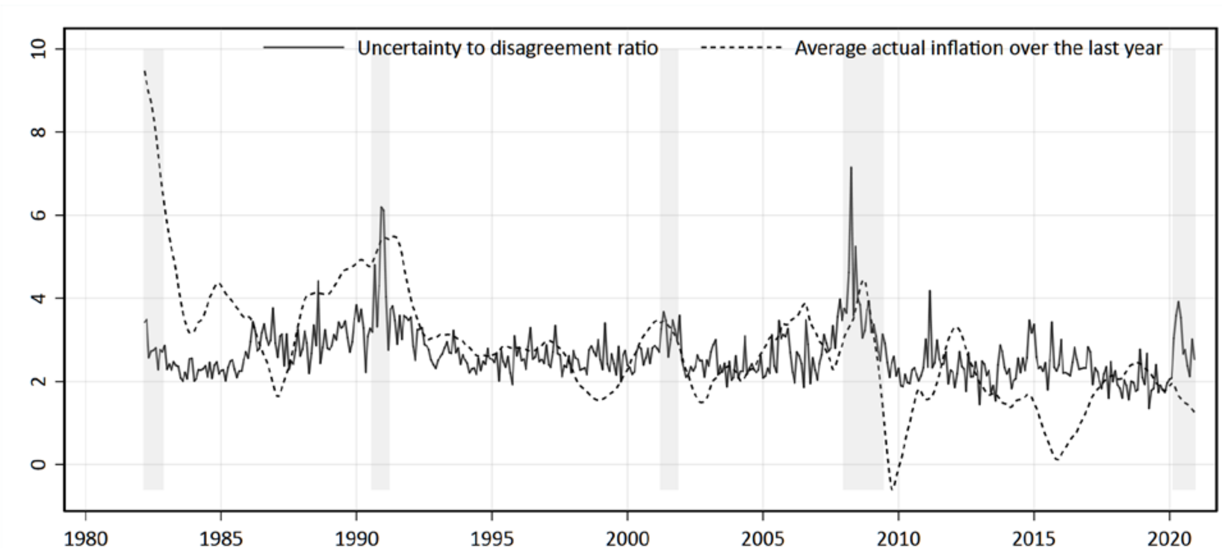
This figure shows the standard deviation of aggregate forecast density implied by the qualitative responses versus the sample standard deviation of the quantitative expectations. The standard deviation of aggregate forecast density depicted in the figure equals the square root of the sum of the squared uncertainty and disagreement.

Figure 6. Disagreement vs. MSY



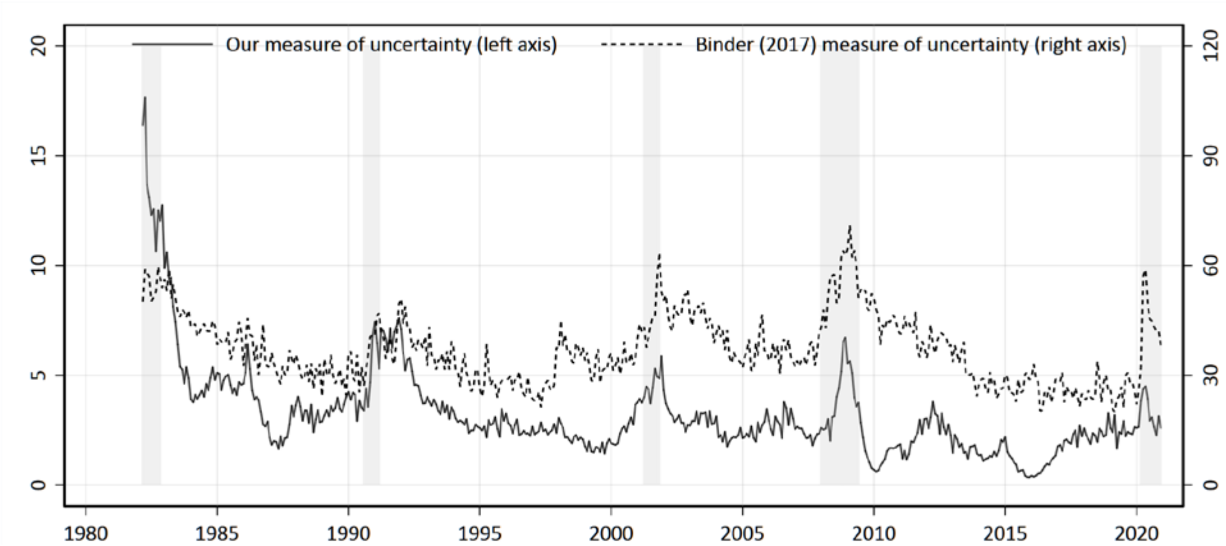
This figure compares our estimates of disagreement about inflation expectations and the existing measure MSY, which is presented in Section 3 of the paper.

Figure 7. The ratio of uncertainty to disagreement and the average actual inflation rate over the previous year



This figure plots the ratio of uncertainty to disagreement and the rolling average actual inflation rate over the previous 12 months. Both the uncertainty and the disagreement measures are our estimates from the HOPIT model. The ratio of the two shows their relative weights, with higher ratios meaning a higher weight for uncertainty and a correspondingly lower weight for disagreement.

Figure 8. Comparing our measure of uncertainty with that of Binder (2017)



This figure compares our measure of uncertainty based on qualitative data with the measure proposed in Binder (2017) that is based on the rounding of quantitative data. Both measures are based on the same Michigan survey and are about the same horizon. The measure of Binder (2017), depicted on the right vertical axis, is an index that takes values from 0 to 100. The scales of the figure are chosen to facilitate comparisons – the values of Binder's index and our measure are not changed. The correlation between the two series is around 0.52.