Survey Framing and Household Inflation Expectations: Evidence from an Emerging Market Economy*

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Abstract

This paper examines how survey design influences the measurement of household inflation expectations in an emerging market context. Using original data from three field pilots we designed and implemented in Mexico, we compare elicitation formats that gather point forecasts and subjective probability distributions. We document substantial heterogeneity in the level, dispersion, and uncertainty of reported expectations across sociodemographic groups and survey designs, and show that the relationship between point forecasts and distribution-based measures varies systematically across formats. The study further investigates the sources of cross-sectional heterogeneity by assessing differences in dispersion across formats after accounting for respondent characteristics, examining variation in expectations both across and within individuals, and estimating a structural model to identify potential drivers of measurement error. By documenting the importance of question framing for data quality, this study offers guidance for the design of household surveys and contributes to broader efforts to improve the measurement of expectations across diverse national contexts.

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1. Introduction

Understanding how households form and report inflation expectations is essential for effective policy design, as these beliefs influence key economic decisions such as consumption, saving, and wage negotiation (Mishkin, 2008). Accurate measurement of these expectations is therefore essential. Nevertheless, most existing evidence is derived from high-income countries with advanced survey infrastructures, where population characteristics differ markedly from those in low- and middle-income countries. As a result, the applicability of those methods and findings to other contexts remains limited. This paper presents evidence from multiple pilot surveys conducted in Mexico to elicit household inflation expectations, documenting how survey design matters for reported responses and highlighting heterogeneity across elicitation formats and socioeconomic groups.

We conducted three successive pilot experiments to test alternative survey formats for eliciting inflation expectations, adapting established methods to the Mexican context based on evidence from focus groups and small-scale field tests. In each pilot, we collected two measures per individual: a point forecast and a distribution-based measure of central tendency. To elicit the latter, the first pilot used a bin-based format, similar to the New York Fed, in which respondents allocated probabilities across predefined inflation intervals. The second introduced a scenario-based format in which respondents reported inflation for low, middle, and high scenarios and assigned probabilities, allowing them to define the relevant range of outcomes. The third pilot refined this approach through two variants: one elicited a respondent-defined range with probabilities assigned below, within, or above it, and the other elicited three inflation levels ("low," "normal," and "high") ranked by likelihood with associated probabilities. These design differences are important because elicited distributions are sensitive to the specification of support and bin structure (Boctor et al., 2024).

Because expectations are not directly observable, the analysis focuses on how respondents report beliefs across different elicitation formats. Using point forecasts and the mean of the subjective distribution, the study examines heterogeneity in the level and dispersion of inflation expectations across sociodemographic groups and survey designs. Additionally, inflation uncertainty, measured as the standard deviation of individuals' subjective probability distributions, is analyzed along the same dimensions. The results indicate systematic variation in reported expectations and uncertainty across groups and survey formats.

Building on the descriptive evidence, the present analysis investigates the relationship between point forecasts and distribution-based measures. The findings indicate systematic differences across elicitation formats in the relationship between these two measures, indicating that survey design influences how respondents translate underlying beliefs into reported expectations. The robustness of these findings is evaluated through various sensitivity analyses, including matching

estimators, bounds analysis as described by Oster (2019), and an instrumental variables approach based on Lewbel (2012). Alternative samples and aggregation levels are also considered, such as restricting the analysis to respondents in Mexico City and constructing pseudo-panels using time-invariant cohort characteristics. The results remain consistent across specifications. Overall, the evidence suggests that the relationship between alternative measures of inflation expectations systematically varies with elicitation format; however, these findings should be interpreted as suggestive rather than causal.

Finally, cross-sectional variation in elicited inflation expectations is further examined through a three-step analysis. First, we show that differences in dispersion across survey formats persist after controlling for respondent characteristics. Second, a cross-measure framework evaluates how point forecasts and the mean of the subjective distribution jointly vary across individuals, allowing for decomposition of overall variation into between-individual differences and differences across measures for a given individual. Third, a structural model of expectation formation under noisy private signals is developed to separate the discrepancy between point forecasts and the central tendency of the reported distribution into measurement error in each component and their covariance. Together, these analyses comprehensively characterize the relationships among survey design, respondent characteristics, and the cross-sectional distribution of inflation expectations.

Related Literature. How people perceive and form expectations about inflation has long intrigued researchers (Blomqvist, 1983; Wärneryd, 1986; Ranyard, 2008; Armantier et al., 2013; Binder and Kamdar, 2022). A key strand of this literature highlights the persistent divergence between perceived and official inflation, attributing it to psychological mechanisms such as salience, recall bias, and anchoring. In response, several studies have proposed alternative methods to capture perceptions more accurately, including distributional and experience-based measures (Antonides, 2008; Brachinger, 2008; Ranyard et al., 2008; Bruine de Bruin et al., 2011b; Huber, 2011).

While consumer sentiment surveys are widespread in both developed and developing countries, nationally representative surveys that rigorously elicit household inflation expectations remain relatively rare in low- and middle-income settings (Curtin, 2007; Tyagi, 2009; Albrizio et al., 2023). This gap is significant, as research shows that households form expectations using heuristics, limited attention, and personal experience rather than through rational processing with complete information (D'Acunto et al., 2024; Cavallo et al., 2017). Expectations are also shaped by beliefs about the causes of inflation and policy trade-offs (Binetti et al., 2024), and higher-order expectations often reflect first-order beliefs, suggesting limited strategic reasoning and sensitivity to framing effects (Kieren et al., 2023). Cross-country evidence shows that household expectations are typically upwardly biased and vary systematically by gender, education, age, and financial literacy (D'Acunto et al., 2023; D'Acunto and Weber, 2024). Likewise, evidence shows that in certain inflationary environments, individuals tend to anchor their expectations to salient prices—such as

food—rather than to official statistics, which can undermine the credibility and effectiveness of policy communication (Weber et al., 2023).

The absence of reliable and representative data on inflation expectations poses a significant challenge for developing countries, where validated instruments and clear benchmarks for survey design are often lacking.[1] This study contributes to addressing this gap by developing and instrumenting alternative survey formats to elicit household inflation expectations in Mexico. Using original data from field pilots, we document heterogeneity in reported expectations across elicitation formats and demographic groups, and analyze how different response types provided by the same individual—namely, point forecasts and measures of central tendency from subjective probability distributions—relate to each other. By showing how survey design and respondent characteristics shape these patterns, the paper provides new evidence on the measurement of expectations and the potential factors influencing belief formation in low- and middle-income settings.

Our approach builds on the use of probabilistic measures of expectations, as advocated by Manski (2004), which address limitations of qualitative questions by capturing both central tendencies and uncertainty. Recent studies also document systematic differences between point forecasts and measures derived from subjective distributions, indicating that elicitation formats shape how beliefs are expressed (Hayo and Méon, 2023; Boctor et al., 2024). This paper contributes to this literature in three ways. First, it documents systematic heterogeneity in reported expectations and subjective uncertainty across three elicitation formats—bin-based, scenario-based, and simplified scenario-based—and across sociodemographic groups. Second, it analyzes the relationship between point forecasts and distribution-based measures of central tendency, revealing meaningful variation across formats. Third, it investigates the sources of cross-sectional variation in inflation expectations underlying different elicited measures, providing a comprehensive characterization of how survey design and respondent characteristics are associated with the observed dispersion in inflation expectations.

Our findings highlight the role of question framing in shaping how respondents express their expectations. These results are relevant for the design of inflation expectations surveys, particularly in developing-country contexts where evidence remains limited. The paper contributes to the expanding literature on subjective expectations and uncertainty (see, e.g., Bruine de Bruin et al., 2011a; Kenny et al., 2014; Binder, 2018; Rumler and Valderrama, 2020; Zhao, 2023) by extending its empirical scope to underrepresented settings. Prior studies, including Bruine de Bruin et al. (2012) and Bruine de Bruin et al. (2017), show that reported expectations are sensitive to question

[1] In the case of Mexico, for example, existing evidence is sparse. Murillo Garza and Sánchez-Romeu (2014) constructed a diffusion index based on qualitative responses with limited predictive value, while Campos-Vázquez et al. (2022) collected point forecasts in a non-representative sample, documenting wide dispersion and strong sensitivity to information treatments.

wording and survey mode, but this evidence is largely drawn from high-income countries. To our knowledge, this study is among the first to examine how survey format relates to the elicitation of inflation expectations using original field data from an emerging market economy. By examining multiple dimensions of heterogeneity and documenting their association with design choices, we provide a structured characterization of data properties in survey-based expectations research. More broadly, the findings contribute to ongoing efforts to measure economic expectations across diverse institutional environments.

Outline. The remainder of the paper is structured as follows. Section 2 describes the data and key features of the survey instruments. Section 3 examines the distributional properties of elicited inflation expectations. Section 4 examines the relationship between point forecasts and distribution-based measures. Section 5 analyzes the sources of cross-sectional dispersion using regression analysis, a cross-measure decomposition, and a structural framework. Section 6 concludes.

2. Data and Measurement

2.1. The Context of Inflation Expectation Surveys

As mentioned above, while many countries—including those in the developing world—regularly conduct consumer sentiment surveys, dedicated instruments focused specifically on household inflation expectations remain uncommon in these settings (Curtin, 2007; Tyagi, 2009; Albrizio et al., 2023). This absence is striking given the importance of inflation expectations for understanding household behavior and policy effectiveness. In most developing economies, inflation questions are often embedded within broader consumer surveys, limiting their depth, comparability, and analytical utility. Assessing monetary policy's credibility or tailoring communication strategies becomes challenging without specialized tools to capture how households form and report expectations. This highlights the need for reliable, context-sensitive survey instruments that can generate consistent and interpretable measures of household inflation expectations across diverse institutional and informational environments.

In the case of Mexico, two distinct surveys currently collect information on inflation expectations—one targeting economic experts and another aimed at firms. These surveys employ quantitative formats based on subjective probability distributions: Respondents are asked to assign probabilities to a range of possible inflation outcomes, allowing researchers to recover individual-level density forecasts and calculate distributional moments such as the mean or variance. A third survey used to measure consumer confidence includes a qualitative question about the direction and intensity of expected price changes, such as whether prices will increase "a little" or "a lot ". While this format may reduce cognitive burden compared to questions that ask for numerical estimates,

it also limits comparability and the precision with which beliefs can be recovered and analyzed. The lack of a quantitative, probabilistic measure of household inflation expectations underscores the need to design and validate new survey instruments that can capture more nuanced and reliable information from consumers in the Mexican context.

2.2. Pilot Surveys

A sequence of three pilot experiments was conducted to implement alternative formats for eliciting inflation expectations. These pilots were designed to assess the reliability and robustness of information obtained under varying question structures. Each survey instrument was organized into two modules. The first module focused exclusively on eliciting inflation expectations, using different question formats. The second module collected detailed information on the socioeconomic characteristics of respondents, as well as behavioral and attitudinal variables that may influence expectation formation and reporting. These include, for example, measures of financial literacy, purchase behavior, and intra-household decision-making. This structure enables analysis not only of the internal consistency of reported expectations, but also of how such consistency may vary systematically across different population subgroups.

To facilitate respondents' comprehension of probabilistic concepts, as emphasized by Manski (2018), all the pilots began with a warm-up exercise intended to familiarize respondents with the corresponding probabilistic response tasks. Across all elicitation formats, the warm-up section presented responses from two hypothetical individuals to a probabilistic question about a good (*piñatas*) that people would not relate to inflation behavior (not salient), after which respondents completed a similar exercise before proceeding to the inflation expectation questions.

The order of the expectation questions was determined through expert consultation, evidence from small-scale pre-pilots, and focus group feedback, given the lack of consensus in the literature. Feedback suggested that beginning with a warm-up example and eliciting subjective distributions before point forecasts enhanced respondents' comprehension and engagement. In contrast, starting with point forecasts increased hesitation and created a test-like atmosphere. Therefore, the survey was structured to introduce the warm-up example first, followed by the subjective distribution question and then the point forecast question. Additionally, because our objective is to study the behavior of the subjective probability distribution, we elicited the distribution before the point forecast in order to minimize numerical anchoring, which could otherwise influence the shape and dispersion of the reported distribution. This sequencing represents a context-specific design choice rather than a claim of universal optimality. All surveys were administered via in-person interviews.

The first pilot survey (baseline) employed a bin-based format, similar to that used by the Federal Reserve Bank of New York, in which respondents assigned probabilities to inflation falling

within predefined intervals, allowing for the construction of individual-level subjective probability distributions. This approach has been widely adopted in the literature.

Recognizing that such formats may impose high informational demands, particularly in contexts with noteworthy asymmetries in access to information, levels of education, and economic literacy, we developed a second version using a scenario-based approach more contextually adapted to the local population. In this version, respondents were first asked to report their expected inflation rate under three distinct scenarios: low, intermediate, and high. They then assigned probabilities to each scenario, starting with the one they considered most likely. The goal was to allow respondents to set the support of their subjective distribution, in contrast to the bin-based format where the support is predetermined. This approach builds on the methodology proposed by Altig et al. (2022).

The third version refined the scenario-based format based on insights from the field implementation of the second version. In this version, the innovation was that respondents first defined a plausible range for future inflation. Then, they assigned probabilities to inflation being below, within, or above that range. The design preserved the contextual relevance of the scenario approach, focused on feasible scenarios, and simplified the task. Also, this format yields a continuous distribution of expected inflation.

The first pilot included 1,872 households across all 32 federal entities, covering both rural and urban areas. Of these, 1,869 had eligible members aged 18 or older, from which one was randomly selected per household. The survey was conducted from June 26 to July 7, 2023. The second pilot interviewed 2,090 adults aged 18 to 79 in localities with at least 50,000 inhabitants, conducted from November 2 to 15, 2023. The third pilot tested two alternative wordings for the question on the distribution of inflation expectations, with 251 interviews per version (502 in total) targeting adults in Mexico City. Both versions were administered in the same areas: Wording A from September 19 to 24, and Wording B from September 26 to October 1, 2024.

For the analysis, we restrict the sample to individuals who report both a point estimate and a subjective measure of inflation expectations. For each survey format, we calculate the absolute difference between the two measures and exclude the bottom and top 5% of the distribution. Individuals with missing data on any observable characteristics are also excluded. After applying the filtering criteria, the share of retained responses was 43% in the baseline survey, 55% in the alternative survey, 71% under wording A, and 63% under wording B. The final sample consists of 2,286 individuals. The response rates for completion of both inflation expectations questions, specifically the point forecast and the subjective probability distribution, were 53.08% for the Baseline survey, 64.40% for the Alternative survey, 83.67% for Wording A, and 74.50% for Wording B. No monetary or in-kind incentives were provided to participants.

2.3. Eliciting Inflation Expectations

The study will use three pilot experiments that tested four distinct survey versions together. While the first two pilots each included a single survey version (Baseline and Alternative, respectively), the third pilot tested two additional versions with modified wording. Across all survey versions, two types of responses were collected: (i) a subjective probability distribution over possible inflation outcomes, and (ii) a point estimate of expected inflation, typically elicited through a direct question about what respondents believed inflation would be over a specific time horizon (e.g., one year ahead).

In the first pilot, respondents assign probabilities to six fixed inflation intervals (or bins), ranging from "Less than 0%" to "More than 10.1%," in 2-percentage-point increments. To recover individual subjective inflation distributions, we follow the method proposed by Engelberg et al. (2009). The estimation approach depends on the number of bins used in each response. We fit a triangular distribution when respondents assign probabilities to only one or two bins. For responses with at least three bins, we fit a beta distribution. If a selected bin is open-ended in the beta specification, the corresponding upper or lower bound is estimated endogenously, but constrained to lie within a predefined range, with the lower bound set no lower than –15 and the upper bound no higher than 25. We show in the Online Appendix that the distribution is not sensitive to these parameters. In the second pilot, respondents report expected inflation under three scenarios: low, intermediate, and high. Then, they were asked to assign a probability to each scenario. Individual-level subjective inflation distributions are recovered by computing the weighted average of the three values, using the assigned probabilities as weights.

In the third pilot, the Wording A format required respondents to define a plausible range for future inflation and assign probabilities to inflation falling below, within, or above that range, resulting in three bins: a respondent-defined central interval and two open-ended tails. When all three bins received positive probability, a beta distribution was fitted to recover individual-level subjective inflation distributions, with the reported range symmetrically extended to define lower and upper bounds (e.g., a 5–10 percent range implies bounds of –5 and 20 percent). If any bin received zero probability, a triangular distribution was fitted instead. Under the Wording B format, respondents reported three inflation levels—"low," "normal," and "high"—ranked them by likelihood, and assigned probabilities to each. Individual-level subjective distributions were then recovered using the same approach as in the second pilot, employing probability-weighted averages of the reported values. In terms of the concentration of probability mass, the scenario-based formats show that under Wording A, 3.81% of respondents assigned non-zero probability to only one scenario, and 35.24% assigned non-zero probability to only two scenarios. Under Wording B, the corresponding figures were 5.35% and 20.32%, respectively.

2.4. Descriptive Statistics

Descriptive statistics for the four survey formats, Baseline (pilot 1), Alternative (pilot 2), Wording A (from pilot 3), and Wording B (from pilot 3), are reported in Table 1. The table presents mean, median, and standard deviation values for various variables related to inflation expectations, sociodemographic characteristics, and behavioral indicators.

Inflation expectations differ across formats, underscoring the role of question-wording. In the Baseline version, the median of the subjective central measure is 5.00% (mean: 4.94%), increasing to 10.40% (mean: 20.20%) in the Alternative, 14.87% (mean: 29.61%) in Wording A, and 16.25% (mean: 27.10%) in Wording B. Point estimates follow a similar trend, with the median rising from 6.00% (mean: 12.45%) in the Baseline to 10.00% (mean: 21.31%) in the Alternative, and holding at 12.00% in Wording A (mean: 26.23%) and 14.00% in Wording B (mean: 24.35%).

These levels are consistent with findings from other household surveys, where median inflation expectations often exceed actual inflation by a factor of two or more. This tendency reflects well-documented biases in household forecasting, such as upward skew in perceived price changes and limited information. The rise in medians across formats suggests that specific aspects of bin design, particularly the selection of support and interval partition, may influence reported expectations. In bin-based formats, these elements are fixed ex ante and may constrain how respondents express beliefs if the support is not well aligned with the perceived range of outcomes. This sensitivity to support specification is consistent with evidence that elicited distributions depend on bin definitions, which can shape reported expectations (Boctor et al., 2024). Selecting an appropriate set of bins is particularly challenging in environments with volatile or shifting inflation, where predefined supports may quickly diverge from respondents' expectations. These findings highlight the practical challenges associated with bin specification, rather than indicating an inherent limitation of the bin-based approach, and demonstrate the value of alternative elicitation methods.

The sociodemographic composition of respondents is relatively consistent across versions. The share of female respondents ranges from 44% to 51%, and the average age spans from 42.53 to 47.63 years. Between 40% and 52% identify as heads of household. Most respondents report completing at least high school (63% to 72%), and financial literacy scores range from 0.59 to 0.83. Employment rates remain high across all versions (74% to 85%), and 52% to 79% of respondents fall into the high socioeconomic group. Patterns of household behavior and spending intentions show modest variation. Roughly half of respondents report being primarily responsible for grocery shopping and major purchases, though delegation appears more common in Wording A. Investment and consumption plans vary more markedly: for instance, 28% of Baseline respondents plan to build or remodel a home, compared to 33% in the Alternative and 41% in Wording B. Intentions to purchase durable goods are also more frequent in the experimental formats—49% of Wording

B respondents report plans to buy furniture or appliances, compared to 33% in the Baseline.

Table 1. Descriptive Statistics

	Baseline			Alternative			Wording A			Wording B		
	Mean	Med.	S.D.	Mean	Med.	S.D.	Mean	Med.	S.D.	Mean	Med.	S.D.
Inflation												
Inf. exp. central measure	4.94	5.00	3.01	20.20	10.40	19.72	29.61	14.87	28.22	27.10	16.25	24.80
Inf. exp. point estimate	12.45	6.00	15.82	21.31	10.00	22.16	26.23	12.00	27.11	24.35	14.00	25.41
Sociodemographics												
Woman	0.51	–	0.50	0.48	–	0.50	0.44	–	0.50	0.44	–	0.50
Age	43.33	41.00	15.91	42.53	42.00	15.63	47.63	49.00	16.05	46.64	49.00	16.84
Head of household	0.52	–	0.50	0.44	–	0.50	0.40	–	0.49	0.48	–	0.50
Schooling												
Up to elementary	0.12	–	0.33	0.11	–	0.31	0.09	–	0.29	0.07	–	0.26
Elementary to junior h.s.	0.25	–	0.43	0.27	–	0.44	0.19	–	0.39	0.22	–	0.42
High school or more	0.63	–	0.48	0.63	–	0.48	0.72	–	0.45	0.71	–	0.46
Financial literacy score	0.83	1.00	0.33	0.82	1.00	0.34	0.62	0.67	0.23	0.59	0.67	0.23
Working	0.75	–	0.43	0.74	–	0.44	0.78	–	0.41	0.85	–	0.35
Socioeconomic group												
High	0.79	–	0.41	0.52	–	0.50	0.60	–	0.49	0.54	–	0.50
Low	0.21	–	0.41	0.48	–	0.50	0.40	–	0.49	0.46	–	0.50
Behavior												
Who does the shopping?												
Mostly me	0.51	–	0.50	0.49	–	0.50	0.44	–	0.50	0.50	–	0.50
Me and others in h.h.	0.17	–	0.37	0.14	–	0.35	0.19	–	0.39	0.14	–	0.35
Someone else	0.32	–	0.47	0.37	–	0.48	0.38	–	0.49	0.36	–	0.48
Who makes major purchases?												
Mostly me	0.44	–	0.50	0.41	–	0.49	0.38	–	0.49	0.43	–	0.50
Me and others in h.h.	0.26	–	0.44	0.21	–	0.41	0.22	–	0.41	0.27	–	0.45
Someone else	0.30	–	0.46	0.38	–	0.49	0.40	–	0.49	0.30	–	0.46
Plans to...												
buy a house	0.07	–	0.26	0.12	–	0.32	0.13	–	0.34	0.15	–	0.36
build or remodel a house	0.28	–	0.45	0.33	–	0.47	0.39	–	0.49	0.41	–	0.49
buy a vehicle	0.15	–	0.36	0.22	–	0.41	0.26	–	0.44	0.28	–	0.45
buy furniture or appliances	0.33	–	0.47	0.41	–	0.49	0.39	–	0.49	0.49	–	0.50
buy electronics	0.27	–	0.44	0.33	–	0.47	0.30	–	0.46	0.38	–	0.49
N		801			1150			178			157	

Notes: The table presents key characteristics of respondents across the three pilot surveys. Two versions of the financial literacy question were used, with scores standardized as the proportion of correct answers. The socioeconomic level index is based on the AMAI methodology, commonly used in Mexican surveys. Because not all relevant questions were included in every pilot to calculate this index, we predicted the AMAI index using a regression on variables common to all surveys. Respondents scoring 168 or above were classified as having high socioeconomic status, and those below as low.

3. Inflation Expectations Across Demographics and Elicitation Formats

3.1. Levels and Dispersion of Inflation Expectations

To examine the distributional characteristics of elicited inflation expectations across demographic groups and survey types, each cell in Table 2 presents the mean, standard deviation, and interquartile range calculated across individuals, facilitating direct comparison of both levels and cross-sectional dispersion across the different measures. The results suggest substantial heterogeneity in

inflation expectations across demographic groups and elicitation formats, both in point estimates and in the central tendency of subjective probability distributions.

Table 2. Inflation Expectations by Demographics and Elicitation Formats

	Subjective Mean				Point Estimate			
	Baseline (1)	Alternative (2)	Wording A (3)	Wording B (4)	Baseline (5)	Alternative (6)	Wording A (7)	Wording B (8)
Sex								
Men	4.58	16.98	22.48	25.09	10.04	16.38	19.07	23.18
	(2.96)	(16.68)	(21.74)	(23.65)	(13.18)	(17.64)	(21.27)	(25.32)
	[3.60]	[19.95]	[31.64]	[34.78]	[7.00]	[15.00]	[20.00]	[25.00]
Women	5.28	23.69	38.54	29.65	14.75	26.66	35.21	25.85
	(3.03)	(22.06)	(32.68)	(26.14)	(17.69)	(25.15)	(30.86)	(25.62)
	[3.80]	[31.80]	[54.08]	[42.80]	[16.00]	[43.00]	[51.00]	[34.00]
Sociodemographic Group								
Low	4.48	20.77	25.00	25.27	10.51	22.31	22.00	23.16
	(2.67)	(20.14)	(24.02)	(23.07)	(13.29)	(23.45)	(24.20)	(24.46)
	[3.00]	[28.51]	[32.07]	[36.15]	[7.00]	[24.00]	[35.00]	[24.00]
High	5.06	19.68	32.67	28.64	12.97	20.38	29.04	25.36
	(3.09)	(19.34)	(30.42)	(26.21)	(16.40)	(20.89)	(28.64)	(26.28)
	[4.00]	[26.25]	[46.23]	[42.80]	[6.10]	[25.00]	[44.00]	[35.00]
Age								
18–24	4.27	13.35	19.57	14.21	10.74	13.14	15.34	10.67
	(3.10)	(12.51)	(16.50)	(16.95)	(14.10)	(15.28)	(14.28)	(9.36)
	[2.55]	[10.50]	[17.18]	[9.00]	[7.00]	[10.00]	[15.00]	[12.00]
25–54	4.77	20.55	27.15	26.27	12.67	22.35	24.04	23.35
	(2.78)	(19.97)	(27.09)	(22.67)	(16.54)	(22.70)	(25.26)	(23.61)
	[3.30]	[28.00]	[32.92]	[35.40]	[7.00]	[24.00]	[35.00]	[24.00]
55–65	5.76	24.40	42.63	34.91	13.30	24.23	38.05	31.24
	(3.77)	(22.80)	(33.24)	(30.39)	(15.71)	(23.23)	(34.13)	(29.99)
	[4.23]	[32.00]	[53.47]	[58.60]	[10.00]	[34.00]	[53.00]	[54.00]
66+	5.60	21.17	24.30	29.36	11.78	22.27	22.67	30.05
	(2.84)	(18.77)	(23.78)	(22.53)	(12.96)	(23.31)	(21.91)	(29.07)
	[3.37]	[29.80]	[31.02]	[38.23]	[11.00]	[24.00]	[26.50]	[43.50]
Education								
Up to Elementary	5.65	26.84	50.44	46.68	12.54	28.57	48.00	38.45
	(3.13)	(24.10)	(32.86)	(31.70)	(15.42)	(24.96)	(33.13)	(35.07)
	[4.00]	[37.90]	[58.29]	[65.50]	[11.00]	[42.00]	[66.50]	[75.00]
Elementary to junior	4.98	25.11	35.52	34.64	14.93	26.08	29.62	33.83
	(3.11)	(21.28)	(27.76)	(27.19)	(17.60)	(23.66)	(25.86)	(29.81)
	[4.00]	[30.90]	[43.74]	[53.50]	[16.00]	[32.00]	[40.00]	[55.00]
High school or more	4.78	17.02	25.51	22.78	11.43	18.08	22.67	19.97
	(2.94)	(17.42)	(26.49)	(21.84)	(15.04)	(20.31)	(25.40)	(21.47)
	[3.31]	[19.55]	[32.24]	[28.70]	[6.50]	[15.50]	[25.00]	[17.00]
HH Head								
No	4.82	19.45	29.71	25.74	11.89	20.55	25.30	23.54
	(3.09)	(19.37)	(28.00)	(24.52)	(15.02)	(21.27)	(25.87)	(24.43)
	[3.43]	[25.50]	[41.00]	[36.20]	[6.50]	[25.00]	[34.00]	[25.00]
Yes	5.05	21.15	29.47	28.59	12.96	22.26	27.61	25.24
	(2.94)	(20.14)	(28.75)	(25.18)	(16.50)	(23.22)	(28.96)	(26.57)
	[3.78]	[28.58]	[43.23]	[44.25]	[8.00]	[24.00]	[44.50]	[34.00]
Work								
No	5.31	20.75	44.11	41.29	13.30	23.08	37.96	38.39
	(3.52)	(20.03)	(34.04)	(28.35)	(16.24)	(23.54)	(33.27)	(31.13)
	[3.54]	[27.31]	[60.46]	[53.25]	[11.00]	[32.00]	[63.00]	[61.00]
Yes	4.82	20.01	25.54	24.66	12.17	20.69	22.94	21.95
	(2.82)	(19.63)	(25.03)	(23.40)	(15.68)	(21.64)	(24.24)	(23.60)
	[3.35]	[27.00]	[32.43]	[34.70]	[7.00]	[25.00]	[29.00]	[25.00]

Notes: This table reports inflation expectations segmented by demographic characteristics and elicitation format. For each individual, both a point estimate and the mean of the subjective probability distribution are obtained. Subsequently, the statistics are calculated across individuals within each group in the cross-section. Each cell displays the cross-sectional mean in the first row, the standard deviation in parentheses in the second row, and the interquartile range in brackets in the third row.

Among demographic groups, the baseline format produces lower average expectations and more compressed cross-sectional distributions than the Alternative, Wording A, and Wording B formats. These findings indicate that elicitation design systematically shapes both the reported level of expectations and their cross-sectional dispersion.

Gender differences are pronounced and robust across formats. Women consistently report higher inflation expectations than men for both point estimates and distribution means, with especially large gaps under wording A and wording B. These differences are accompanied by higher dispersion among women, as reflected in both SDs and IQRs, suggesting greater cross-sectional heterogeneity in beliefs. Under the baseline format, expectations for both men and women are tightly clustered, while alternative wordings, particularly wording A, are associated with a sharp increase in dispersion, especially for the subjective distribution mean.

Clear gradients are observed across sociodemographic status, educational attainment, and labor market participation. Individuals in lower sociodemographic groups, with less education, and those not participating in the workforce report higher and more widely dispersed inflation expectations, particularly under wording A and wording B.

Conversely, respondents with higher education and employment status demonstrate lower and more narrowly concentrated expectations across all formats. These patterns are evident in both SDs and IQRs, indicating that differences in cross-sectional dispersion are not driven solely by extreme observations but reflect broader shifts in the distribution of beliefs.

Age-related heterogeneity is similarly pronounced. Younger respondents (ages 18–24) report the lowest and least dispersed inflation expectations, especially under the baseline format. Both the level and cross-sectional dispersion of expectations increase steadily with age, with respondents aged 55 and older exhibiting the highest means and widest interquartile ranges, particularly under wording-based formats. This pattern holds for both point estimates and subjective distribution means, indicating that older respondents not only expect higher inflation but also display greater within-group disagreement.

Differences by household head status are more modest in average expectations but remain visible in cross-sectional dispersion measures. Household heads generally report slightly higher expectations and higher SDs and IQRs than non-heads, especially under wording A and wording B, while baseline elicitation again produces comparatively compressed distributions for both groups.

Overall, the evidence shows that heterogeneity in inflation expectations, both in levels and cross-sectional dispersion, is strongly associated with demographic characteristics and is systematically amplified by elicitation formats that use alternative wording or scenario-based descriptions. Importantly, these patterns are broadly consistent across point estimates and subjective distribution means and are reflected in both cross-sectional standard deviations and interquartile ranges. These

findings highlight that survey design choices materially shape reported inflation expectations and their dispersion across demographic groups, underscoring the importance of careful elicitation design.

3.2. Uncertainty of Inflation Expectations

Individual-level inflation uncertainty is measured as the standard deviation of each respondent's subjective probability distribution. The Online Appendix presents the cross-sectional distribution of this measure. Across elicitation formats, average uncertainty is consistently lower in the Baseline format compared to the Alternative, Wording A, and Wording B formats. For each demographic group and elicitation format, Table 3 reports the mean, standard deviation, and interquartile range across individuals. The findings indicate that both the level and distribution of subjective uncertainty vary substantially across elicitation formats, and that demographic patterns are heterogeneous and depend on the survey design.

With respect to sex, women report higher average uncertainty than men in the Baseline, Alternative, and Wording A formats, while differences are minimal in Wording B. Differences by sociodemographic group are limited in the Baseline but vary across formats, with higher uncertainty observed for the low group in the Alternative format and for the high group in Wording A and Wording B. Age-related patterns are non-monotonic and differ across formats; however, older respondents (66+) generally exhibit lower uncertainty in the Baseline and Wording A formats. Educational gradients are also format-dependent; less educated respondents report higher uncertainty in the Alternative and Wording B formats, whereas patterns are less systematic in the Baseline and Wording A. Overall, these findings indicate that elicitation format is closely associated with both the level of reported uncertainty and its relationship with observable characteristics.

A central issue is whether the observed differences across elicitation formats reflect distortions introduced by the measurement approach or a more accurate representation of respondents' underlying beliefs, particularly compared with the baseline bin-based method. While part of the variation may be related to the specific bin structure used in the baseline survey, the results more broadly highlight a fundamental design challenge inherent in bin-based elicitation. The effectiveness of the bin-based approach depends critically on the ex ante specification of the support. As emphasized by Boctor et al. (2024), predefined bins can act as anchors that shape reported probabilities and summary statistics. Selecting an appropriate bin structure is particularly challenging in environments characterized by volatile inflation, where fixed supports may not align with respondents' beliefs. Taken together, these findings underscore the practical challenges associated with implementing bin-based designs, rather than indicating a general shortcoming of the approach itself.

Table 3. Uncertainty of Subjective Inflation Expectations by Demographics and Elicitation Formats

	Subjective Standard Deviation			
	Baseline (1)	Alternative (2)	Wording A (3)	Wording B (4)
Sex				
Men	1.61	5.44	12.72	7.37
	(1.67)	(6.54)	(20.36)	(7.50)
	[1.95]	[6.40]	[9.77]	[10.83]
Women	1.72	6.90	19.40	7.54
	(1.88)	(7.37)	(22.46)	(7.38)
	[2.06]	[9.47]	[20.22]	[9.87]
Sociodemographic Group				
Low	1.67	6.41	13.79	6.77
	(1.83)	(7.24)	(21.30)	(6.99)
	[1.94]	[8.74]	[11.69]	[8.11]
High	1.67	5.89	16.94	8.01
	(1.77)	(6.74)	(21.66)	(7.77)
	[2.06]	[7.18]	[18.67]	[11.26]
Age				
18–24	1.95	3.97	19.90	4.43
	(1.59)	(4.44)	(21.48)	(4.56)
	[1.77]	[3.39]	[19.40]	[2.98]
25–54	1.73	6.45	14.69	7.61
	(1.91)	(7.22)	(22.06)	(7.04)
	[2.06]	[9.19]	[11.94]	[11.86]
55–65	1.35	7.08	18.94	8.95
	(1.41)	(7.89)	(23.82)	(9.40)
	[1.94]	[8.40]	[22.72]	[13.48]
66+	1.43	5.81	10.53	7.30
	(1.57)	(6.32)	(13.29)	(6.39)
	[1.90]	[7.24]	[10.99]	[8.13]
Education				
Up to Elementary	1.37	8.15	14.00	11.30
	(1.51)	(8.59)	(17.45)	(8.60)
	[1.94]	[10.19]	[13.64]	[14.49]
Elementary to junior	1.59	7.24	18.75	9.82
	(1.72)	(7.31)	(24.48)	(7.52)
	[1.94]	[9.95]	[18.76]	[13.71]
High school or more	1.76	5.34	15.11	6.31
	(1.85)	(6.40)	(21.24)	(7.03)
	[1.99]	[6.44]	[13.74]	[8.01]
HH Head				
No	1.83	5.96	17.84	7.39
	(1.98)	(6.90)	(24.37)	(7.09)
	[2.24]	[7.29]	[17.51]	[11.17]
Yes	1.52	6.36	12.52	7.50
	(1.57)	(7.09)	(16.08)	(7.83)
	[1.94]	[8.11]	[11.29]	[9.57]
Work				
No	1.65	6.21	18.44	10.61
	(1.75)	(7.15)	(22.63)	(7.64)
	[1.95]	[7.47]	[20.01]	[15.18]
Yes	1.67	6.11	14.91	6.90
	(1.79)	(6.93)	(21.21)	(7.28)
	[2.05]	[7.71]	[13.34]	[9.57]

Notes: Inflation uncertainty is initially calculated at the individual level as the standard deviation of each respondent's subjective probability distribution. For each demographic group and elicitation format, the mean, standard deviation, and interquartile range of this individual-level uncertainty measure are subsequently computed across individuals and reported. Each cell presents the mean (first row), standard deviation in parentheses (second row), and interquartile range in brackets (third row).

4. Relationship Between Point and Distribution-Based Expectations

This section investigates how the relationship between point forecasts and distribution-based measures differs across elicitation formats, emphasizing the influence of survey design and respondent characteristics. In the benchmark analysis, point forecasts are compared to the mean of the subjective distribution, which serves as a natural reference. However, the analysis does not assume that point forecasts necessarily correspond to this moment. As a robustness check, the analysis is replicated using the median of the subjective distribution (see Online Appendix), yielding qualitatively similar results.

4.1. Simple Correlation between Point Estimates and Subjective Expectations

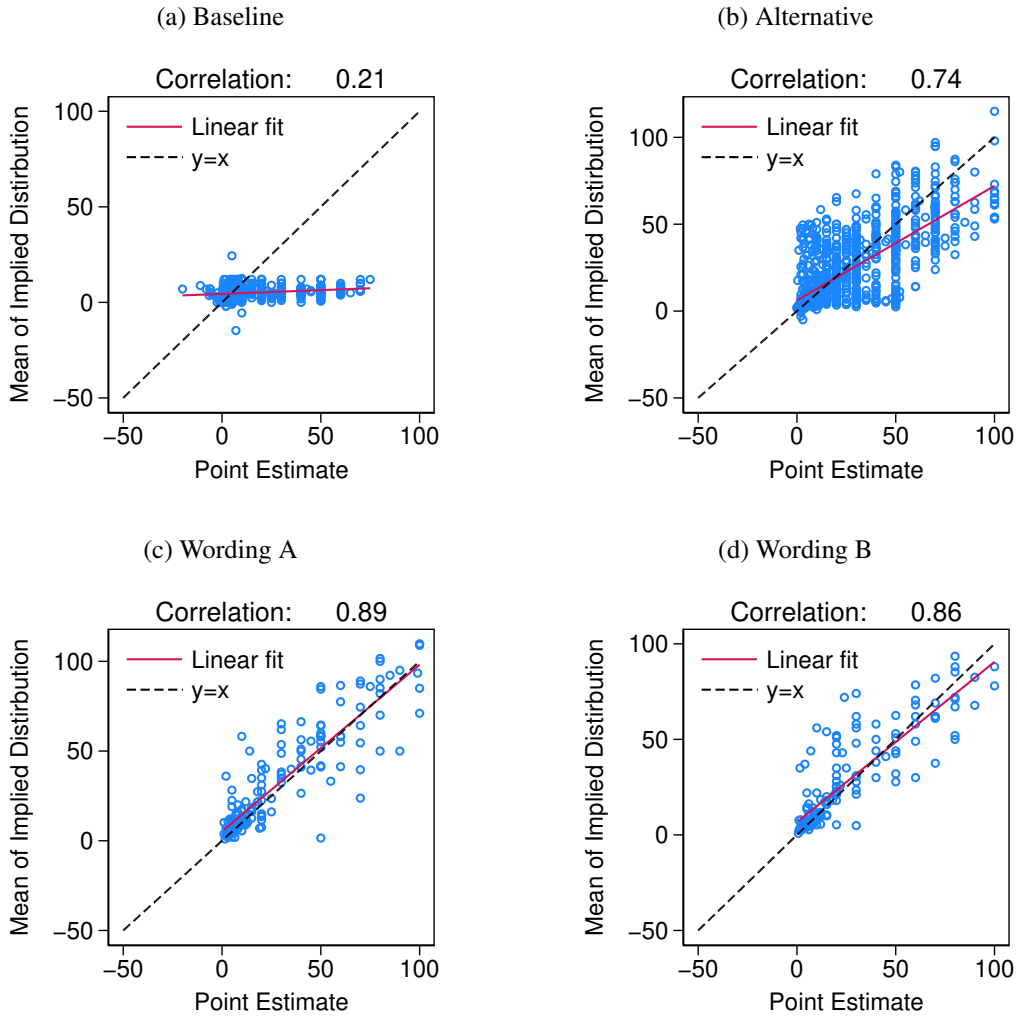
As a first step, we examine the relationship between different measures of inflation expectations using correlation plots of point forecasts and the implied mean of subjective distributions. This descriptive approach offers an initial characterization of how individuals express expectations across formats and highlights heterogeneity in these relationships, thereby providing insight into how elicitation methods capture beliefs about future inflation.

The relationship between respondents' point forecasts of expected inflation and the implied mean of their subjective probability distributions is illustrated in Figure 1 for the four pilot survey formats. Each panel presents individual observations, a fitted regression line, and a 45-degree reference line indicating equality between the two measures. The strength and slope of this relationship vary substantially across formats, revealing heterogeneity in how individuals translate beliefs into responses. While the 45-degree line provides a benchmark, point forecasts do not necessarily correspond to the mean; respondents may report different summary statistics, such as the median or mode, or forecasts reflecting individual loss functions (Engelberg et al., 2009). Deviations may therefore reflect reporting conventions, misunderstandings of probability, anchoring, rounding, or noise. To assess the robustness of these findings, the analysis was repeated using the median of the subjective distribution (see Online Appendix), and similar results were obtained.

The Baseline version (Panel A) shows a relatively weak association between the point estimate and the implied mean of the subjective distribution, indicated by a correlation coefficient of 0.21. The scatter plot indicates that responses are concentrated within the 0 to 10 percent range—particularly around mid-range values—consistent with the summary statistics reported in Table 2, and exhibit limited alignment along the 45-degree line. In the Alternative version (Panel B), the relationship between the two measures is stronger, with a correlation of 0.74 and a clearer positive association, as reflected in a more pronounced linear pattern in the data. Wording A (Panel C) exhibits a very strong association between the point estimate and the implied mean, with a correlation of 0.89 and

a tight clustering of observations along the 45-degree line. Wording B (Panel D) shows a similarly strong relationship, with a correlation of 0.86, though with somewhat greater dispersion around the linear trend. Collectively, these findings indicate substantial heterogeneity in the alignment between point forecasts and probabilistic assessments across survey formats. This variation implies that respondents exposed to different survey designs may differ in their ability to align point forecasts with their probabilistic beliefs.

Figure 1. Correlation between Point Estimate and Mean of Inflation Expectations

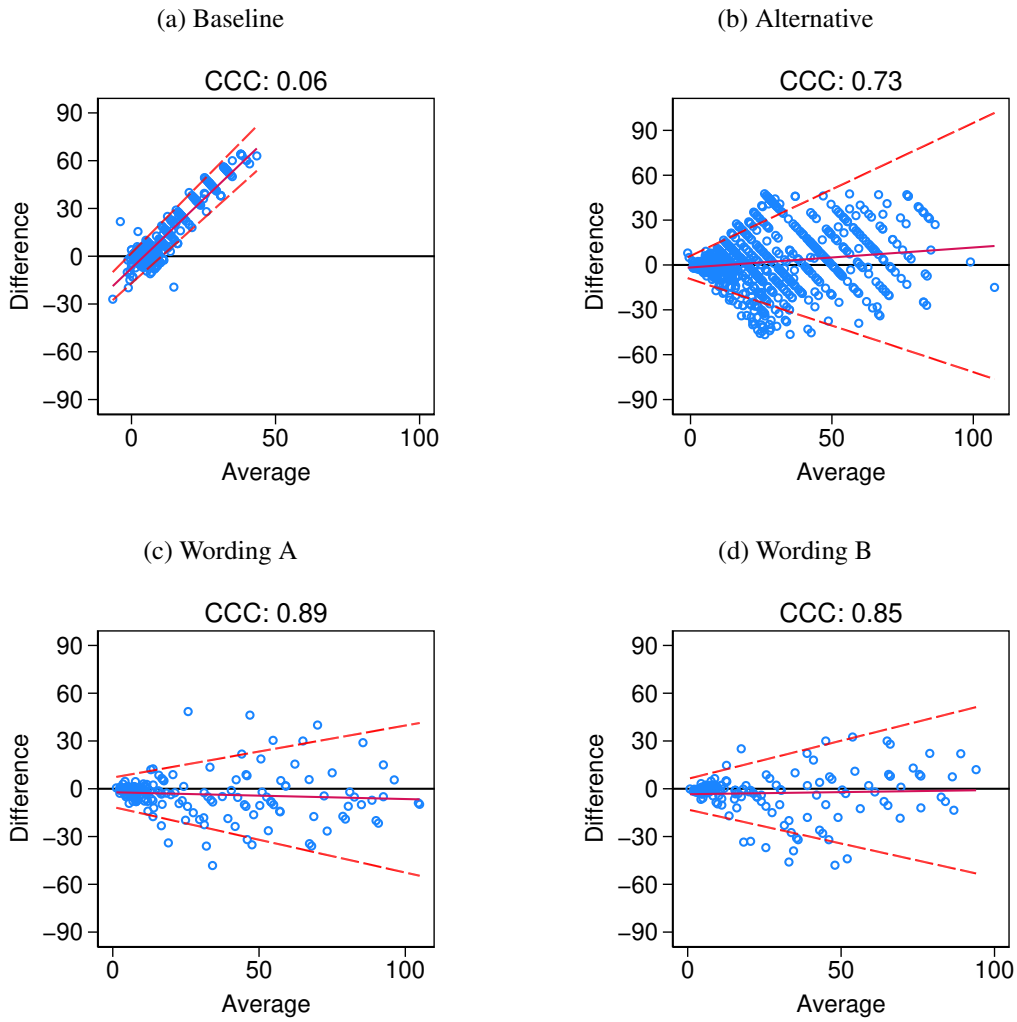


Notes: Each panel displays the correlation between respondents' point estimates and the mean of their subjective probability distribution of expected inflation. The dashed 45-degree line represents perfect alignment, where the point estimate equals the distributional mean. The solid red line shows the linear fit. Panel (a) corresponds to the baseline bin-style format; panel (b) shows the original scenario-based alternative; and panels (c) and (d) present results from two simplified scenario-based formats with different wordings.

4.2. Alternative Measures of Alignment

To further characterize the relationship between respondents' point estimates of expected inflation and the means implied by their subjective probability distributions, Bland–Altman plots and Lin's concordance correlation coefficient (CCC) are employed. These complementary tools facilitate the assessment of systematic differences and dispersion between the two response types and provide a summary of their alignment across individuals and elicitation formats.

Figure 2. Bland-Altman Plots



Notes: Each panel illustrates the agreement between the point estimate and the mean of the subjective distribution of expected inflation using Bland-Altman methodology. The horizontal axis shows the average of the two measures, while the vertical axis shows their difference. The solid blue line represents the mean difference (bias), and the dashed red lines indicate the 95% limits of agreement. A narrower spread and clustering around zero suggest better alignment. The concordance correlation coefficient (CCC) quantifies overall agreement, accounting for both precision and accuracy.

The Bland–Altman plot offers a graphical representation of systematic and random discrepancies

by plotting the difference between two measurements against their mean, which facilitates the identification of patterns across the response distribution. Lin's CCC supplements this visual approach by providing a single summary statistic that incorporates both precision, as measured by the Pearson correlation, and accuracy, as indicated by deviations from the 45-degree line of perfect concordance. CCC values approaching one signify strong agreement between the two measurement methods (see, e.g., Bland and Altman, 1986, 1999; Lin et al., 2002).

Bland–Altman plots for the four versions of the expectations module are shown in Figure 2. In the Baseline version (Panel A), the agreement between point estimates and implied means is weak, as indicated by a concordance correlation coefficient (CCC) of 0.06. The plot shows a pronounced negative relationship in the differences across the range of expected values, suggesting substantial dispersion in the relationship between the two measures. In contrast, the Alternative version (Panel B) yields a higher CCC of 0.73, and the differences are more symmetrically distributed around zero with narrower limits of agreement. This result indicates a distinct pattern of alignment between the two measures.

The Wording A and Wording B treatments (Panels C and D) exhibit similarly strong associations, with CCCs of 0.89 and 0.85, respectively. In these versions, differences are more tightly concentrated around zero and display less variation across the range of averages. Taken together, the Bland–Altman plots reveal considerable heterogeneity in the relationship between point estimates and probabilistic assessments across survey formats, confirming that alternative question designs are associated with distinct patterns in the alignment of elicited inflation expectations.

4.3. Survey Design and the Relationship Between Measures

This section analyzes the link between survey design and the relationship between two responses from the same individual: the point forecast of inflation and the mean of the subjective probability distribution. For each individual i, we define the deviation variable D_i as the difference between the point estimate of expected inflation, denoted PointExp_i, and the mean of the subjective probability distribution, denoted MeanProbExp_i:

$$D_i = \text{PointExp}_i - \text{MeanProbExp}_i \tag{1}$$

As an alternative measure, we use a relative difference defined as:

$$\tilde{D}_i = \frac{|D_i|}{\frac{|\text{PointExp}_i| + |\text{MeanProbExp}_i|}{2}} \tag{2}$$

This expression is a version of the symmetric mean absolute percentage error (sMAPE), adapted

to our setting. It measures the relative deviation between the point estimate (PointExp_i) and the mean of the subjective probability distribution (MeanProbExp_i) for each individual. By scaling the absolute difference $|D_i|$ by the average magnitude of the two responses, the normalized measure $\tilde{D}_i$ facilitates comparisons across individuals with different expectation levels and avoids division-by-zero issues when either response equals zero. Smaller values of $\tilde{D}_i$ indicate greater alignment between the two expectation measures.

Our objective is to evaluate whether the survey type influences this deviation. We model the survey assignment with a binary indicator variable S_i, where $S_i = 0$ if individual i responded to the baseline survey, and $S_i = 1$ if they responded to the alternative surveys. In addition, we observe a vector X_i of socioeconomic and behavioral characteristics, such as sex, education, age, and patterns of purchase, which may also affect the difference. We specify the following linear model for the deviation measures:

$$D_i = \alpha + \beta S_i + X_i'\gamma + \varepsilon_i \tag{3}$$

where β captures the average difference in the deviation associated with being interviewed using an alternative survey design in relation to the baseline survey design, γ is a vector of coefficients associated with the control variables X_i, and ε_i is an idiosyncratic error term. Equation (3) is estimated using ordinary least squares (OLS). The interpretation of β is straightforward: it measures the change in the deviation between the point estimate and the subjective mean that is attributable to participating in an alternative survey, relative to the baseline survey, holding constant observable individual characteristics. The control variables X_i are included to account for potential confounders that might influence both the individual's inflation expectations and their sensitivity to the survey format.

The results from regressions examining the deviation between respondents' point estimates and the central tendency of their subjective distributions (columns 1–4), as well as the relative deviation normalized by the central measure (columns 5–8) across different survey versions, are reported in Table 4. In all specifications, the Baseline version serves as the reference category. Respondents in all alternative formats—Alternative, Wording A, and Wording B—show significantly lower deviations than the Baseline. For example, in column (4), the difference between the point estimate and the subjective mean is 5.9 percentage points smaller in the Alternative format, 11.1 percentage points smaller in Wording A, and 10.7 percentage points smaller in Wording B, relative to the Baseline format, after controlling for observable characteristics.

The results remain robust across model specifications, both with and without controls. Columns (5) through (8) demonstrate similar patterns when the relative deviation is used as the outcome, with reductions between 0.32 and 0.38 units depending on the survey version. The consistent and

statistically significant differences in both absolute and relative deviations across question formats indicate substantial heterogeneity in the alignment between the two measures of inflation expectations. These findings imply that survey design affects the internal relationship of respondents' answers, potentially due to differences in how individuals interpret and process the elicitation task.

Table 4. Survey Format and Alignment in Inflation Expectation Measures

	(1) Diff.	(2) Diff.	(3) Diff.	(4) Diff.	(5) Diff. Rel.	(6) Diff. Rel.	(7) Diff. Rel.	(8) Diff. Rel.
Not baseline	-7.347***	-6.196***			-0.314***	-0.322***		
	(0.669)	(0.801)			(0.028)	(0.029)		
Alternative			-5.747***	-5.917***			-0.311***	-0.319***
			(0.788)	(0.804)			(0.028)	(0.030)
Wording A			-10.467***	-11.098***			-0.351***	-0.371***
			(1.524)	(1.568)			(0.048)	(0.049)
Wording B			-9.832***	-10.709***			-0.356***	-0.377***
			(1.587)	(1.671)			(0.049)	(0.050)
Constant	7.510***	10.538***	7.119***	11.625***	0.775***	0.977***	0.779***	0.989***
	(0.547)	(2.712)	(0.595)	(2.725)	(0.023)	(0.089)	(0.023)	(0.090)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	2286	2286	2286	2286	2286	2286	2286	2286

Notes: This table reports the results from regressions examining the relationship between survey elicitation format and the alignment between respondents' point forecasts and the central tendency (mean) of their subjective probability distributions. Columns (1)–(4) use the absolute difference as the dependent variable, while Columns (5)–(8) use a relative deviation measure. The omitted category is the baseline bin-style format. Columns with controls include sociodemographic and behavioral covariates. Robust standard errors are shown in parentheses. *p<0.05, **p<0.01, ***p<0.001.

Robustness. To evaluate the robustness of the baseline results, we conduct a series of sensitivity analyses. These include bounds based on Oster (2019) and the heteroskedasticity-based identification approach of Lewbel (2012) to assess the potential role of unobserved confounders. We also implement matching estimators—nearest neighbor matching and coarsened exact matching—to address differences in observable characteristics across surveys. We also replicate replicate the analysis using the median of the subjective distribution. In addition, we examine a subsample restricted to Mexico City, which allows direct comparison across all elicitation formats in a more homogeneous setting, and estimate a pseudo-panel using cohorts defined by time-invariant characteristics. Across all of the sensitivity analyses, the results remain qualitatively and quantitatively consistent with the baseline findings, supporting the stability of our conclusions. The details can be found in the Online Appendix.

4.4. Discussion of Results

As with any empirical analysis, several limitations merit consideration. First, although the three pilot surveys were carefully designed with aligned fieldwork protocols, they were implemented by

different polling organizations, so unobserved differences in implementation cannot be fully ruled out. Second, while the analysis documents informative patterns in the relationship between the two expectation measures, it does not establish causal effects and should therefore be interpreted as suggestive. Third, differences in deviations across formats may reflect the timing of the surveys. The baseline was fielded in mid-2023, closer to the high-inflation period of 2022, whereas the alternative formats were administered during lower-inflation periods in 2023 and 2024. However, existing evidence suggests the opposite mechanism: individuals tend to hold weaker priors in low-inflation environments (Cavallo et al., 2017), and households and firms become more attentive and responsive to inflation when inflation is high (Weber et al., 2025). According to this interpretation, respondents in the baseline survey would be expected to be more informed and consistent rather than less.

One could argue that our results are influenced by the specific design of the bin-based baseline survey, including both the number of bins and the support over which they are defined. This concern highlights a broader design challenge. Specifying appropriate bin structures that accurately reflect respondents' beliefs is inherently difficult, particularly in developing country contexts. Suboptimal choices regarding the number or range of bins can distort reported probabilities and summary measures. These findings underscore the importance of carefully determining the distribution's support and illustrate the complexities involved in defining it in advance.

It is also relevant to mention that relative to bin-based and quantile-based methods, the statistical properties of scenario-based elicitation are less well understood, particularly with respect to tail behavior, sensitivity to wording, and the implications of summarizing beliefs using a limited number of discrete outcomes. These broader methodological issues lie beyond the scope of this study. Instead, we contribute to the literature by providing a descriptive comparison of elicitation formats used in the pilot surveys, showing that different formats can produce systematically different summaries of inflation expectations. The findings inform survey design and highlight the need for further research on how scenario definitions, wording, and the number of scenarios shape reported beliefs, especially in emerging market settings.

Finally, although the pilot surveys included all 32 states of Mexico, their non-probabilistic design prevents the generation of nationally representative estimates. Consequently, the findings should be interpreted as evidence regarding the relative performance of elicitation formats rather than as indicators of population-level inflation expectations. Nevertheless, the pilot studies offer important guidance for future large-scale surveys, demonstrating that pilot testing is effective for refining elicitation formats, especially for subjective probability measures that require precise calibration and wording, prior to national implementation.

5. Unpacking Dispersion: Sources of Variation in Elicited Expectation

Building on the documented cross-sectional heterogeneity in inflation expectations, this section examines its sources using three complementary approaches. First, it characterizes dispersion within each measure across formats and assesses differences in cross-sectional dispersion after controlling for respondent characteristics. Second, a cross-measure framework compares point forecasts and the mean of the subjective distribution within individuals, decomposing overall dispersion into between-individual differences (belief heterogeneity) and within-individual differences across measures (reporting behavior). Third, a structural model of expectation formation under noisy private signals separates discrepancies between the two measures of inflation expectations into measurement error components and their covariance. These approaches provide a more detailed characterization of how survey design and respondent characteristics are associated with the observed cross-sectional distribution of inflation expectations.

5.1. Dispersion in Inflation Expectations Conditional on Observables

This section examines cross-sectional dispersion in inflation expectations to assess whether the heterogeneity documented earlier reflects differences in survey design or differences in respondent composition. While previous sections focused on differences in the level of reported expectations across formats, the analysis here shifts to how tightly individual responses are clustered around the central tendency. Specifically, we evaluate whether dispersion differs systematically across elicitation formats and whether these differences persist after accounting for observable characteristics. We measure dispersion using the median absolute deviation (MAD), a robust statistic that is well suited to survey data and less sensitive to extreme responses than variance-based measures. For each individual i, survey format f, and expectation measure k—either the point forecast or the mean of the respondent's subjective distribution—we define the outcome as the absolute deviation of the individual expectation from the sample median:

$$\text{MAD}_{if}^{k} = \left| \pi_{if}^{k} - \text{median}\left(\pi_{f}^{k}\right) \right| \tag{4}$$

where π_{if}^{k} denotes individual i's reported inflation expectation under format f. We then study how this individual-level measure of dispersion varies with survey design and respondent characteristics by estimating regressions of the form:

$$\text{MAD}_{if}^{k} = \alpha + \mathbf{S}_f'\beta + \mathbf{X}_i'\gamma + \varepsilon_{if} \tag{5}$$

where $\mathbf{S}_f$ includes indicators for elicitation format and question wording, and $\mathbf{X}_i$ is a rich set of

demographic and socioeconomic controls.

Table 5. Survey Elicitation Format and Median Absolute Deviation (MAD)

	(1) MAD_P	(2) MAD_P	(3) MAD_P	(4) MAD_P	(5) MAD_M	(6) MAD_M	(7) MAD_M	(8) MAD_M
Not baseline	7.047***	7.308***			12.544***	12.967***		
	(0.730)	(0.854)			(0.549)	(0.600)		
Alternative			6.693***	7.106***			12.044***	12.553***
			(0.839)	(0.856)			(0.556)	(0.600)
Wording A			11.933***	11.594***			20.680***	20.769***
			(2.246)	(2.220)			(2.062)	(2.023)
Wording B			10.219***	9.596***			18.912***	18.956***
			(2.164)	(2.169)			(1.823)	(1.809)
Age		0.071**		0.065*		0.094***		0.082***
		(0.027)		(0.027)		(0.022)		(0.022)
Financial literacy score		-3.068*		-2.716*		-1.769		-1.014
		(1.225)		(1.237)		(0.975)		(0.962)
Woman		6.697***		6.753***		3.352***		3.456***
		(0.854)		(0.856)		(0.662)		(0.662)
Socioeconomic group								
High		0.970		0.890		0.868		0.721
		(0.816)		(0.813)		(0.683)		(0.675)
Working		0.166		0.131		0.138		0.040
		(1.006)		(1.005)		(0.825)		(0.812)
Schooling								
Elementary to junior high school		-0.778		-0.752		-1.588		-1.556
		(1.633)		(1.628)		(1.388)		(1.375)
High school or more		-5.046**		-5.123***		-4.851***		-5.014***
		(1.550)		(1.545)		(1.341)		(1.324)
Head of household		1.339		1.394		0.012		0.098
		(0.903)		(0.904)		(0.775)		(0.772)
Who makes major purchases?								
Mostly me		-0.343		-0.261		-0.616		-0.469
		(1.061)		(1.061)		(0.894)		(0.892)
Me and other members of the h.h.		-1.300		-1.090		-0.570		-0.191
		(1.038)		(1.038)		(0.856)		(0.847)
Who does the shopping?								
Mostly me		0.893		0.877		1.377		1.341
		(1.017)		(1.016)		(0.783)		(0.776)
Me and other members of the h.h.		-1.176		-1.268		-0.580		-0.723
		(1.119)		(1.123)		(0.886)		(0.886)
Plans to...								
...build or remodel		-1.811*		-1.717		-0.593		-0.406
		(0.877)		(0.883)		(0.678)		(0.683)
...buy a vehicle		1.507		1.563		1.124		1.238
		(0.895)		(0.894)		(0.741)		(0.739)
...buy furniture or appliances		-1.635		-1.546		-0.900		-0.691
		(0.883)		(0.882)		(0.713)		(0.714)
...buy electronics		0.262		0.223		0.234		0.172
		(0.884)		(0.884)		(0.725)		(0.724)
Constant	9.182***	9.866**	8.762***	9.131**	2.825***	0.907	2.005***	-0.669
	(0.509)	(3.355)	(0.585)	(3.349)	(0.239)	(2.623)	(0.252)	(2.633)
Observations	2286	2286	2286	2286	2286	2286	2286	2286

Notes: This table reports OLS estimates from regressions where the dependent variable is the median absolute deviation (MAD) of individual inflation expectations. For each individual, MAD is defined as the absolute deviation of the reported expectation from the cross-sectional median within each elicitation format, computed separately for point forecasts (Columns 1–4) and for the mean of the subjective probability distribution (Columns 5–8). Robust standard errors are shown in parentheses. *p<0.05, **p<0.01, ***p<0.001.

The results for point forecasts (columns 1 to 4) and subjective distribution means (columns 5 to 8) are presented in Table 5. The primary finding is that differences in dispersion across elicitation formats remain substantial and statistically significant after accounting for respondent characteristics. This indicates that dispersion is more strongly linked to survey design than to respondent composition. Compared to the baseline, alternative formats lead to a considerable increase in dispersion, with especially pronounced effects for Wording A and Wording B. Although some observable characteristics are associated with dispersion—responses are more dispersed among older individuals and women, and less dispersed among those with higher education—their influence is modest relative to the impact of format. These trends are consistent across both measures and are more pronounced for subjective distribution means, indicating that design-related differences are amplified when expectations are elicited in probabilistic terms.

5.2. Within- and Between-Individual Variation in Elicited Expectations

A central question is whether differences across elicitation formats reflect variations in underlying beliefs or in the expression of those beliefs. Addressing this issue requires distinguishing cross-individual differences from within-individual differences across elicitation measures. The dataset provides two measures of inflation expectations for each individual: a direct point estimate and the mean or median derived from the individual's subjective probability distribution. Although both measures are intended to capture the same underlying belief, differences in response behavior and cognitive processing frequently result in discrepancies between them. This dual-format structure enables the exploitation of within-individual variation while controlling for unobserved heterogeneity across individuals, thereby enabling the separation of differences in reported expectations into cross-individual and within-individual components across elicitation measures.

We formalize this approach through a cross-measure model, where each individual's reported expectation is modeled as the sum of an individual-specific effect, a format-specific effect, and an idiosyncratic error term. Specifically, we estimate:

$$y_{if} = \alpha_i + \delta_f + u_{if} \tag{6}$$

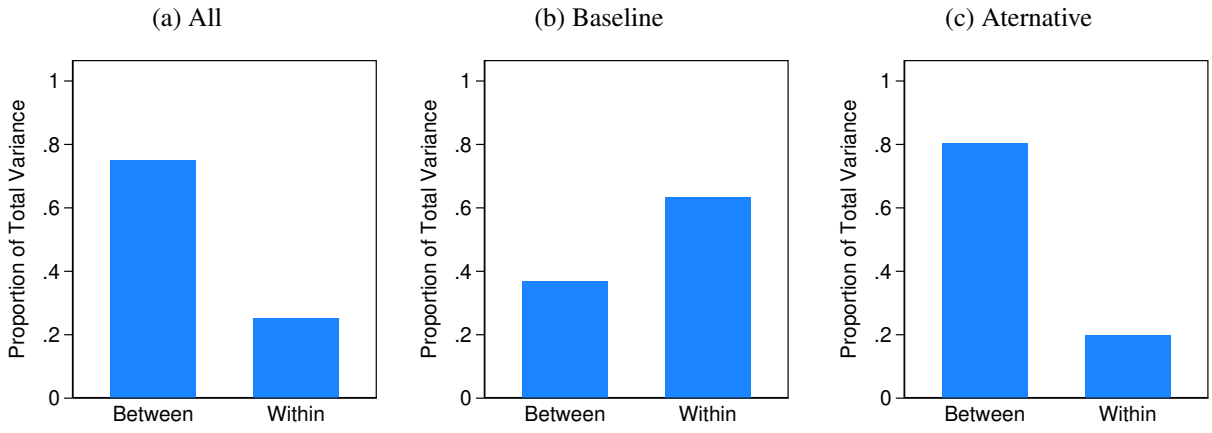
where y_{if} denotes the reported expectation by individual i under elicitation format f. The term α_i captures persistent differences across individuals, while δ_f accounts for systematic differences between the point estimate and the distribution-based measure. The residual u_{if} reflects random variation within individuals. This specification enables a variance decomposition that distinguishes between variability arising from stable differences across individuals and residual variation within individuals after accounting for the elicitation format. Since the format effect δ_f is a fixed constant,

it does not contribute to variance. The total variance is therefore driven by the individual-specific and idiosyncratic components.

Estimating this model provides insight into the relative importance of cross-individual heterogeneity versus within-individual variability in reported inflation expectations. A higher share of between-individual variance indicates that differences in expectations are largely explained by persistent individual factors, whereas a greater within-individual component suggests more substantial random variation across formats or noise in respondents' reporting behavior.

The variance decomposition in Figure 3 demonstrates that the sources of variability in reported inflation expectations differ across survey designs. In the Baseline survey, within-individual variation constitutes a substantial portion of total variance, reflecting significant differences between the point estimate and the distribution-based measure reported by the same respondent. This finding aligns with the larger discrepancies between these measures documented previously. In the Alternative surveys, a greater proportion of total variation is attributable to differences across individuals, while the within-individual component is comparatively smaller. The pooled results reveal a similar trend, with between-individual variation accounting for the majority of overall variance. Collectively, these findings suggest that the relative importance of within- and between-individual variation systematically depends on the elicitation format.

Figure 3. Sources of Variation



Notes: The figure displays a variance decomposition derived from a cross-measure model that utilizes point estimates and the mean of the subjective probability distribution. The model initially accounts for systematic differences across elicitation formats, specifically the differences between point estimates and distribution-based measures. The remaining variation is subsequently divided into two components: stable differences across individuals and residual differences within the same individual across measures. Results are presented separately for each survey version as well as for the pooled data. This methodology facilitates a comparison of the relative significance of cross-individual heterogeneity and within-individual variation in reported inflation expectations.

5.3. A Model of Expectation Formation

This section develops and estimates a simple structural model in which individuals form expectations about future inflation based on noisy private signals. The model captures the idea that information available to individuals is imperfect, and that the precision of their beliefs may vary systematically across the population. This framework allows us to characterize both the process through which expectations are formed and the way in which these expectations are measured through survey responses. Specifically, we model how households form and report inflation expectations using two survey-based measures: a point estimate and the mean of the subjective distribution of a subjective probability distribution.

While many studies focus on how expectations are formed, we examine how they are measured, specifically why two widely used formats—point forecasts and central tendency measures from subjective probability distributions—often yield different results. Although both aim to capture the respondent's belief about future inflation, discrepancies between them are common and often systematic. We explain these gaps not as reflecting distinct beliefs but as noisy signals of a single latent expectation. In this framework, differences arise from heterogeneous and potentially correlated measurement errors introduced by survey design, cognitive constraints, or response behavior. We allow the precision of responses to vary across individuals and account for correlation in errors due to shared unobserved factors such as attention, motivation, or fatigue. By explicitly modeling these components, the framework allows us to disentangle the underlying inflation expectation from the noise introduced by survey measurement and identify which factors are most strongly associated with reporting error. This is valuable input to guide the improvement of survey interpretation and design in capturing household expectations.

Latent Inflation Expectation and Measurement. We assume that each individual i holds a single latent expectation about future inflation, denoted by π_i^*. This belief represents the individual's true, unobserved view about future inflation. The observed survey responses consist of the reported point estimate P_i and the subjective mean M_i. These observed measures from the survey are modeled as noisy signals of π_i^*:

$$P_i = \pi_i^* + \varepsilon_i^P \tag{7}$$

$$M_i = \pi_i^* + \varepsilon_i^M \tag{8}$$

Measurement errors ε_i^P and ε_i^M capture distortions arising from reporting behavior, comprehension issues, rounding, context effects, or other cognitive limitations. These errors are assumed to follow a joint normal distribution with zero mean, individual-specific variances, and constant correlation:

$$\begin{pmatrix} \varepsilon_i^P \\ \varepsilon_i^M \end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_{P,i}^2 & \rho\,\sigma_{P,i}\sigma_{M,i} \\ \rho\,\sigma_{P,i}\sigma_{M,i} & \sigma_{M,i}^2 \end{pmatrix} \right) \tag{9}$$

Specifically, the variances of the measurement errors vary across individuals according to:

$$\sigma_{P,i}^2 = \exp(X_i\beta_P) \quad , \quad \sigma_{M,i}^2 = \exp(X_i\beta_M) \tag{10}$$

where X_i is a vector of observable characteristics and β_P and β_M are parameter vectors to be estimated. The correlation parameter ρ captures unobserved factors that simultaneously affect both responses.

Identification and Estimation. Identification relies on the maintained structure of the measurement model rather than on repeated observations over time. Specifically, both observed measures load one-for-one on a common latent inflation expectation, measurement errors are additive and jointly normal with zero mean, and their variances vary systematically with observable characteristics while their correlation is restricted to be constant. Under these assumptions, the model is identified using cross-sectional variation, as in standard latent-variable frameworks. The parameters β_P, β_M, ρ, and the latent expectations π_i^* are jointly estimated by maximum likelihood.

Variance Decomposition of the Difference Between Measures. To characterize the sources of discrepancies between the point estimate P_i and the subjective mean M_i, we decompose the variance of their difference, $\text{diff}_i = P_i - M_i$, as:

$$\text{Var}(\text{diff}_i) = \sigma_{P,i}^2 + \sigma_{M,i}^2 - 2\rho\,\sigma_{P,i}\sigma_{M,i}. \tag{11}$$

Discrepancies thus reflect three components: noise in the point estimate, noise in the subjective mean, and their covariance. Because the covariance term can offset the variance components, direct attribution may yield negative shares. To ensure interpretability, we use absolute contributions, defining $C_P = \sigma_{P,i}^2$, $C_M = \sigma_{M,i}^2$, and $C_\rho = |2\rho\,\sigma_{P,i}\sigma_{M,i}|$, with total $\text{Total} = C_P + C_M + C_\rho$. The corresponding shares are $\text{Share}_P = \frac{C_P}{\text{Total}}$, $\text{Share}_M = \frac{C_M}{\text{Total}}$, and $\text{Share}_\rho = \frac{C_\rho}{\text{Total}}$. This approach ensures that all shares are positive and sum to one, providing a clear and consistent interpretation of how much each source contributes to the observed differences between the two measures.

Results. Estimates from the structural model are reported in Table 6. Column (1) reports results from the full sample, and Columns (2) and (3) report results separately for the baseline and alternative surveys. Covariates are included in the variance for the point estimate and the subjective mean, allowing us to assess how individual characteristics influence the precision of each response format.

In the model estimated using the full sample, several respondent characteristics are significantly

associated with the variance of the point estimate. Specifically, female respondents exhibit a 0.683-unit increase in the log-variance of measurement error in the point estimate, compared with male respondents, controlling for other variables.[2] Higher education and financial literacy are associated with lower variance. Age is significantly and positively related to the variance of the subjective mean, but not to the variance of the point estimate. Planning to purchase a vehicle exhibit greater variance in the point estimate, whereas those intending to build or remodel their home exhibit lower variance.

The indicator for alternative survey formats ("not baseline") is positively associated with higher variance, likely reflecting differences in question framing. Analysis of disaggregated results suggest that this increase is attributable to meaningful individual-level heterogeneity in reporting precision and measurement error, rather than random noise. These findings indicate that alternative formats are associated with distinct patterns in how respondents form and express expectations.

Comparing survey formats reveals an important difference. In the baseline survey (Column 2), measurement error in the point estimate varies with respondent characteristics, such as gender and planned purchases. However, most covariates do not have a significant relationship with the variance of the subjective mean, suggesting that this measure is less sensitive to respondent traits under the baseline design. In contrast, the alternative survey (Column 3) produces more structured results: gender, age, and education are significantly associated with the variance of both the point estimate and the subjective mean. These patterns indicate that alternative formats capture systematic heterogeneity in reporting precision differently across respondents.

The estimated correlation between measurement errors, reported as $\text{atanh}(\rho)$, is positive and statistically significant in all specifications and is substantially larger in the alternative format. Because ρ represents the correlation between measurement errors in the point estimate and the subjective mean, a higher value indicates stronger co-movement in reporting errors across these two measures. Consequently, errors are more likely to be of similar magnitude, which increases the extent to which they offset each other. Therefore, a more positive ρ reduces the variance of the discrepancy between the two measures. These findings indicate that the dependence structure of measurement errors varies across survey designs, influencing the degree of alignment between point forecasts and probabilistic assessments.

Consistent with the data, the estimated latent expectation π_i^* is higher in the alternative format. A specification that relaxes the common-latent-belief restriction, reported in the Online Appendix, indicates that this restriction is not rejected for the alternative format but is rejected for the baseline.

[2] Another way to interpret the coefficient on the indicator for women is as follows: a value of 0.683 in the point estimate equation implies that holding other characteristics constant, women exhibit nearly double the variance in measurement error relative to men ($e^{0.683} \approx 1.98$), corresponding to approximately a 41% increase in the standard deviation of the error term ($\sqrt{e^{0.683}} \approx 1.41$), indicating substantially less precise responses in the point forecast format.

These findings suggest that the extent to which the two measures can be reconciled within a unified latent representation differs across survey designs.

Table 6. Results of the Structural Models

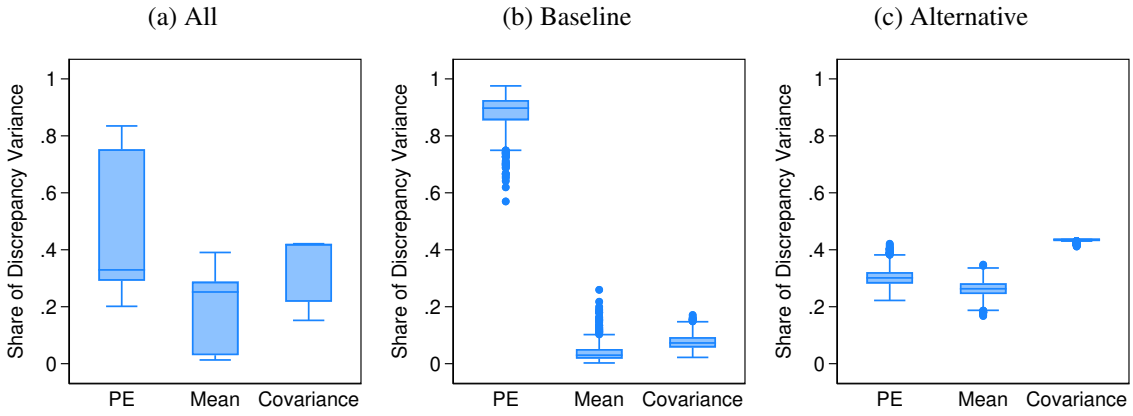
	(1) All		(2) Baseline		(3) Alternative	
π_i^*	4.454***		4.842***		19.240***	
	(0.144)		(0.132)		(0.631)	
	PE	Mean	PE	Mean	PE	Mean
Age	0.003	0.010*	-0.016*	0.004	0.008*	0.011***
	(0.004)	(0.004)	(0.007)	(0.006)	(0.004)	(0.003)
Financial literacy score	-0.449***	-0.363**	-0.576	-0.286	-0.226	-0.371**
	(0.128)	(0.116)	(0.299)	(0.169)	(0.132)	(0.126)
Woman	0.683***	0.329***	1.079***	0.019	0.531***	0.376***
	(0.101)	(0.098)	(0.219)	(0.156)	(0.106)	(0.095)
Socioeconomic group						
High	0.130	0.177*	0.568*	0.095	-0.003	0.176*
	(0.092)	(0.075)	(0.250)	(0.131)	(0.090)	(0.082)
Working	-0.000	-0.049	-0.077	-0.293	0.122	0.151
	(0.104)	(0.119)	(0.233)	(0.186)	(0.106)	(0.094)
Schooling						
Elementary to junior high school	-0.125	-0.230*	0.080	0.067	-0.191	-0.336*
	(0.138)	(0.115)	(0.323)	(0.191)	(0.147)	(0.138)
High school or more	-0.475***	-0.541***	-0.420	0.017	-0.408**	-0.627***
	(0.139)	(0.114)	(0.319)	(0.196)	(0.146)	(0.134)
Head of household	0.084	-0.097	0.480*	-0.005	0.054	-0.116
	(0.097)	(0.079)	(0.225)	(0.124)	(0.103)	(0.090)
Who makes major purchases?						
Mostly me	0.160	-0.019	0.535	-0.095	0.032	0.004
	(0.112)	(0.097)	(0.275)	(0.159)	(0.113)	(0.107)
Me and other members of the h.h.	-0.094	-0.147	0.307	-0.352*	-0.151	-0.059
	(0.128)	(0.107)	(0.295)	(0.167)	(0.123)	(0.120)
Who does the shopping?						
Mostly me	-0.100	0.010	-0.427	-0.314	-0.036	0.081
	(0.109)	(0.097)	(0.254)	(0.165)	(0.114)	(0.105)
Me and other members of the h.h.	-0.168	-0.079	-0.272	-0.270	-0.093	-0.034
	(0.159)	(0.120)	(0.352)	(0.178)	(0.151)	(0.138)
Plans to...						
...build or remodel	-0.240*	-0.121	-0.128	-0.207	-0.186	-0.060
	(0.096)	(0.080)	(0.212)	(0.126)	(0.102)	(0.091)
...buy a vehicle	0.251*	0.119	0.585*	-0.075	0.199	0.126
	(0.122)	(0.099)	(0.290)	(0.146)	(0.124)	(0.109)
...buy furniture or appliances	-0.142	-0.006	-0.166	0.378**	-0.017	-0.032
	(0.103)	(0.086)	(0.244)	(0.125)	(0.108)	(0.094)
...buy electronics	0.108	0.059	-0.216	0.147	0.086	0.037
	(0.113)	(0.107)	(0.276)	(0.183)	(0.115)	(0.102)
Not baseline	0.264*	3.501***				
	(0.119)	(0.111)				
Constant	6.390***	2.899***	5.924***	2.390***	5.844***	5.724***
	(0.421)	(0.349)	(0.965)	(0.555)	(0.418)	(0.375)
atanh(ρ)	0.923***		0.226***		1.031***	
	(0.030)		(0.035)		(0.033)	
N	2286		801		1485	

Notes: The table presents estimates from structural models examining heterogeneity in measurement error variances for point forecasts and subjective means of inflation expectations. Column (1) shows pooled results across formats; Columns (2) and (3) report separate estimates for the baseline and alternative formats. Covariates in the variance equations allow us to assess how respondent characteristics relate to the precision of each measure. Robust standard errors are in parentheses. *p<0.05, **p<0.01, ***p<0.001.

The variance decomposition in Figure 4 indicates that discrepancies in the baseline format are predominantly attributable to noise in the point estimate, with minimal influence from the subjective mean and covariance. This outcome aligns with the observation that the point estimate remains unconstrained, while the subjective mean is restricted by the bin structure and assigned probabilities, limiting its responsiveness. Specifically, predefined bins may serve as anchors and mechanically shape reported expectations, ultimately influencing the reported distribution (see Becker et al., 2023; Boctor et al., 2024). By contrast, in the alternative formats, the contributions from both measures and their covariance are more evenly distributed. The increased covariance component implies that measurement errors are more systematically related, partially offsetting them and reducing the overall discrepancy. The pooled results represent a synthesis of these observed patterns.

Overall, this analysis documents differences across survey designs in the relative contributions of measurement noise and in the relationships between point estimates and probabilistic assessments. The results indicate that elicitation formats generate distinct patterns in the relationships among responses to various expectation questions. These findings underscore the influence of survey design on the properties of elicited expectations and advance understanding of how alternative formats translate respondents' underlying beliefs into observed survey responses.

Figure 4. Variance Decomposition by Source



Notes: The figure shows the variance decomposition of the discrepancy between the point estimate and the mean of the subjective probability distribution. The total discrepancy variance is separated into three components: variance due to noise in the point estimate (PE), variance due to noise in the subjective mean, and the absolute value of their covariance. Results are shown separately for the pooled data, the baseline format, and the alternative scenario-based formats. This decomposition highlights the relative contribution of each source of measurement error across survey designs.

6. Conclusion

This study analyzes original data from three pilot surveys conducted in Mexico to elicit household inflation expectations within an emerging market context. A comparison of a traditional bin-based elicitation format with scenario-based alternatives, where respondents define and assign probabilities to their own inflation ranges, reveals substantial heterogeneity in the level, dispersion, and uncertainty of reported inflation expectations across sociodemographic groups and survey designs. These findings demonstrate systematic variation in the expression of expectations across elicitation formats and underscore the significant influence of question framing on the measurement of household beliefs.

Building on descriptive evidence, the study examines the relationship between two widely used measures of inflation expectations: point forecasts and the central tendency of respondents' subjective probability distributions. Systematic variation emerges in the relationship between these measures across elicitation formats, with scenario-based designs displaying distinct patterns relative to the traditional bin-style approach. These differences remain robust across multiple validation and sensitivity exercises. To clarify the sources of divergence, the analysis investigates how discrepancies vary by survey format and respondent characteristics. In the baseline bin-style format, within-individual variation accounts for a substantial portion of overall dispersion, whereas alternative formats exhibit a different balance between within- and between-individual variation, indicating heterogeneity in how respondents translate beliefs into reported expectations.

A structural variance decomposition provides further insight into these differences by demonstrating that discrepancies across formats result from distinct combinations of variation in point forecasts, subjective distributions, and their covariance. In the baseline bin-style format, a greater proportion of discrepancy variance is attributable to noise in point forecasts. In contrast, scenario-based formats exhibit a more balanced distribution, with point estimates, subjective means, and covariance each contributing approximately equally to the discrepancy variance. These results indicate that elicitation formats differ in how they translate underlying expectations into observed responses, rather than suggesting that any single approach is universally optimal. This analysis highlights that the performance and characteristics of elicited expectations are highly dependent on contextual factors and specific survey design choices.

A key consideration is that the results may partly reflect the bin structure in the baseline survey, particularly the top-coded upper tail, which may have limited the range of reported expectations relative to alternative formats. Expanding the upper tail is not a neutral adjustment, as higher bounds may anchor responses toward larger inflation outcomes. This highlights a broader challenge in bin-based elicitation: the support must be specified ex ante, yet different choices can shape the distribution of reported beliefs. As emphasized by Boctor et al. (2024), predefined bins

affect reported probabilities and summary measures. Approaches that allow the support to adapt to respondents' beliefs seek to address this issue. In this context, the scenario-based formats analyzed in this study enable respondents to define or imply the relevant range of outcomes. These findings highlight the critical role of support design in shaping elicited expectations.

By integrating complementary empirical approaches to compare alternative measures of inflation expectations, this paper contributes to the methodological literature by documenting how survey design shapes the properties of elicited data. The findings provide descriptive evidence on how elicitation formats influence reported expectations, highlighting the role of socioeconomic characteristics and respondents' interaction with survey instruments. These insights are particularly relevant for low- and middle-income countries, where standard designs from high-income contexts may not be directly applicable and require careful adaptation.

The findings provide valuable insights for central banks, statistical agencies, and researchers engaged in measuring household expectations across diverse contexts. Recognizing the association between elicitation formats and heterogeneity in reported expectations enhances the interpretation of survey data for policy analysis, communication, and modeling. Furthermore, this study advances the literature on subjective expectations by demonstrating how survey design interacts with respondent behavior to shape the empirical characteristics of expectation data.

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Online Appendix for
Survey Framing and Household Inflation Expectations: Evidence from an Emerging Market Economy

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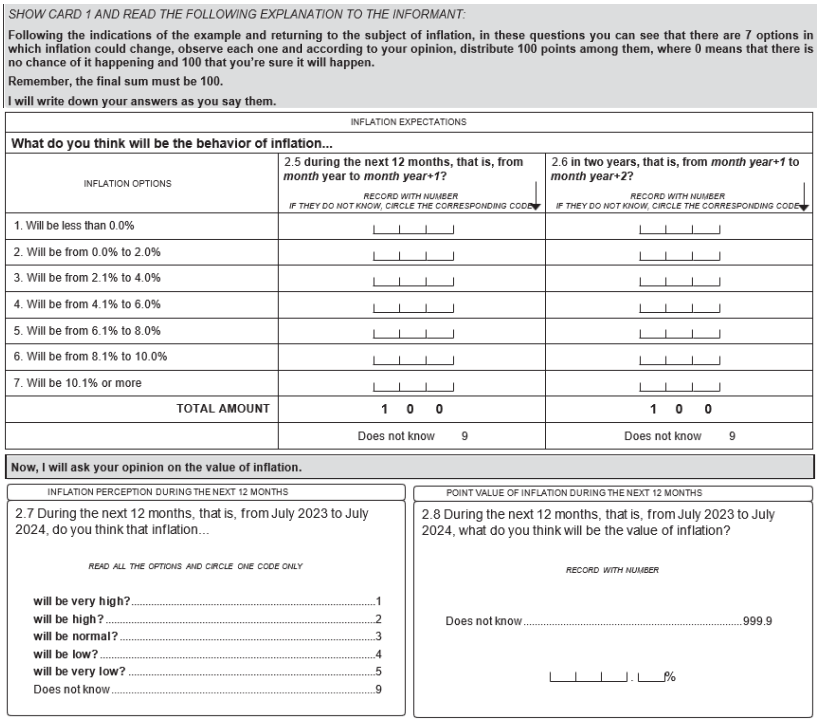
April 2026

A. Format of Inflation Expectation Questions

Figure A.1. Question for Baseline



SHOW CARD 1 AND READ THE FOLLOWING EXPLANATION TO THE INFORMANT:

Following the indications of the example and returning to the subject of inflation, in these questions you can see that there are 7 options in which inflation could change, observe each one and according to your opinion, distribute 100 points among them, where 0 means that there is no chance of it happening and 100 that you're sure it will happen.

Remember, the final sum must be 100.

I will write down your answers as you say them.

INFLATION EXPECTATIONS

What do you think will be the behavior of inflation...

INFLATION OPTIONS	2.5 **during the next 12 months, that is, from *month* year to *month year+1*?** *RECORD WITH NUMBER IF THEY DO NOT KNOW, CIRCLE THE CORRESPONDING CODE*	2.6 **in two years, that is, from *month year+1* to *month year+2*?** *RECORD WITH NUMBER IF THEY DO NOT KNOW, CIRCLE THE CORRESPONDING CODE*
1. Will be less than 0.0%	___	___
2. Will be from 0.0% to 2.0%	___	___
3. Will be from 2.1% to 4.0%	___	___
4. Will be from 4.1% to 6.0%	___	___
5. Will be from 6.1% to 8.0%	___	___
6. Will be from 8.1% to 10.0%	___	___
7. Will be 10.1% or more	___	___
TOTAL AMOUNT	**1 0 0**	**1 0 0**
	Does not know 9	Does not know 9

Now, I will ask your opinion on the value of inflation.

INFLATION PERCEPTION DURING THE NEXT 12 MONTHS

2.7 During the next 12 months, that is, from July 2023 to July 2024, do you think that inflation...

READ ALL THE OPTIONS AND CIRCLE ONE CODE ONLY

will be very high? 1
will be high? 2
will be normal? 3
will be low? 4
will be very low? 5
Does not know 9

POINT VALUE OF INFLATION DURING THE NEXT 12 MONTHS

2.8 During the next 12 months, that is, from July 2023 to July 2024, what do you think will be the value of inflation?

RECORD WITH NUMBER

Does not know 999.9

___. __%

Figure A.2. Question for Alternative

INFLATION EXPECTAITONS

SHOW CARD 1 **What do you think will inflation be between November 2023 and November 2024 under the following scenarios?**
INTERVIEWER: For question 2.6a the high scenario must always be greater than the intermediate scenario, which in turn must be greater than the low scenario.

SCENARIOS	2.6a **inflation will be around…** *WRITE DOWN A NUMBER IF THEY DON'T KNOW, CIRCLE THE CORRESPONDING CODE*	2.6b **Please distribute 100 points between the three scenarios, starting by giving more points to the scenario you consider most likely.** *WRITE DOWN A NUMBER IF THEY DON'T KNOW, CIRCLE THE CORRESPONDING CODE*
1. In a low scenario,	___ | ___ | ___	___ | ___ | ___
2. In an intermediate scenario,	___ | ___ | ___	___ | ___ | ___
3. In a high scenario,	___ | ___ | ___	___ | ___ | ___
	TOTAL SUM	**1 0 0**
	Doesn't know……...99.9	Doesn't know…… 999

PERCEPTION OF INFLATION FOR THE NEXT 12 MONTHS

2.7 **Then, from November 2023 to November 2023, do you believe inflation will be...**

LEA TODAS LAS OPCIONES Y CIRCULE UN SOLO CÓDIGO

- **very low?** 1
- **low?** 2
- **normal?** 3
- **high?** 4
- **very high?** 5
- Doesn't know 9

POINT ESTIMATE OF INFLATION FOR THE NEXT 12 MONTHS

2.8 **And more precisely, from November 2023 to November 2024, what do you think will be the value of inflation?**

Doesn't know 999.9

___ \| ___ \| ___ . ___ %

Figure A.3. Question for Wording A

1 YEAR INFLATION EXPECTATIONS - RANGE

GIVE CARD 2

4.3a **In which range do you think inflation between September 2024 and September 2025 will end up? Please tell me a percentage range, that is, approximately between what two percentages do you think inflation is going to be. Please write it down with a marker on the card.**
IF THE RESPONDENT DOESN'T WRITE ON THE CARD, WRITE DOWN THE VALUES.

WRITE DOWN THE PERCENTAGE
(THE FIRST NUMBER MUST BE LESS THAN THE SECOND ONE. ALLOW NEGATIVE NUMBERS.)

Between |___|___|___| . |___| **% and** |___|___|___| . |___| **%**
4.3a1 *4.3a2*

Doesn't know 999.9
Doesn't know: Skip to 4.4

Now, tell me how would you assign 100 points between the following three options
USE CARD 2 AS AN AID POINTING TO THE CORRESPONDING NUMBERS

INFLATION EXPECTATIONS – PROBABILITIES

4.3b1 **First, tell me what do you think is more likely?** *ROTAR ORDEN 1 A 3 O 3 A 1 Y LEER OPCIONES* **It will be less than** *(ANSWER TO 4.3a1)* **%**..... 1 **It will be between** *(ANSWER TO 4.3a)* **%**..... 2 **It will be greater than** *(ANSWER TO 4.3a2)* **%** ..... 3 **Doesn't know**..... 99	4.3c1 **From 0 to 100, how many points would you assign to the possibility that, in one year, inflation** *(ANSWER TO 4.3b1)* **? Please write it down with a marker on the card.** *IF THE RESPONDENT DOESN'T WRITE ON THE CARD, WRITE DOWN THE VALUES.* *WRITE DOWN THE NUMBER*|___|___|___| Doesn't know ..... 999.9 *Doesn't know: Skip to 4.4*
4.3b2 **Now, what do you think is the second most likely option?** *ONLY READ OPTIONS IF NECESSARY* *SKIP OPTION ALREADY USED IN 4.3b1* **It will be less than** *(ANSWER TO 4.3a1)* **%**..... 1 **It will be between** *(ANSWER TO 4.3a)* **%**..... 2 **It will be greater than** *(ANSWER TO 4.3a2)* **%** 3	4.3c3 **And how many points would you assign to the possibility that** *(ANSWER TO 4.3b2)***?** *WRITE DOWN THE NUMBER* |___|___|___| Doesn't know 999.9
4.3b3 **Least likely option DON'T ASK** **It will be less than** *(ANSWER TO 4.3a1)* **%**..... 1 **It will be between** *(ANSWER TO 4.3a)* **%**..... 2 **It will be greater than** *(ANSWER TO 4.3a2)* **%** 3	4.3c3 **And how many points would you assign to the possibility that** *(**ANSWER TO 4.3b3**)***?** *WRITE DOWN THE NUMBER* |___|___|___| Doesn't know 999.9
	VERIFY THAT THE SUM IS EQUAL TO 100

Figure A.4. Question for Wording B

1 YEAR INFLATION EXPECTATIONS - SCENARIOS

GIVE CARD 2

4.3a1 **What do you think would be a normal level of inflation between September 2024 and September 2025? Please tell me a percentage and write it down with a marker on the card.** *IF THE RESPONDENT DOESN'T WRITE ON THE CARD, WRITE DOWN THE VALUES. IF THEY SAY THERE WILL BE NO CHANGE WRITE DOWN 0%.*

WRITE DOWN THE PERCENTAGE.
ALLOW NEGATIVE NUMBERS

|___|___|___| . |___| %

Doesn't know..... 999.9
Doesn't know: Skip to 4.4

4.3a2 **What do you think would be a low level of inflation?** *IF THE RESPONDENT DOESN'T WRITE ON THE CARD, WRITE DOWN THE VALUES.*

WRITE DOWN THE PERCENTAGE.
ALLOW NEGATIVE NUMBERS

|___|___|___| . |___| %

Doesn't know..... 999.9
Doesn't know: Skip to 4.4

4.3a3 **And what do you think would be a high level of inflation?** *IF THE RESPONDENT DOESN'T WRITE ON THE CARD, WRITE DOWN THE VALUES.*

WRITE DOWN THE PERCENTAGE.
ALLOW NEGATIVE NUMBERS

|___|___|___| . |___| %

Doesn't know..... 999.9
Doesn't know: Skip to 4.4

Now, please tell me how you would assign 100 points between the following three options

USE CARD 2 AS AN AID *POINTING TO THE CORRESPONDING NUMBERS*

INFLATION EXPECTATIONS – PROBABILITIES

4.3b1 **First, tell me what do you think is more likely?**

ROTATE ORDER 1 TO 3 OR 3 TO 1 AND READ OPTIONS

It will be low, of *(ANSWER TO 4.3a2)* **%**..... 1
It will be normal, of *(ANSWER TO 4.3a1)* **%**..... 2
It will be high, of *(ANSWER TO 4.3a3)* **%**..... 3
Doesn't know..... 99

4.3c1 **From 0 to 100, how many points would you assign to the possibility that, in one year, inflation** *(ANSWER TO 4.3b1)* **? Please write it down with a marker on the card.** *IF THE RESPONDENT DOESN'T WRITE ON THE CARD, WRITE DOWN THE VALUES.*

WRITE DOWN THE NUMBER

|___|___|___|

Doesn't know..... 999.9
Doesn't know: Skip to 4.4

4.3b2 **Now, what do you think is the second most likely option?**

ONLY READ OPTIONS IF NECESSARY

SKIP OPTION ALREADY USED IN 4.3b1

It will be low, of *(ANSWER TO 4.3a2)* **%**..... 1
It will be normal, of *(ANSWER TO 4.3a1)* **%**..... 2
It will be high, of *(ANSWER TO 4.3a3)* **%**..... 3
Doesn't know..... 99

4.3c3 **And how many points would you assign to the possibility that** *(ANSWER TO 4.3b2)***?**

WRITE DOWN THE NUMBER

|___|___|___|

Doesn't know..... 999.9

4.3b3 **Least likely option** *DON'T ASK*

It will be low, of *(ANSWER TO 4.3a2)* **%**..... 1
It will be normal, of *(ANSWER TO 4.3a1)* **%**..... 2
It will be high, of *(ANSWER TO 4.3a3)* **%**..... 3
Doesn't know..... 99

4.3c3 **And how many points would you assign to the possibility that** *(**ANSWER TO 4.3b3**)***?**

WRITE DOWN THE NUMBER

|___|___|___|

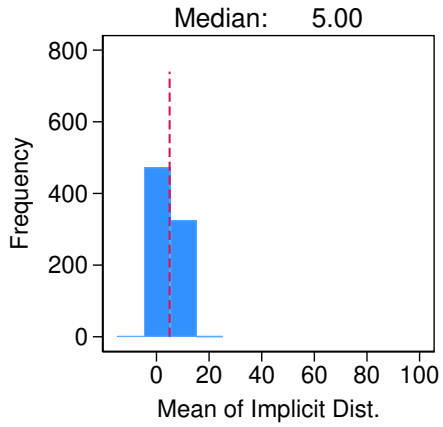
Doesn't know..... 999.9

VERIFY THAT THE SUM IS EQUAL TO 100

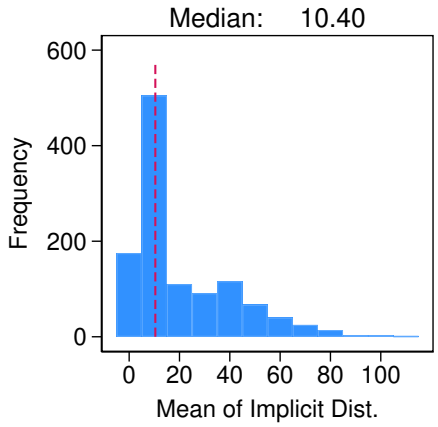
B. Distributions of Inflation Expectations Measures

Figure B.1. Histograms of Mean of Inflation Expectations

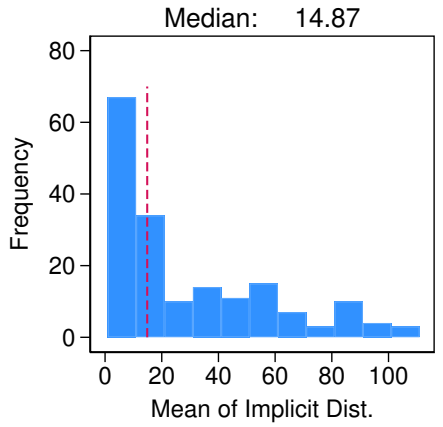
(a) Baseline - Mean



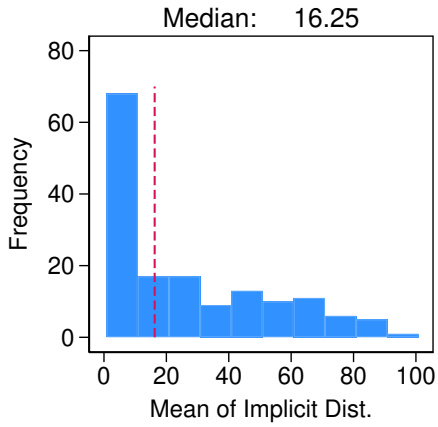
(b) Alternative - Mean



(c) Wording A - Mean



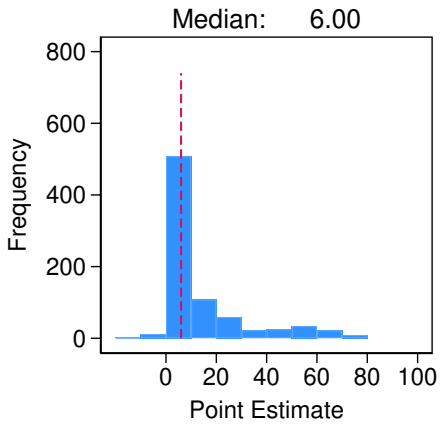
(d) Wording B - Mean



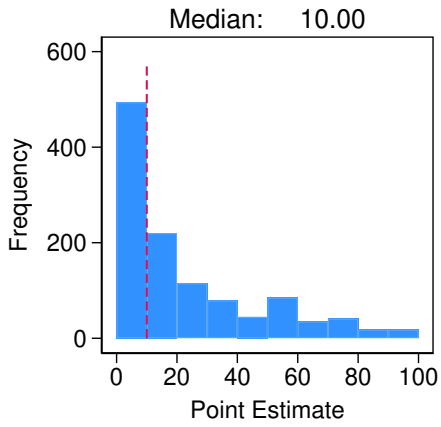
Notes: Each panel displays the distribution of the mean of respondents' subjective probability distributions of expected inflation, shown separately for each survey version. The red dashed line indicates the median value for each format.

Figure B.2. Histograms of Point Estimate Inflation Expectations

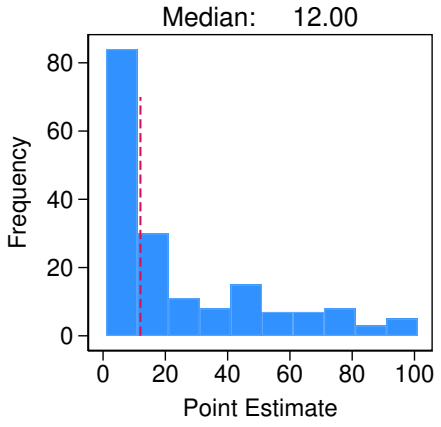
(a) Baseline - Point estimate



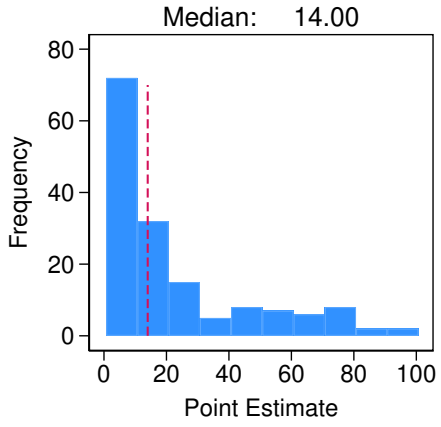
(b) Alternative - Point estimate



(c) Wording A - Point estimate



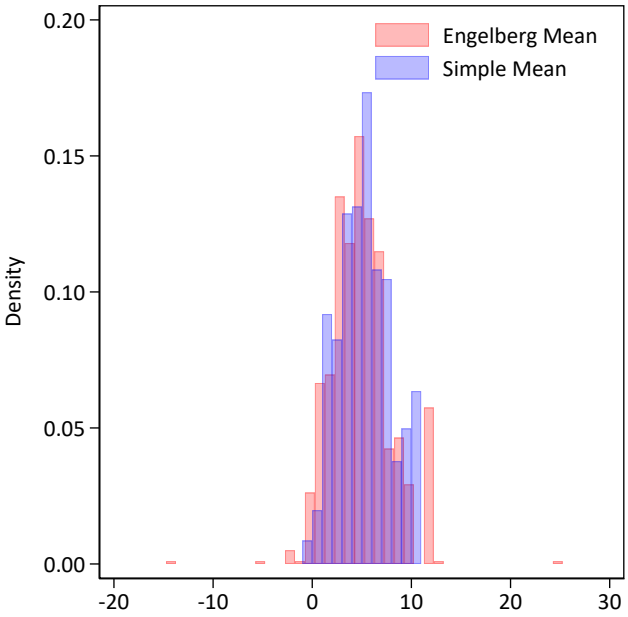
(d) Wording B - Point estimate



Notes: Each panel displays the distribution of point estimates for expected inflation across different survey formats. The red dashed line marks the median value in each case.

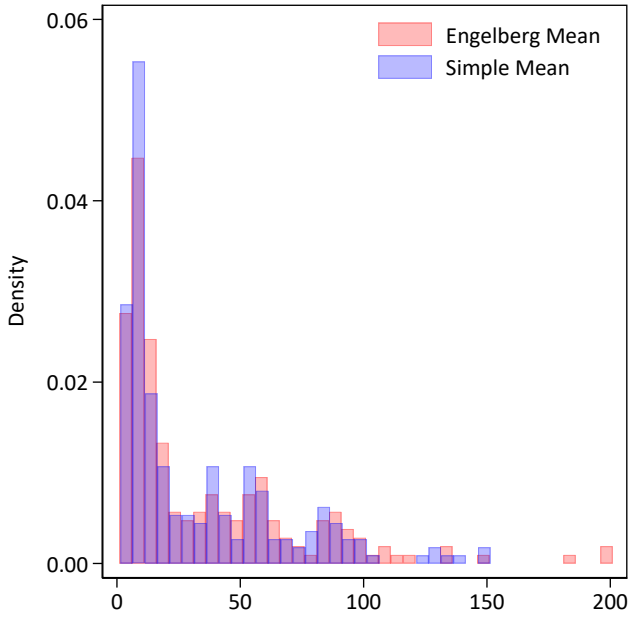
C. Parametric Sensibility

Figure C.1. Distribution of Subjective Means for the Baseline Survey by Method



Notes: The figure shows the distribution of subjective means when obtaining the subjective mean using the approach suggested by Engelberg et al. (2009) as well as a more rudimentary approach we call "simple mean". For the latter, we obtain the mean as the weighed sum of the midpoints of each bin. For the extreme bins, we simply assume that the bin is just as wide as all the others. Therefore, the formula to obtain the "simple mean" is $Mean_{simple} = Prob(Bin1) * (-1) + Prob(Bin2) * (1) + Prob(Bin3) * (3) + Prob(Bin4) * (5) + Prob(Bin5) * (7) + Prob(Bin6) * (9) + Prob(Bin7) * (11)$. The mean for the "Engelberg mean" distribution is 5.07 and the mean for the "Simple mean" distribution is 5.08. This comparison is meant to show that the parameters selected for recovering the subjective distributions do not exert any undue influence in the distribution of individual means.

Figure C.2. Distribution of Subjective Means for Wording A by Method

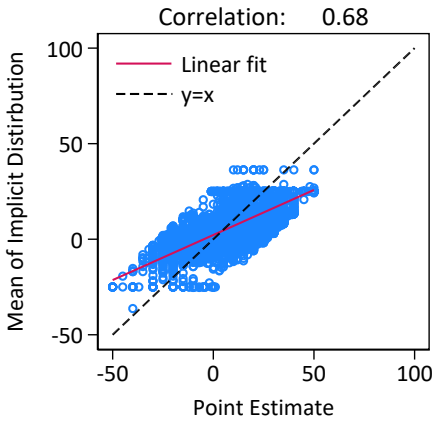


Notes: The figure shows the distribution of subjective means when obtaining the subjective mean using the modified version of the approach suggested by Engelberg et al. (2009) as well as a more rudimentary approach we call "simple mean". For the latter, we obtain the mean as the weighed sum of the midpoints of each bin. For the two extreme bins, we simply assume that those bins are just as wide as the central one. Therefore, for a given range that spans from $Lower$ to $Upper$ with a $Range = Upper - Lower$ the formula to obtain the "simple mean" is $Mean_{simple} = Prob(X < Lower) * (\frac{Lower+(Lower-Range)}{2}) + Prob(Lower < X < Upper) * (\frac{Lower+Upper}{2}) + Prob(X > Upper) * (\frac{Upper+(Upper+Range)}{2})$. The mean for the "Engelberg mean" distribution is 34.88 and the mean for the "Simple mean" distribution is 32.38. This comparison is meant to show that the parameters selected for recovering the subjective distributions do not exert any undue influence in the distribution of individual means.

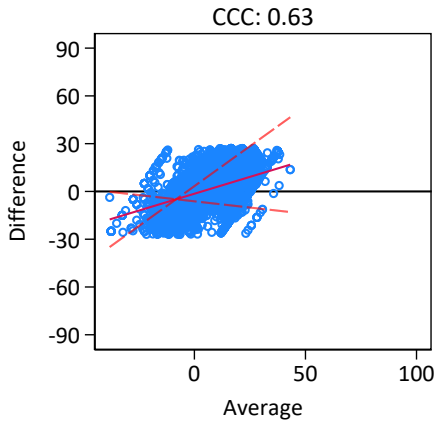
D. Comparison to Other Surveys.

Figure D.1. Alignment of Measures for FRBNY-SCE

(a) Partial Correlation



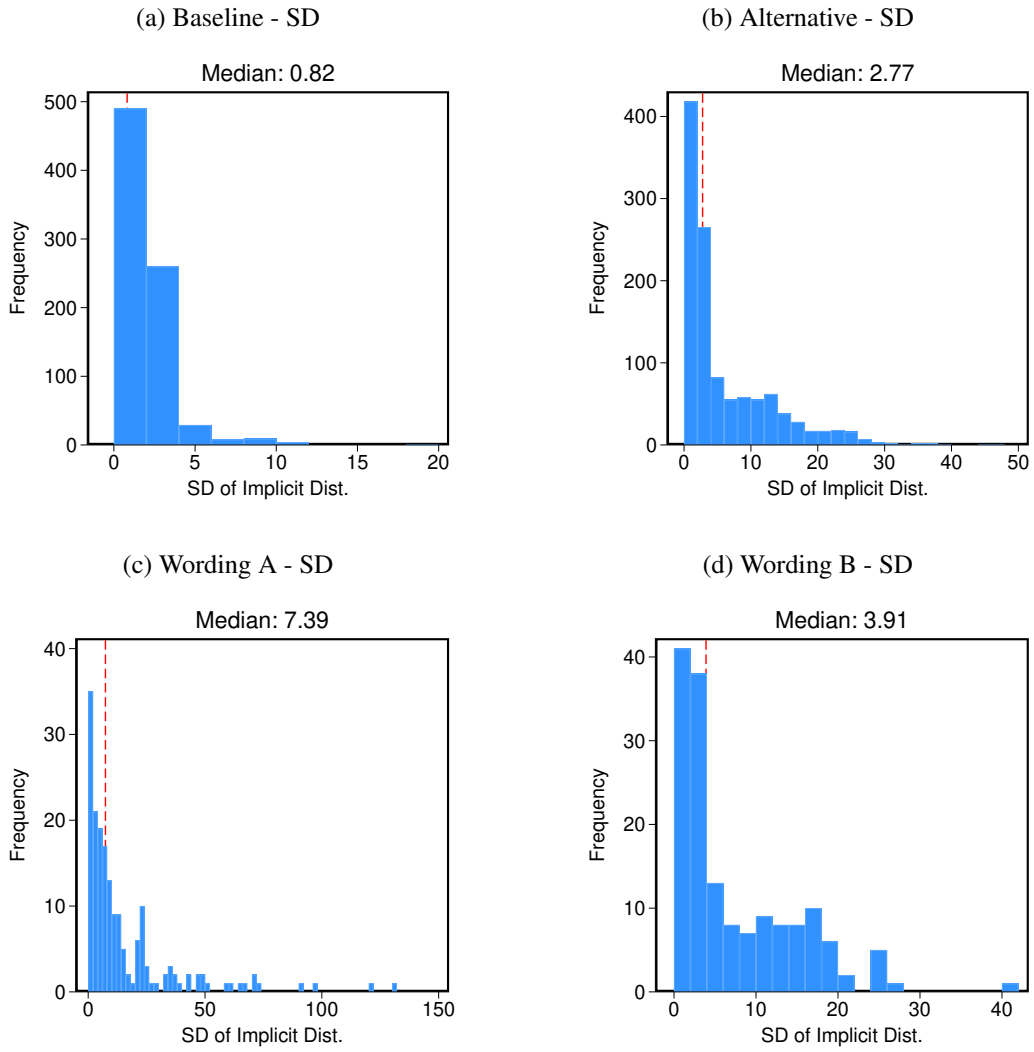
(b) Bland-Altman



Notes: Panel (a) shows the correlation between respondents' point forecasts and the mean of their subjective inflation distributions, controlling for sociodemographic factors. The dashed line represents perfect consistency, and the solid line shows the linear fit. Panel (b) presents a Bland-Altman plot comparing the same two measures: the vertical axis displays their difference, and the horizontal axis their average. The solid line indicates the mean difference (bias), and the dashed lines represent 95% limits of agreement. The concordance correlation coefficient (CCC) summarizes overall agreement.

E. Additional Results

Figure E.1. Distribution of Inflation Expectation Uncertainty



Notes: Each panel displays the cross-sectional distribution of individual-level inflation uncertainty. Uncertainty is measured as the standard deviation of each respondent's subjective probability distribution. Results are displayed separately for each survey version. The red dashed line indicates the median value for each format.

Table E.1. Survey Format and Alignment in Inflation Expectation Measures (Extended Results)

	(1) Diff.	(2) Diff.	(3) Diff.	(4) Diff.	(5) Diff. Rel.	(6) Diff. Rel.	(7) Diff. Rel.	(8) Diff. Rel.
Not baseline	-7.347***	-6.196***			-0.314***	-0.322***		
	(0.669)	(0.801)			(0.028)	(0.029)		
Alternative			-5.747***	-5.917***			-0.311***	-0.319***
			(0.788)	(0.804)			(0.028)	(0.030)
Wording A			-10.467***	-11.098***			-0.351***	-0.371***
			(1.524)	(1.568)			(0.048)	(0.049)
Wording B			-9.832***	-10.709***			-0.356***	-0.377***
			(1.587)	(1.671)			(0.049)	(0.050)
Age		-0.023		-0.015		-0.001		-0.001
		(0.023)		(0.023)		(0.001)		(0.001)
Financial literacy score		-1.631		-2.153		-0.060		-0.066*
		(1.099)		(1.117)		(0.032)		(0.033)
Woman		3.560***		3.494***		-0.014		-0.015
		(0.734)		(0.733)		(0.024)		(0.024)
Socioeconomic group								
High		0.069		0.162		0.001		0.001
		(0.666)		(0.662)		(0.022)		(0.022)
Working		-0.069		0.007		0.012		0.013
		(0.768)		(0.769)		(0.025)		(0.025)
Schooling								
Elementary to junior high school		0.848		0.834		0.016		0.016
		(1.338)		(1.336)		(0.038)		(0.038)
High school or more		-0.146		-0.034		-0.062		-0.061
		(1.265)		(1.266)		(0.036)		(0.037)
Head of household		1.487*		1.438		-0.025		-0.025
		(0.749)		(0.749)		(0.024)		(0.024)
Who makes major purchases?								
Mostly me		0.087		-0.005		-0.001		-0.002
		(0.844)		(0.843)		(0.028)		(0.028)
Me and other members of the h.h.		-0.836		-1.073		-0.028		-0.030
		(0.873)		(0.872)		(0.028)		(0.029)
Who does the shopping?								
Mostly me		-0.514		-0.489		-0.002		-0.002
		(0.838)		(0.835)		(0.027)		(0.027)
Me and other members of the h.h.		-1.142		-1.062		0.019		0.019
		(1.002)		(1.001)		(0.033)		(0.033)
Plans to...								
...build or remodel		-1.479*		-1.604*		-0.037		-0.038
		(0.728)		(0.724)		(0.023)		(0.023)
...buy a vehicle		-0.224		-0.301		0.004		0.003
		(0.782)		(0.780)		(0.027)		(0.027)
...buy furniture or appliances		-0.437		-0.588		0.021		0.020
		(0.741)		(0.744)		(0.024)		(0.025)
...buy electronics		0.085		0.120		-0.019		-0.019
		(0.772)		(0.772)		(0.026)		(0.026)
Constant	7.510***	10.538***	7.119***	11.625***	0.775***	0.977***	0.779***	0.989***
	(0.547)	(2.712)	(0.595)	(2.725)	(0.023)	(0.089)	(0.023)	(0.090)
Observations	2286	2286	2286	2286	2286	2286	2286	2286

Notes: This table reports the results from regressions examining the relationship between survey elicitation format and the alignment between respondents' point forecasts and the central tendency (mean) of their subjective probability distributions. Columns (1)–(4) use the absolute difference as the dependent variable, while Columns (5)–(8) use a relative deviation measure. The omitted category is the baseline bin-style format. Robust standard errors are shown in parentheses. *p<0.05, **p<0.01, ***p<0.001.

Table E.2. Sensitivity of Results

	(1) OLS	(2) Matching	(3) Matching	(4) Matching	(5) Bounds	(6) Bounds	(7) HB-IV	(8) CDMX	(9) Panel
		NN	CEM	CEM	LB	UB			
Panel A: Difference									
Not baseline	-6.196***	-5.582***	-5.291***	-5.082**	-7.059***	-4.596***	-7.804**	-9.206***	-6.407***
	(0.801)	(1.086)	(0.888)	(1.761)	(0.642)	(0.997)	(2.886)	(2.208)	(1.449)
N	2286	2286	1556	327	2286	2286	2286	527	386
Panel B: Absolute Difference									
Not baseline	-0.322***	-0.274***	-0.302***	-0.261***	-0.343***	-0.247***	-0.282**	-0.294***	-0.375***
	(0.029)	(0.043)	(0.045)	(0.077)	(0.021)	(0.051)	(0.095)	(0.088)	(0.056)
N	2286	2286	1556	327	2286	2286	2286	527	386

Notes: This table reports sensitivity analyses evaluating the robustness of the relationship between elicitation format and the alignment between respondents' point forecasts and the central tendency of their subjective distributions. Panel A presents results for the signed difference, while Panel B focuses on the absolute difference. Column (1) shows baseline OLS estimates. Columns (2)–(4) use matching techniques: nearest neighbor (NN) and coarsened exact matching (CEM) using only sociodemographic variables, and then sociodemographic and behavioral variables. Columns (5) and (6) apply Oster (2019) bounds to assess sensitivity to omitted variable bias, reporting lower (LB) and upper bounds (UB). Column (7) uses the Lewbel (2012) heteroskedasticity-based IV method. Robust standard errors are shown in parentheses. The IV estimates satisfy standard diagnostic criteria: the Kleibergen–Paap Wald F-statistic is 10.64, indicating reasonable instrument relevance, and Hansen's J-statistics are 13.997 (p-value = 0.603) for the difference and 18.385 (p-value = 0.243) for the absolute difference, which provide additional evidence in support of the model and estimator. Column (8) restrict the sample to only Mexico City to make the result more comparable. Column (9) reports estimates from a pseudo-panel constructed by aggregating individuals into cells defined by cohort, gender, and region. In the case of Oster (2019) bounds the standard errors are obtained with a bootstrap procedure with 300 replications. *p<0.05, **p<0.01, ***p<0.001.

Table E.3. survey Format and Alignment in Inflation Expectation Measures - Quantile Regression (Baseline vs. others)

	(1) 10th Diff.	(2) 25th Diff.	(3) 50th Diff.	(4) 75th Diff.	(5) 90th Diff.	(6) 10th Rel. Diff.	(7) 25th Rel. Diff.	(8) 50th Rel. Diff.	(9) 75th Rel. Diff.	(10) 90th Rel. Diff.
Not baseline	-6.648***	-6.456***	-6.270***	-6.020***	-5.492**	-0.106***	-0.155***	-0.251***	-0.455***	-0.639***
	(0.696)	(0.624)	(0.721)	(1.008)	(1.806)	(0.020)	(0.020)	(0.025)	(0.043)	(0.060)
Observations	2286	2286	2286	2286	2286	2286	2286	2286	2286	2286

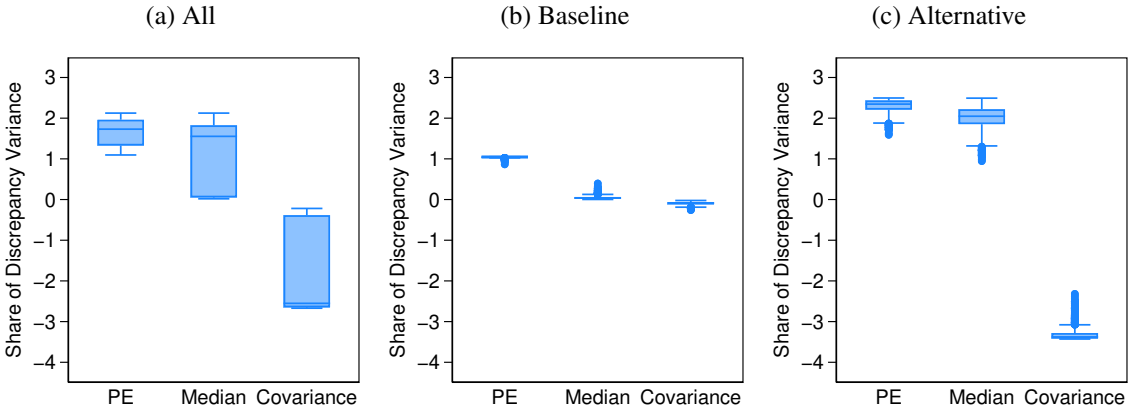
Notes: This table presents quantile regression results estimating the impact of using non-baseline (scenario-based) elicitation formats on the alignment between point estimates and the central tendency of respondents' subjective distributions. Columns (1)–(5) report estimates at different quantiles of the absolute deviation distribution; Columns (6)–(10) report results for the relative deviation measure. The baseline category corresponds to the bin-style format. All specification include controls. Robust standard errors are shown in parentheses. *p<0.05, **p<0.01, ***p<0.001.

Table E.4. survey Format and Alignment in Inflation Expectation Measures - Quantile Regression (By survey)

	(1) 10th Diff.	(2) 25th Diff.	(3) 50th Diff.	(4) 75th Diff.	(5) 90th Diff.	(6) 10th Rel. Diff.	(7) 25th Rel. Diff.	(8) 50th Rel. Diff.	(9) 75th Rel. Diff.	(10) 90th Rel. Diff.
Alternative	-6.435***	-6.218***	-5.999***	-5.701***	-5.100**	-0.103***	-0.153***	-0.249***	-0.449***	-0.635***
	(0.702)	(0.630)	(0.727)	(1.024)	(1.811)	(0.020)	(0.020)	(0.025)	(0.044)	(0.060)
Wording A	-9.765***	-10.323***	-10.887***	-11.655***	-13.202***	-0.145***	-0.197***	-0.298***	-0.508***	-0.703***
	(1.572)	(1.394)	(1.462)	(1.908)	(3.328)	(0.032)	(0.031)	(0.039)	(0.073)	(0.107)
Wording B	-9.680***	-10.111***	-10.546***	-11.139***	-12.332***	-0.143***	-0.197***	-0.301***	-0.519***	-0.721***
	(1.857)	(1.610)	(1.593)	(1.956)	(3.354)	(0.033)	(0.032)	(0.040)	(0.076)	(0.112)
Observations	2286	2286	2286	2286	2286	2286	2286	2286	2286	2286

Notes: This table presents quantile regression results estimating the effect of each non-baseline elicitation format—Alternative, Wording A, and Wording B—on the alignment between respondents' point estimates and the central tendency of their subjective probability distributions. Columns (1)–(5) show results across quantiles of the absolute deviation; Columns (6)–(10) report results for the relative deviation. The omitted category is the bin-style baseline format. All specifications include controls. Robust standard errors are shown in parentheses. *p<0.05, **p<0.01, ***p<0.001.

Figure E.2. Raw Variance Decomposition by Source



Notes: The figure shows the variance decomposition of the discrepancy between the point estimate and the mean of the subjective probability distribution. The total discrepancy variance is separated into three components: variance due to noise in the point estimate (PE), variance due to noise in the subjective mean, and the absolute value of their covariance. Results are shown separately for the pooled data, the baseline format, and the alternative scenario-based formats. This decomposition highlights the relative contribution of each source of measurement error across survey designs.

Table E.5. Results of the Structural Models (Test Difference in π_i^*)

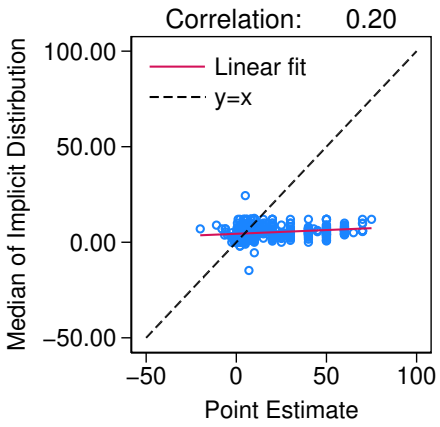
	(1) All		(2) Baseline		(3) Alternative	
Difference in π_i^*	6.139***		5.435***		-0.062	
	(0.363)		(0.637)		(0.455)	
	PE	Mean	PE	Mean	PE	Mean
Age	0.003	0.010*	-0.016**	0.005	0.008*	0.011***
	(0.004)	(0.004)	(0.006)	(0.006)	(0.004)	(0.003)
Financial literacy score	-0.422**	-0.342**	-0.567*	-0.297	-0.227	-0.371**
	(0.130)	(0.115)	(0.278)	(0.172)	(0.132)	(0.125)
Woman	0.676***	0.295**	0.976***	0.024	0.533***	0.376***
	(0.101)	(0.097)	(0.202)	(0.157)	(0.109)	(0.095)
Socioeconomic group						
High	0.121	0.167*	0.504*	0.119	-0.003	0.176*
	(0.091)	(0.074)	(0.210)	(0.132)	(0.090)	(0.082)
Working	-0.010	-0.056	-0.068	-0.300	0.123	0.150
	(0.101)	(0.117)	(0.201)	(0.191)	(0.106)	(0.094)
Elementary to junior high school	-0.157	-0.218	-0.021	0.048	-0.191	-0.336*
	(0.140)	(0.114)	(0.301)	(0.193)	(0.147)	(0.138)
High school or more	-0.452**	-0.515***	-0.433	0.001	-0.408**	-0.627***
	(0.141)	(0.114)	(0.293)	(0.198)	(0.147)	(0.134)
Head of household	0.127	-0.093	0.494**	0.003	0.053	-0.116
	(0.096)	(0.078)	(0.187)	(0.124)	(0.103)	(0.089)
Who makes major purchases?						
Mostly me	0.150	-0.032	0.469	-0.116	0.033	0.003
	(0.111)	(0.096)	(0.239)	(0.162)	(0.114)	(0.107)
Me and other members of the h.h.	-0.072	-0.140	0.218	-0.370*	-0.152	-0.059
	(0.124)	(0.105)	(0.254)	(0.169)	(0.124)	(0.119)
Who does the shopping?						
Mostly me	-0.066	0.022	-0.358	-0.296	-0.036	0.081
	(0.109)	(0.096)	(0.225)	(0.166)	(0.115)	(0.104)
Me and other members of the h.h.	-0.126	-0.067	-0.236	-0.254	-0.094	-0.034
	(0.156)	(0.117)	(0.300)	(0.179)	(0.152)	(0.138)
Plans to...						
...build or remodel	-0.209*	-0.113	-0.100	-0.206	-0.187	-0.060
	(0.097)	(0.078)	(0.191)	(0.127)	(0.103)	(0.090)
...buy a vehicle	0.275*	0.113	0.463	-0.059	0.199	0.126
	(0.119)	(0.096)	(0.240)	(0.147)	(0.124)	(0.109)
...buy furniture or appliances	-0.168	-0.007	-0.232	0.377**	-0.017	-0.032
	(0.100)	(0.084)	(0.206)	(0.125)	(0.108)	(0.094)
...buy electronics	0.101	0.053	-0.174	0.157	0.087	0.037
	(0.108)	(0.106)	(0.216)	(0.182)	(0.115)	(0.101)
Not baseline	0.370***	3.649***				
	(0.109)	(0.113)				
Constant	5.898***	2.765***	6.025***	2.279***	5.842***	5.725***
	(0.416)	(0.339)	(0.853)	(0.559)	(0.419)	(0.375)
atanh(ρ)	0.788***		0.247***		1.031***	
	(0.028)		(0.032)		(0.033)	
Observations	2286		801		1485	

Notes: The table reports estimates from structural models that assess heterogeneity in the measurement error variances of point estimates and the mean of the subjective probability distribution of inflation expectations. Column (1) presents results from a pooled model combining all survey formats, while Columns (2) and (3) show results separately for the baseline and alternative formats. Covariates are included in the variance equations for both the point estimate and the subjective mean, allowing us to examine how respondent characteristics relate to the precision of each measure. Robust standard errors are shown in parentheses. *p<0.05, **p<0.01, ***p<0.001.

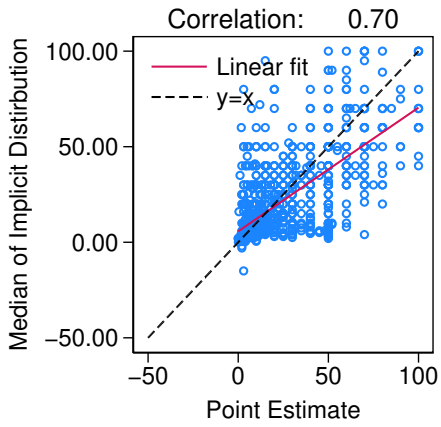
F. Robustness Check using the Median of the Subjective Probability Distribution

Figure F.1. Correlation between Point Estimate and Median of Inflation Expectations

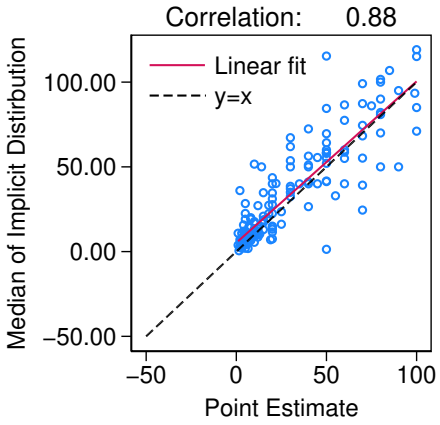
(a) Baseline



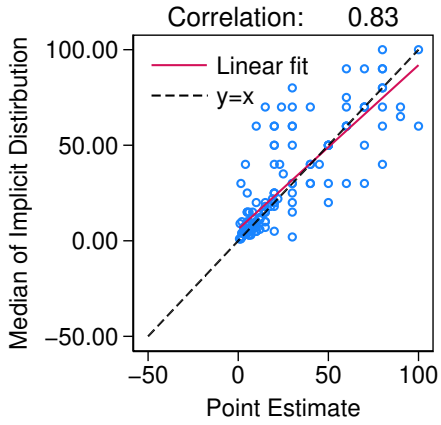
(b) Alternative



(c) Wording A

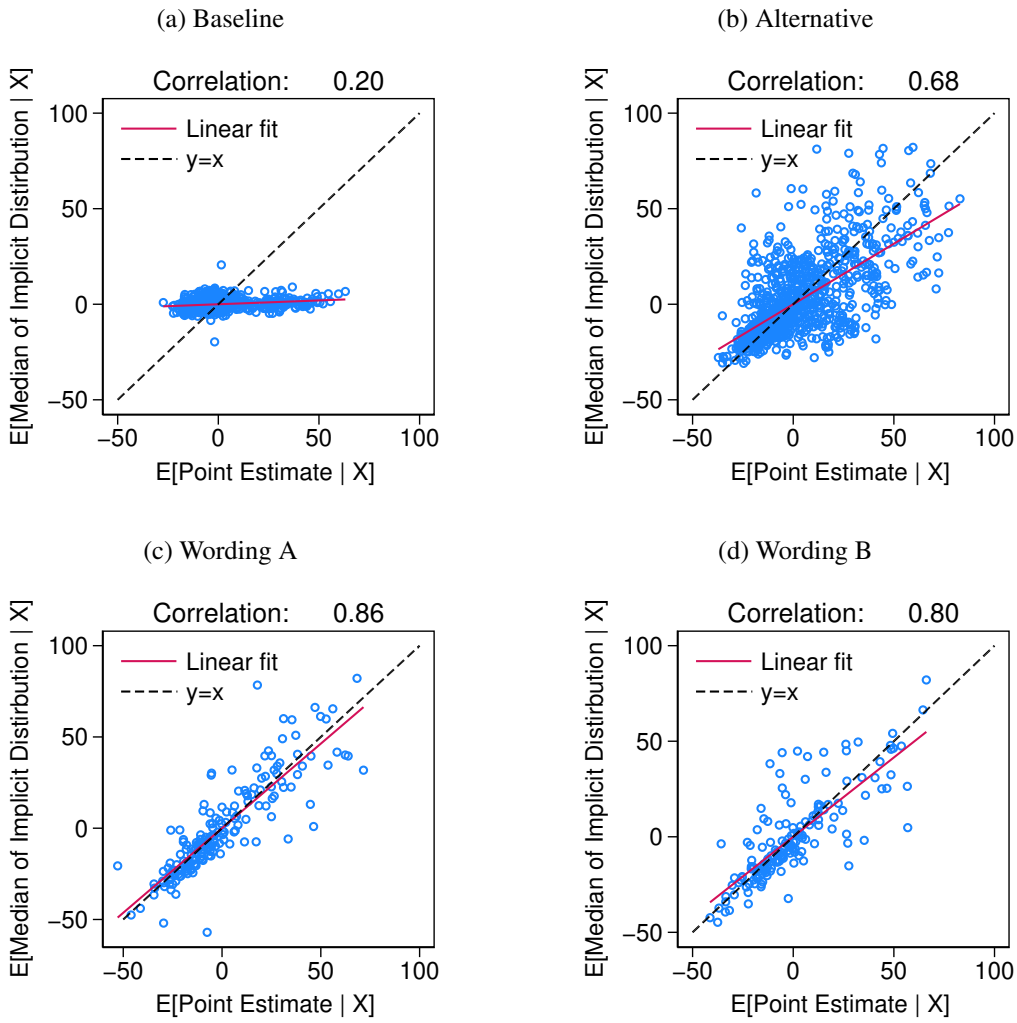


(d) Wording B



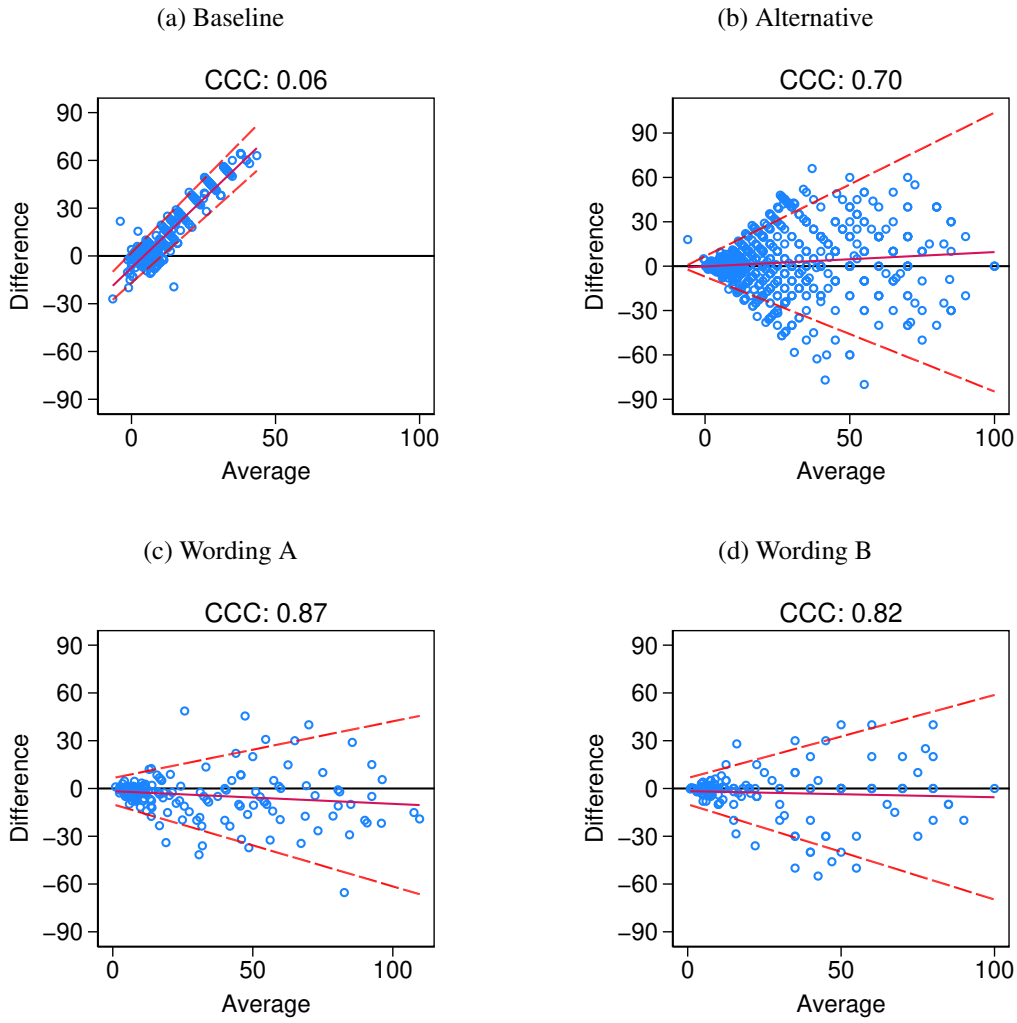
Notes: Each panel displays the correlation between respondents' point estimates and the median of their subjective probability distribution of expected inflation. The dashed 45-degree line represents perfect alignment, where the point estimate equals the distributional median. The solid red line shows the linear fit. Panel (a) corresponds to the baseline bin-style format; panel (b) shows the original scenario-based alternative; and panels (c) and (d) present results from two simplified scenario-based formats with different wordings.

Figure F.2. Partial Correlation between Residuals of Point Estimate and Median of Inflation Expectations



Notes: Each panel displays the partial correlation between respondents' point estimates and the median of their subjective probability distribution of expected inflation, controlling for observable characteristics. The dashed 45-degree line represents perfect alignment, where the point estimate equals the distributional median. The solid red line shows the linear fit. Panel (a) corresponds to the baseline bin-style format; panel (b) shows the original scenario-based alternative; and panels (c) and (d) present results from two simplified scenario-based formats with different wordings.

Figure F.3. Bland-Altman Plots



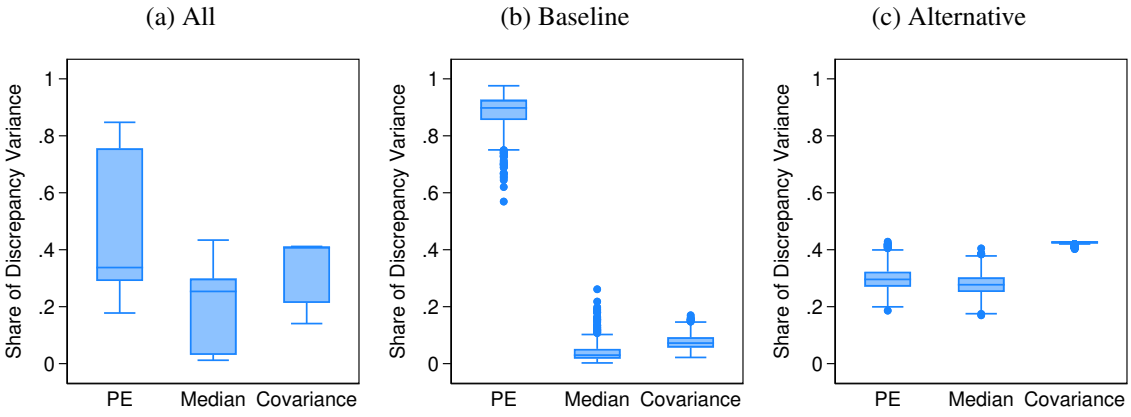
Notes: Each panel illustrates the agreement between the point estimate and the median of the subjective distribution of expected inflation using Bland-Altman methodology. The horizontal axis shows the average of the two measures, while the vertical axis shows their difference. The solid blue line represents the mean difference (bias), and the dashed red lines indicate the 95% limits of agreement. A narrower spread and clustering around zero suggest better internal consistency. The concordance correlation coefficient (CCC) quantifies overall agreement, accounting for both precision and accuracy.

Table F.1. Sensitivity of Results

	(1) OLS	(2) Matching	(3) Matching	(4) Matching	(5) Bounds	(6) Bounds	(7) HB-IV
		NN	CEM	CEM	LB	UB	
Panel A: Difference							
Not baseline	-5.496***	-5.126***	-4.471***	-3.715*	-6.450***	-3.903***	-6.163*
	(0.829)	(1.099)	(0.910)	(1.840)	(0.691)	(1.019)	(3.056)
N	2286	2286	1556	327	2286	2286	2286
Panel B: Absolute Difference							
Not baseline	-0.317***	-0.269***	-0.300***	-0.261***	-0.338***	-0.245***	-0.256**
	(0.030)	(0.043)	(0.045)	(0.077)	(0.022)	(0.050)	(0.098)
N	2286	2286	1556	327	2286	2286	2286

Notes: This table reports sensitivity analyses evaluating the robustness of the relationship between elicitation format and the discrepancy between respondents' point forecasts and the central tendency of their subjective distributions. Panel A presents results for the signed difference, while Panel B focuses on the absolute difference. Column (1) shows baseline OLS estimates. Columns (2)–(4) use matching techniques: nearest neighbor (NN) and coarsened exact matching (CEM) using only sociodemographic variables, and then sociodemographic and behavioral variables. Columns (5) and (6) apply Oster (2019) bounds to assess sensitivity to omitted variable bias, reporting lower (LB) and upper bounds (UB). Column (7) uses the Lewbel (2012) heteroskedasticity-based IV method. Robust standard errors are shown in parentheses. The IV estimates satisfy standard diagnostic criteria: the Kleibergen–Paap Wald F-statistic is 10.64, indicating reasonable instrument relevance, and Hansen's J-statistics are 13.937 (p-value = 0.530) for the difference and 16.111 (p-value = 0.375) for the absolute difference, which provide additional evidence in support of the model and estimator. In the case of Oster (2019) bounds the standard errors are obtained with a bootstrap procedure with 300 replications. *p<0.05, **p<0.01, ***p<0.001.

Figure F.4. Variance Decomposition by Source



Notes: The figure shows the variance decomposition of the discrepancy between the point estimate and the median of the subjective probability distribution. The total discrepancy variance is separated into three components: variance due to noise in the point estimate (PE), variance due to noise in the subjective median, and the absolute value of their covariance. Results are shown separately for the pooled data, the baseline format, and the alternative scenario-based formats. This decomposition highlights the relative contribution of each source of measurement error across survey designs.

Table F.2. Results of the Structural Models using the Median

	(1) All		(2) Baseline		(3) Alternative	
π_i^*	4.480***		4.828***		18.727***	
	(0.149)		(0.133)		(0.655)	
	PE	Median	PE	Median	PE	Median
Age	0.003	0.011*	-0.016*	0.004	0.008*	0.013***
	(0.004)	(0.004)	(0.007)	(0.006)	(0.004)	(0.004)
Financial literacy score	-0.436***	-0.363**	-0.576	-0.283	-0.203	-0.371**
	(0.131)	(0.128)	(0.299)	(0.168)	(0.139)	(0.144)
Woman	0.678***	0.283**	1.079***	0.017	0.547***	0.347***
	(0.104)	(0.108)	(0.219)	(0.156)	(0.114)	(0.105)
Socioeconomic group						
High	0.131	0.187*	0.570*	0.097	0.014	0.182
	(0.094)	(0.086)	(0.250)	(0.130)	(0.095)	(0.093)
Working	0.018	-0.011	-0.075	-0.287	0.153	0.222*
	(0.105)	(0.124)	(0.233)	(0.186)	(0.112)	(0.105)
Elementary to junior high school	-0.135	-0.274*	0.077	0.064	-0.223	-0.402*
	(0.140)	(0.128)	(0.323)	(0.190)	(0.155)	(0.158)
High school or more	-0.500***	-0.619***	-0.420	0.019	-0.476**	-0.776***
	(0.142)	(0.127)	(0.319)	(0.195)	(0.157)	(0.154)
Head of household	0.078	-0.199*	0.479*	-0.007	0.033	-0.261*
	(0.099)	(0.089)	(0.225)	(0.123)	(0.109)	(0.103)
Who makes major purchases?						
Mostly me	0.154	-0.002	0.535	-0.091	0.032	0.032
	(0.114)	(0.104)	(0.275)	(0.158)	(0.116)	(0.118)
Me and other members of the h.h.	-0.080	-0.082	0.305	-0.341*	-0.106	0.032
	(0.131)	(0.116)	(0.295)	(0.166)	(0.132)	(0.140)
Who does the shopping?						
Mostly me	-0.071	0.042	-0.428	-0.320*	0.009	0.144
	(0.111)	(0.103)	(0.254)	(0.163)	(0.118)	(0.112)
Me and other members of the h.h.	-0.147	0.038	-0.272	-0.275	-0.068	0.157
	(0.164)	(0.147)	(0.352)	(0.176)	(0.162)	(0.179)
Plans to...						
...build or remodel	-0.220*	-0.079	-0.125	-0.199	-0.180	-0.026
	(0.097)	(0.091)	(0.211)	(0.126)	(0.105)	(0.105)
...buy a vehicle	0.226	0.064	0.583*	-0.070	0.156	0.072
	(0.123)	(0.121)	(0.290)	(0.145)	(0.129)	(0.134)
...buy furniture or appliances	-0.148	-0.008	-0.166	0.368**	-0.012	-0.011
	(0.102)	(0.100)	(0.244)	(0.124)	(0.111)	(0.116)
...buy electronics	0.102	0.076	-0.216	0.153	0.082	0.037
	(0.113)	(0.123)	(0.276)	(0.183)	(0.119)	(0.130)
Not baseline	0.357**	3.585***				
	(0.121)	(0.116)				
Constant	6.330***	2.860***	5.923***	2.372***	5.827***	5.785***
	(0.439)	(0.376)	(0.965)	(0.557)	(0.458)	(0.450)
atanh(ρ)	0.866***		0.224***		0.964***	
	(0.031)		(0.035)		(0.035)	
N	2286		801		1485	

Notes: The table presents estimates from structural models examining heterogeneity in measurement error variances for point forecasts and subjective medians of inflation expectations. Column (1) shows pooled results across formats; Columns (2) and (3) report separate estimates for the baseline and alternative formats. Covariates in the variance equations allow us to assess how respondent characteristics relate to the precision of each measure. Robust standard errors are in parentheses. *p<0.05, **p<0.01, ***p<0.001.