Greater Than the Sum of Its Parts: Aggregate vs. Aggregated Inflation Expectations

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Abstract

We introduce a new concept for measuring consumer inflation expectations: aggregating inflation forecasts elicited separately for categories covering the full range of personal consumption expenditures (PCE). Drawing on close to 60,000 respondents over two years, our data cover both the low-inflation environment of the COVID pandemic and the 2021 inflation surge. Compared to conventionally measured consumer headline-inflation expectations, *aggregated* measures emerge as more informative indicators. They tend to yield a lower forecast, with less disagreement and volatility. The aggregated measures also serve as stronger predictors of consumers' spending plans.

Keywords: Household expectations, Survey, Sectoral expectations, Inflation expectations
JEL-Codes: C83, E31, E52

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1 Introduction

Inflation expectations represent a decisive factor for charting the path of monetary policy, and central banks "spend a lot of time watching them" (Powell, 2021), with attention directed especially at consumer expectations, which affect households' consumption-saving decisions (e.g., Bachmann et al., 2015; Crump et al., 2022; Ryngaert, 2022) and wage-price spirals (e.g., Blanchard, 1986; Hajdini et al., 2022; Lorenzoni and Werning, 2023). Consumer inflation expectations, however, are notoriously difficult to capture accurately with prevailing survey methods (e.g., Bullard, 2016), as respondents have low financial literacy (Bruine de Bruin et al., 2010; D'Acunto et al., 2022), and responses are vulnerable to a host of cognitive biases (Cavallo et al., 2017; D'Acunto et al., 2019, 2021; Georganas et al., 2014). Moreover, some consumers have great difficulty grasping the concept of aggregate inflation (D'Acunto et al., 2022; Weber et al., 2022)[1], leading them to rely on salient cues, such as extreme price movements (Bruine de Bruin et al., 2011) or changes in grocery and gas prices (Binder, 2018; D'Acunto et al., 2021), when they report survey expectations.

The ostensible mismatch between consumers' cognitive capacity and the demands of conventional elicitation techniques have led us to devise a survey that makes the task of reporting inflation expectations potentially more manageable. The idea is simple: Because aggregate inflation is a complicated, abstract concept, we decompose it into its more tangible constituent parts—price changes for disaggregated categories of goods and services. Our survey elicits consumers' inflation forecasts for such consumption categories, spanning span the full range of personal consumption expenditures (PCE). This granular elicitation allows us to construct a novel measure of *aggregated* consumer inflation expectations, by combining category-specific forecasts, and we find that *aggregated* inflation expectations are not only less noisy than the conventional measure of aggregate inflation expectations, but also predict planned consumer spending better. This holds consistently across respondents in the population. Arguably, therefore, *aggregated* inflation expectations yield a more accurate representation of consumers' effective beliefs about future inflation—that is, the beliefs on which they make future consumption plans—highlighting the appeal of *aggregated* inflation expectations for policy makers who aim to elicit effective beliefs across groups of respondents in the population.

We collect these expectations from almost 60,000 US consumers in a nationally representative survey, at a daily frequency between July 2020 and August 2022, as part of the Federal Reserve Bank of Cleveland's Daily Survey of Consumers (Knotek et al., 2020). The survey measures 12-month-ahead inflation expectations in two distinct ways. First, it elicits aggregate inflation expectations following the conventional point-estimate approach from the New York Fed's Survey of Consumer Expectations (SCE). Second, the survey asks consumers about inflation expectations for each of 11

[1] D'Acunto et al. (2022) find that low-IQ respondents, especially, seem to have very limited understanding of the concept of aggregate inflation; low-IQ respondents report that they associate inflation with price changes of specific, salient goods rather than macroeconomic variables, and they have difficulty with probabilistic terms.

consumption categories, covering the entire range of PCE. In so doing, we match closely the conventional question format of the SCE for aggregate inflation expectations. While the SCE also elicits inflation expectations for several salient products—such as gasoline, housing, and groceries—to the best of our knowledge, our survey is the first to yield a dataset of comprehensive category-specific inflation expectations. In addition, we also ask survey participants about personal expenditures and the relative importance of the consumption categories, along with their consumption plans.

We aggregate up these disaggregated responses to compare them to conventional, aggregate inflation expectations. In particular, we evaluate eight different procedures for aggregating category-specific inflation expectations, across two types: (i) *plausibly rational* and (ii) *behavioral* aggregations. The three aggregations within the first type use weights arguably reasonable for a rational agent: self-reported expenditure weights, self-reported importance weights, and the official PCE weights. In contrast, the behavioral aggregations capture weighting schemes that depart from plausibly rational procedures in favor of heuristic mechanisms known in the literature, such as reliance on salient categories (D'Acunto et al., 2021) or price changes (Bruine de Bruin et al., 2011) in forming aggregate inflation expectations: equally weighted categories, core and non-core inflation expectations, a max operator selecting the highest category expectation, and a second-max selecting the second highest. These aggregations thus take into account insensitivity to category weights, heavy weight on salient categories, and attention to salient price changes, respectively.

When we compare aggregate inflation expectations, elicited conventionally, with the *aggregated* measures in the cross-section, we find that the latter are generally lower and less dispersed than the former. The *aggregated* measures are on average also less volatile over time. Turning to a comparison at the respondent level, we obtain significant aggregation gaps between aggregate and *aggregated* inflation expectations, and the absolute gaps vary meaningfully with socioeconomic characteristics: higher education, for example, yields a much closer alignment between aggregate and *aggregated* expectations.[2] Moreover, we find that both subjective uncertainty about aggregate inflation expectations and the individual dispersion of category expectations correlate strongly with the absolute aggregation gap. We interpret this finding as evidence that the more uncertain consumers are about their aggregate forecast, or the less aligned expected price changes are across categories, the more the complexity of the aggregation task bears on consumers' ability to perform the associated computations. This interpretation resonates with the finding from psychology that individuals adapt the heuristics at play according to the demands of the task at hand (Payne et al., 1993). The aggregation gaps also reveal an inconsistency with rational expectations: Aggregation by PCE weights should align with the conventional aggregate forecast—but it does not.[3] This

[2]Several other papers have investigated inconsistencies between responses to question formats in consumer surveys asking about aggregate inflation expectations (Stanisławska et al., 2021) or consumer spending (Winter, 2004). Similar to our results, inconsistencies increase with lower socioeconomic status. Professional forecasters, however, seem to be consistent in their forecasts for aggregate inflation, across different question formats (Engelberg et al., 2009).

[3]Likewise, the gap resulting from aggregation by personal expenditure weights, as well as that by importance weights, may be interpreted as inconsistent with rational expectations, given a suitable model.

finding complements those of Coibion and Gorodnichenko (2012), who reject the hypothesis of full information and rational expectations (FIRE) by examining expectations and realizations. Our work addresses the issue from another angle, demonstrating a potential *internal inconsistency* between expectations at the individual level.

Finally, we provide evidence for the superior predictive power of our measure of *aggregated* inflation expectations for consumer demand, compared to the conventional aggregate inflation expectations. Theoretically, the link between expected inflation and consumer spending is described by the consumer Euler equation (see for example, Galí, 2015). As the survey elicits planned changes in consumer spending for different goods and services, we can estimate the consumer Euler equation, following Crump et al. (2022). We find that our measures of *aggregated* inflation expectations *all* emerge as stronger predictors of planned consumer spending. Category-specific inflation expectations, therefore, appear more representative of the beliefs used in actions and planning, and thus more informative for monetary policy, both during the COVID-19 pandemic and the 2021-inflation surge. Moreover, the relative benefit of using expenditure-weighted, *aggregated* over aggregate inflation expectations to predict spending plans increases with the individual-level gap between the two measures. This highlights the appeal of our measure of *aggregated* inflation expectations for policy makers who aim to elicit effective beliefs across respondent groups in the population.

Our paper builds on a growing literature addressing the formation of consumer inflation expectations and the role of cognitive heuristics, such as reliance on salient cues. Bruine de Bruin et al. (2011), for example, provide evidence that households rely on salient, extreme prices to form their aggregate inflation expectations. In a similar spirit, but with different methods, D'Acunto et al. (2021) find that consumers rely on observed changes in grocery prices to form their aggregate inflation expectations and that the relative weights products receive depend on the frequency of purchase, rather than expenditure. Others, moreover, have documented extrapolation from gasoline prices for aggregate inflation expectations (e.g., Armantier et al., 2016; Binder and Makridis, 2022; Binder, 2018; Coibion and Gorodnichenko, 2015) or importance of goods in the consumption basket Cavallo (2020) and Cavallo et al. (2017). Notably, however, neither groceries nor gasoline form part of core inflation, and Arora et al. (2013) as well as Trehan (2011) find that aggregate inflation expectations react excessively to non-core price changes. Relatedly, Dietrich (2022) shows that consumers are relatively more attentive to their internal food and energy inflation forecasts. Beyond the domain of inflation expectations, past experiences seem to impact expectations about future macroeconomic conditions (Malmendier and Nagel, 2011), which Kuchler and Zafar (2019) have shown for forecasts of housing prices.

Our paper also draws on methodological insights from survey studies across areas of economics and related fields that find data-quality advantages from decomposing broad questions into their constituent parts. Menon (1997), for example, shows that the accuracy of frequency reports depends on the question format matching the cognitive processes employed by the respondent and that decomposed questions, therefore, improve frequency judgments of irregular events by easing the cognitive reporting burden. Consistent with these results, Winter (2004) finds that disaggregated questions yield improved data quality for nondurable consumption compared to questions asking about aggregates, and discrepancies vary with socioeconomic characteristics, similarly to what we find with the variation in the gaps between aggregate and *aggregated* inflation expectations. Along the same lines, but in the domain of development economics, Deaton (2019) argues that surveys of consumption spending with disaggregated questions are more reliable than those with questions about aggregates. Hurd and Rohwedder (2008, 2012) field surveys to ask households about past spending using disaggregated category questions. Taken together, this literature implies a possibility for improving measurement of consumer inflation expectations by eliciting expectations at the disaggregated, category-specific as opposed to the aggregate level.

Our paper proceeds as follows: Section 2 outlines the concept of behavioral inflation expectations. Section 3 describes our novel survey data. Section 4 examines category-specific inflation expectations and compares them to aggregate inflation expectations. Section 5 investigates procedures for aggregating category-specific inflation expectations and the gap between aggregate and *aggregated* inflation expectations. Section 6 relates aggregate and *aggregated* expectations to household spending plans in Euler equation estimations. A final section concludes.

2 Human Forecasts and Inflation Expectations

When consumer surveys ask respondents to report their inflation expectations, they are in effect asking for forecasts of an uncertain, abstract variable. The canonical work by Tversky and Kahneman (1974) on heuristics and biases, however, shows that the human mind isn't optimally wired for the task; judgments of uncertain events rely on heuristics—simple rules of thumb—which often lead to predictable discrepancies from rational norms (Fischhoff and Broomell, 2020). A common manifestation of this is the salience bias, whereby human judgment is biased by salient information. For example, consumers exposed to price spikes in their grocery bundles may report higher inflation expectations (D'Acunto et al., 2021); their expectations may reflect their expenditure bundles (Cavallo et al., 2017); or, under conditions with rapid price increases in specific categories, their inflation expectations may selectively reflect the salient, category-specific rises (Niu and Harvey, 2022). A similar phenomenon, driven by the representativeness heuristic of Kahneman and Tversky (1972), is formalized by Gennaioli and Shleifer (2010) and applied by Bordalo et al. (2018) to model credit cycles. Moreover, Bordalo et al. (2022) show that selective, automatic memory can account for both over- and underestimation of novel risk.

Even experts struggle to incorporate multiple cues into a reliable forecast. Starting with the influential work of Meehl (1954), psychologists discovered that clinical expert forecasts—that is, forecasts based on expert intuition—were surprisingly unreliable across a wide range of domains and were consistently outperformed by rudimentary statistical models. Subsequent work by Dawes

(1979) found that linear models with arbitrary weights—including equal weights—outperformed expert human judgment; as long as linear models include the relevant predictor variables, with coefficients set in the correct direction, they prove surprisingly robust (Einhorn and Hogarth, 1975). These findings have held up over time (Dawes et al., 1989), and although they apply to experts, there is little reason to think that lay respondents would perform any better. In fact, professional forecasts of inflation consistently outperform those of lay households (Carroll, 2003; Verbrugge and Zaman, 2021).

By eliciting both category-specific and aggregate inflation forecasts, our analysis adds a unique angle to the study of forecast consistency and aggregation. First, respondents address something tangible and concrete, of which they may have better understanding, presumably leaving them less vulnerable both to biased and to noisy judgments when providing category-specific (as opposed to aggregate) inflation forecasts. Second, our setup provides the opportunity to combine category-specific forecasts mechanically into "bottom-up," aggregated inflation expectations. Such *aggregated* inflation expectations, compared to explicitly articulated expectations of aggregate inflation, might better represent respondents' effective inflation beliefs—which they may not necessarily articulate explicitly, but act as if they hold. The reason for this is that the mere act of articulating the abstract inflation concept—which some respondents may not really understand—could involve cognitive distortion causing both bias and noise.

3 Survey

Our survey is conducted at a daily frequency, as a module within the Federal Reserve Bank of Cleveland's daily survey of consumer expectations, administered by Qualtrics Research Services. It includes a nationally representative sample of 59,920 responses, collected between July 9, 2020 and August 9, 2022, with a daily sampling size of at least 100 respondents. Qualtrics Research Services constructs a representative sample by drawing respondents from several actively managed, double-opt-in market-research panels, complemented with social media (Qualtrics, 2019). Dietrich et al. (2022) and Knotek et al. (2020) provide further information about other parts of the survey.

We require all respondents to be US residents and to speak English as their primary language. Respondents are representative of the US population according to several key demographic and socioeconomic characteristics; they have to be male or female with 50-percent probability; approximately one third are targeted to be between 18 and 34 years of age, another third between 35 and 55, and a final third older than age 55. We also require a distribution across US regions in proportion to population size, drawing 20 percent of our sample from the Midwest, 20 percent from the Northeast, 40 percent from the South and 20 percent from the West. The survey includes filters to eliminate respondents who enter gibberish for at least one response, or who complete the survey in less (more) than five (30) minutes, and CAPTCHA tests to reduce the likelihood that

Table 1: Survey Respondent Characteristics

	Survey	US population		Survey	US population
Age			**Race**		
18-34	33.1%	29.8%	non-Hispanic white	72.7%	60.1%
35-55	33.8%	32.4%	non-Hispanic black	9.3%	12.5%
>55	33.1%	37.8%	Hispanic	10.1%	18.5%
			Asian or other	7.9%	8.9%
Gender					
female	49.9%	50.8%	**Household Income**		
male	49.7%	49.2%	less than 50k$	47.8%	37.8%
other	0.4%	-%	50k$ - 100k$	29.5%	28.6%
			more than 100k$	22.7%	33.6%
Region					
Midwest	20.6%	20.7%	**Education**		
Northeast	21.9%	17.3%	some college or less	50.6%	58.3%
South	39.5%	38.3%	bachelor's degree or more	49.4%	41.7%
West	18.0%	23.7%			
			N=59,920		

Notes: The "Survey" column represents characteristics in our survey; the "US population" column gives the value for the US population, obtained from the US Census Bureau (Household income: CPS ASEC, 2021; gender, education: ACS, 2019, age, race, region: National Population Estimate, 2019).

bots would interfere.[4]

Table 1 provides a breakdown of our sample, showing that our sampling criteria generated a sample roughly representative of the US population along key dimensions. To improve the fit further, we compute a survey weight for each respondent; we apply iterative proportional fitting to create respondent weights following completion of the survey ("raking," see for example, Bishop et al., 1975; Idel, 2016). This allows us to calculate statistics that are *exactly* representative of the US population also according to age, gender, ethnicity, income, census region, and education—that is, the variables in the right-hand column of Table 1.

Within the survey, we ask respondents first about their aggregate inflation expectations over the next 12 months (Q1 in Table 2), using point-forecast questions.[5] Our approach to eliciting aggregate inflation forecasts is methodologically similar to that of other influential household surveys, such as the University of Michigan's Surveys of Consumers (SoC) and the New York Fed's Survey of Consumer Expectations (SCE).[6] Subsequently, we elicit inflation expectations for 11 PCE categories

[4] Qualtrics Research Services provides the filtered data. The daily sample size refers to the number of respondents after filtering. Survey respondents are provided with fair monetary compensation for their time.

[5] On a subset of the data, we switched the ordering, asking about disaggregated category expectations first. We did not find a significant effect.

[6] The SoC has collected data on household inflation expectations since 1978; the SCE started in 2013. Both ask about aggregate inflation or the expected change in *aggregate* prices directly, at a monthly frequency, and they include some kind of panel structure; while the SoC asks a subset of participants to answer the survey again, half a year later, the SCE has a rolling panel structure, with respondents answering 12 consecutive monthly surveys. Our survey

(Q2 in Table 2) using a format closely aligned to that of the aggregate inflation question (Q1). For each category, however, we provide survey participants with at least one example—such as "Public transit tickets and airfare" for "Transportation services"—to reduce the risk of misinterpreting categories. Table 3 in Section 4 shows both the PCE categories used in the survey and some summary statistics. Our PCE-disaggregation is based on that of the US national income and product accounts (NIPA), with some small sectors combined in order to reduce the cognitive burden of completing the survey.[7]

While the SCE also elicits aggregate inflation expectations with a probability-distribution question, we choose to rely on point forecasts both for the aggregate and the category expectations.[8] The principal reason is that point forecasts prove more tractable in the present survey framework, reducing the mental burden on participants who would otherwise have to indicate probability distributions for all 11 PCE categories. Moreover, Clements (2014) finds that point forecasts, relative to probability-distribution forecasts, offer superior data quality for the mean of expectations.

Besides inflation expectations within these categories, we also asked how much survey respondents spent within the respective category during the last month (Q3 in Table 2) and how important they consider the category in their daily lives (Q4 in Table 2). Responses to these questions allow us to compute both expenditure shares per category (relative to total expenditure) and a measure of perceived relative importance.

Following questions about category expectations and expenditure shares, respondents were asked about their expected spending relative to spending in the month prior, looking ahead 12 months. This question was also repeated for more narrowly defined spending categories, namely services spending and expenditures on nondurable consumption goods. Additionally, respondents reported their socioeconomic background and consumer habits. These questions, including demographic information and the exact layout of our inflation questions, are provided in Appendix C.

does not feature a panel structure, but is conducted at a higher frequency (daily).

[7]We use what might be thought of as the third level of disaggregation of PCE-spending—the first would be by goods and services, and the second by durable and nondurable goods and expenditures on services, by households and nonprofit institutions serving households.

[8]We do, nonetheless, feature a probability-distribution question on aggregate inflation, but use it exclusively as a measure of subjective uncertainty.

Table 2: Survey Questions

Aggregate Inflation Question		
Q1	What do you expect the rate of inflation to be over the next 12 months? [...]	I expect [...] to be [positive/negative] ___ percent over the next 12 months.
Category Inflation Questions		
Q2	Twelve months from now, what do you think will have happened to the price of the following items?	I expect the price of [*category*] to [increase/decrease] by ___ percent.
Q3	In terms of consumption spending, how much money did you spend on each of the following broad consumption categories during the last month? [...]	Per category, participants enter an approximate amount in dollars in a bracket.
Q4	Which of the following broad consumption categories matter the most to you right now in your daily life? Please move the slider to indicate the importance for each of them [...]	Participants move a slider from 0 (no importance) to 100 (highest importance), per category.
Spending Questions		
Q5	Compared with your spending last month, how do you expect your total spending to change in the next twelve months?	[up/no change/down] by ___ percent.
Q6	Compared with your spending on services [...] last month, how do you expect your total spending to change in the next twelve months?	[up/no change/down] by ___ percent.
Q7	Compared with your spending on non-durable goods [...] last month, how do you expect your total spending to change in the next twelve months?	[up/no change/down] by ___ percent.

Notes: List of main questions asked in the survey. For other questions, please see Appendix C.

4 Category-Specific Inflation Expectations

This section presents the statistical properties of aggregate (Q1 in Table 2) and category-specific inflation expectations (Q2). We document that mean expectations about aggregate inflation in the cross-section exceed mean inflation expectations for every PCE category. In addition, aggregate expectations exhibit larger disagreement (except for gasoline), as well as higher volatility within the time series.

Table 3 shows summary statistics for aggregate and category-specific inflation expectations. The

Table 3: Summary Statistics

	Mean	Disagreement	Time-Series Volatility
Aggregate expectation	6.39	7.53	2.53
Category expectations			
Motor vehicles	5.49	5.95	1.78
Recreational goods	4.00	6.34	1.61
Other durable goods	4.12	6.14	1.69
Food and beverages	5.27	6.48	1.71
Gasoline	5.28	7.57	2.03
Other nondurable goods	4.15	6.02	1.41
Housing and utilities	4.93	6.46	1.50
Health care	3.96	6.52	1.58
Transportation services	4.82	6.19	1.53
Food services	4.78	6.46	1.54
Other services	4.32	5.64	1.29

Notes: This table presents summary statistics on the mean on expectations, the standard deviation in the cross-section, and the standard deviation in the (daily mean) time series. Mean expectation: Time-series mean of daily Huber-robust and survey-weighted mean expectations (see figure 1, upper row); Disagreement: Time-series mean of daily Huber-robust and survey-weighted standard deviation of expectations (see figure 1, lower row); Time-series volatility: Time-series standard deviation of daily Huber-robust and survey-weighted mean expectations.

table reports the mean expectation and disagreement among households (cross-section standard deviation) in the first and second columns; displayed statistics represent the average over the daily Huber-robust and survey-weighted mean and standard deviation, respectively. The time-series standard deviation, in the third column, represents the volatility over time–that is, the standard deviation of daily mean estimates. Survey participants, between July 2020 and August 2022, expect on average aggregate inflation over the next 12 months to be 6.39 percent. Nevertheless, every category-specific inflation rate is expected to be lower: From 3.96 percent for "Health care services" to 5.49 percent for "Motor vehicles."

A representative agent, therefore, with views mirroring those of the cross-section, expected that aggregate inflation would exceed inflation expectations for *any* category. This pattern is driven by respondents reporting aggregate expectations outside the range of their own individual category-specific expectations. At a micro-level, about 26 percent of respondents state an aggregate expectation larger than they do for any category-specific expectation. For 12 percent of respondents, the opposite holds true; they report aggregate expectations below their smallest category-specific expectation. Consequently, only around 62 percent of respondents report their aggregate within the range of their category-specific expectations. Although such inconsistencies could be explained by random reporting errors on part of the individual respondents (Bertrand and Mullainathan, 2001), white-noise reporting errors are unable to explain the cross-sectional wedge between aggregate and category-specific inflation expectations.

The survey is designed such that all categories combined cover the entire range of US consumption expenditures forming the basis for aggregate inflation, following the statistical methodology of the PCE price index, as reported by the BEA. In theory, therefore, there should exist a linear combination of weights—summing up to unity—such that the weighted category-specific expectations equate to the aggregate inflation expectation, for the representative agent. This is clearly not the case in the data.

A potential explanation for the gap might be that respondents interpret the aggregate inflation question as referring to a macroeconomic variable while they understand the category-specific questions as referring to subjective inflation rates, that is, based on the goods and services that they personally consume (within the specific category). However, the survey is designed to allow a commensurate comparison between aggregate and category-specific expectations, as both question types ask about inflation in general, as opposed to subjective, personal inflation rates. Following the New York Fed SCE, aggregate expectations ask about "inflation/deflation," while category-specific expectations refer to changes in "the price of" a category, with no suggestion that this applies specifically to personal, subjective consumption. Thus, although we cannot rule out a subjective interpretation of every category-specific question, there is little reason to assume that a subjective interpretation, alone, would account for the asymmetric results obtained across aggregation levels.

As opposed to mere white noise, the pattern in Table 3 suggests that differential heuristics and expectations-formation processes are at play when respondents report aggregate versus category-specific inflation expectations. That is, respondents might adapt the heuristics used according to the demands of the task at hand (i.e., Payne et al., 1993). We run a series of robustness checks to investigate this pattern further.

First, in a separate survey, we asked respondents about more technically specific aggregate inflation concepts, namely PCE- or CPI-price-index inflation (see Table 19 in the appendix). Our main findings hold up qualitatively; aggregate inflation expectations exceed inflation expectations for any category. Indeed, when survey participants are asked about CPI or PCE inflation, specifically, the gap to category-specific responses appears to widen. Second, to ascertain that the relationship between aggregate and category-specific expectations is independent of a framing artefact, we randomized the order of aggregate and category-specific inflation questions for a subset of the sample (see Table 20 in the appendix). We find that the mean aggregate expectation exceeds any category-specific expectation, irrespective of whether aggregate or category-specific expectations are presented first.

Third, to explore whether the patterns in the cross-section extend beyond the typical consumer, we administered a miniaturized version of our survey with a small sample of fund managers, who volunteered to participate in the lead-up to a practitioner's conference in November 2022. As seen in Appendix A.13, fund managers reported aggregate inflation expectations higher than category-specific expectations, with the exception of food and beverages. This is roughly consistent with the pattern obtained for consumers (Table 3), but a notable contrast arises for the disagreement in aggregate inflation expectations. Whereas it is smaller than that of any category for fund managers, it is larger for consumers.

Forth, Figure 1 displays results by means of a time series, in order to gauge the stability of our results over time. The upper row of Figure 1 shows the time series, by daily means, for aggregate and mean category-specific inflation expectations during the survey period. The left panel displays category-specific expectations for the durable (red lines) and nondurable (blue lines) consumption goods, while the right panel shows services categories (green lines). All time series displayed are balanced 11-day moving averages.[9] Aggregate inflation expectations, rising from around 4 percent in July 2020 to around 8 percent in July 2022, are higher than any category expectations for most of the sample period.[10] Consequently, for a representative agent, there exists no possible linear combination of category-specific expectations with non-negative aggregation weights that maps category-specific expectations into aggregate expectations.

The bottom row of Figure 1 shows disagreement among respondents for aggregate inflation expectations (black line) and category-specific expectations, where we measure disagreement as the daily standard deviation of the cross-section. The figures display an 11-day moving average, with durable- and nondurable-goods sectors in the left panel and services in the right. For most of the time surveyed, disagreement is much higher for aggregate expectations than it is for category-specific expectations (see also Table 3). Time-series volatility (of expectations) is an important moment in economic analysis, and we find that volatility over time is higher for aggregate inflation expectations than it is for category-specific expectations (see Column 3 in Table 3).

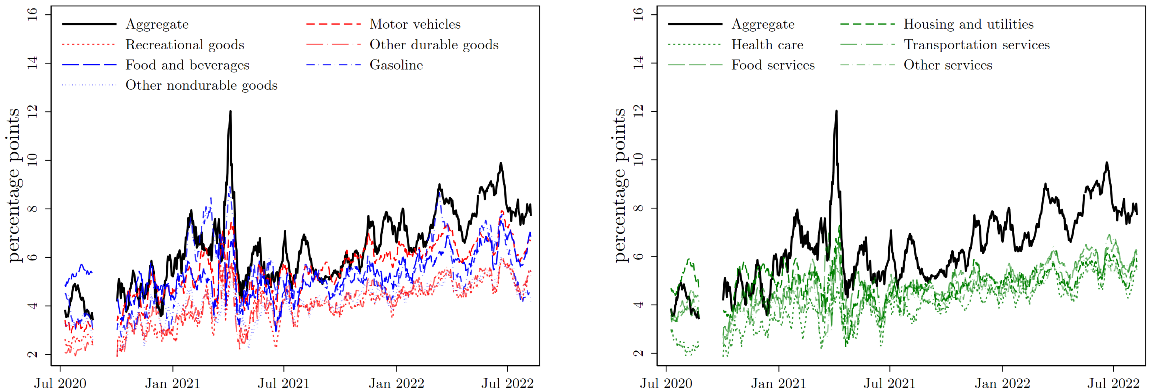
Tables 8 and 9 in the Appendix reveal demographic heterogeneity in the results; we find that lower income and less education are both associated with a substantially higher mean aggregate inflation expectation and higher cross-sectional disagreement. At the same time, category-specific expectations tend to be quite similar across education and income and, where they are not, they do not diverge in a consistent fashion. Across almost all categories, women report higher inflation expectations and greater disagreement; this holds also for aggregate inflation expectations, generally consistent with demographic patterns reported by Bruine de Bruin et al. (2010). An inconsistent pattern, however, arises with age, see Table 10 in the Appendix: For the oldest age group in our sample (older than 55), aggregate inflation expectations are lower than those of younger respondents. For expectations by category, in contrast, the pattern is reversed: older respondents report higher expectations.

[9]The balanced moving average constructs for each day the average of the mean from the respective day and the five days before and after.

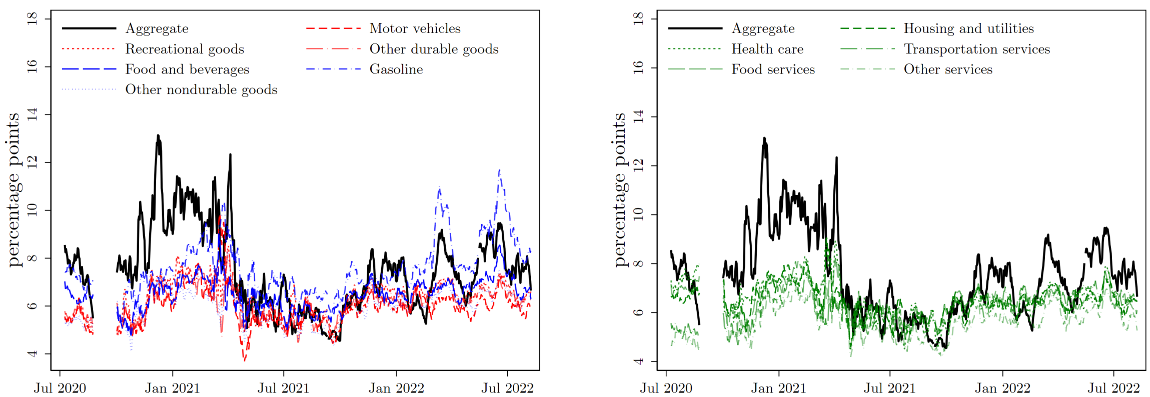
[10]The time series documents a temporary but pronounced increase in inflation expectations and disagreement in early 2021, with a spike around April 2021, coinciding with the surge in realized inflation and inflation news in the US.

Figure 1: Aggregate vs Category-Inflation Expectations

Mean Time Series



Disagreement Time Series



Notes: The top row shows mean aggregate inflation (black line) and category-inflation rates; the bottom row shows disagreement on aggregate inflation; left panels show durable and nondurable goods inflation by category; right panels show services inflation by category; the time series is an 11-day balanced moving average. Underlying daily observations are Huber-robust and survey-weighted means. Questions on inflation expectations were not part of the survey during September 2020.

5 Aggregate vs. Aggregated Inflation Expectations

Next, we study the relationship between reported conventional aggregate inflation expectations and *aggregated* measures of the categories that also describe overall inflation. Section 5.1 introduces the aggregation methods, Section 5.2 the statistical properties of *aggregated* inflation expectations relative to aggregate expectations, and Section 5.3 the relation between aggregate inflation expectations and the *aggregated* measures. We find that both measures differ significantly; *aggregated* inflation expectations tend to be closer to zero than do aggregate expectations, and disagreement among survey participants is higher for the latter. The statistically significant, positive aggregation gap is particularly noteworthy for expenditure- and PCE-weighted aggregations as it reflects internally inconsistent beliefs about inflation. The gap between both measures increases with uncertainty and varies in a meaningful way with socioeconomic and demographic characteristics.

5.1 Aggregated Inflation Expectations

We build several measures of *aggregated* inflation expectations relying on the category expectations of consumers and several sets of weights ω_k. Crucially, for every set of weights we assume that the *aggregated* inflation expectation is a weighted average of categories in the sense that $\omega_k \geq k$ and that $\sum_{k=1}^{N} \omega_k = 1$.

$$\mathbb{E}_t^i \, \pi_{t+1}^{aggregated} = \sum_{k=1}^{N} \left[\omega_k^i \, \mathbb{E}_t^i \, \pi_{k,t+1} \right] \tag{1}$$

$\mathbb{E}_t^i \, \pi_{t+1}^{aggregated}$ denotes the *aggregated* inflation expectation of respondent i, and $\mathbb{E}_t^i \, \pi_{k,t+1}$ his expectations of category k. ω_k^i is the weight assigned to category k by respondent i.

Our analysis considers two types of weights, summarized in Table 4. The first denotes weights that describe a plausibly rational agent, and the second weights that describe a behavioral agent. Among the plausibly rational weights, a first set relies on the official monthly BEA nominal expenditure shares used to construct the official PCE-inflation statistics. In a FIRE general-equilibrium model, multiplying category-specific expectations with category-specific weights yields the aggregate economy-wide inflation expectation precisely up to the usual first-order log-linear approximation.[11] A second set of weights aggregates category inflation expectations with self-reported expenditure shares. A third set uses weights derived from questions asking respondents to indicate the qualitative "importance" of each category for their consumption. The latter two sets of weights should be especially relevant for a respondents who aggregates category-specific expectations according to his personal consumption basket. Together with the first set of weights, our analysis of consistency thus accounts for respondents having potentially different concepts of inflation in mind, either their personal or the official, published inflation rate.

The remaining five sets of weights, in contrast, represent some form of "behavioral" expectations formation. A first gives equal weights, reflecting an agent who notices price changes but neglects expenditure shares. A second takes the self-reported expenditure weights discussed above, but sets food and gasoline weights to zero; this reflects an agent who pays attention to core inflation. A third is the inverse of the aforementioned, reflecting an agent who pays attention to non-core inflation. The non-core weights are motivated by earlier work, which demonstrates the salience of non-core prices for households, such as D'Acunto et al. (2021) for grocery prices or Trehan (2011), Coibion and Gorodnichenko (2015), Binder (2018), or Binder and Makridis (2022) for gas and

[11] Up to second order, aggregate inflation and analogously, its expectation, is given by the (appropriately weighted) mean of category inflation and a second-order variance term: $\pi_t \approx \bar{\pi}_{k,t} + \frac{1}{2} C \text{var}(\pi_{k,t})$ where C denotes a constant. This result follows directly from a Taylor approximation to common price aggregators, and Appendix A.7 provides an example. Our analysis focuses on the first-order approximation. We do so due to the fact presented above about bounds for the range of category expectations relative to the locus of reported aggregate expectations: A large fraction of respondents reports aggregate expectations either above or below the category range. We can thus rule out that a systematic one-sided approximation error drives our results.

Table 4: Aggregated Expectations - Weights

$\mathbb{E}_t^i\,\pi_{t+1}^{aggregated}$	Weights ω_k	Notes
Plausibly rational aggregation		
$\mathbb{E}_t^i\,\pi_{t+1}^{PCE}$	$\omega_k = \frac{C_{k,t}^{PCE}}{\sum_{k=1}^{N} C_{k,t}^{PCE}} \quad \forall k \forall i$	**PCE weights**; $C_{k,t}^{PCE}$ denotes monthly PCE expenditure from BEA.
$\mathbb{E}_t^i\,\pi_{t+1}^{exp}$	$\omega_k^i = \frac{C_{k,t}^i}{\sum_{k=1}^{N} C_{k,t}^i} \quad \forall k$	**Expenditure weights**; $C_{k,t}^i$ denotes average monthly expenditure of i on category k.
$\mathbb{E}_t^i\,\pi_{t+1}^{imp}$	$\omega_k^i = \frac{Imp_{k,t}^i}{\sum_{k=1}^{N} Imp_{k,t}^i} \quad \forall k$	**Importance weights**; $Imp_{k,t}^i \in [0, 100]$ denotes subjective importance to consumption of category k for i.
Behavioral aggregation		
$\mathbb{E}_t^i\,\pi_{t+1}^{equal}$	$\omega_k = \frac{1}{N} \quad \forall k \forall i$	**Equal weights**; each category receives the same weight.
$\mathbb{E}_t^i\,\pi_{t+1}^{core}$	$\omega_k^i = \frac{C_{k,t}^i}{\sum_{k=1}^{N} C_{k,t}^i} \quad \forall k \neq \{Gas,\, Food\}$ $\omega_k = 0 \quad \forall k = \{Gas,\, Food\}$	**Core-inflation weights**; relative average monthly expenditure of i on category k except for food and gasoline. Gas and food weights equal 0.
$\mathbb{E}_t^i\,\pi_{t+1}^{non-core}$	$\omega_k^i = \frac{C_{k,t}^i}{\sum_{k=1}^{N} C_{k,t}^i} \quad \forall k = \{Gas,\, Food\}$ $\omega_k = 0 \quad \forall k \neq \{Gas,\, Food\}$	**Non-core-inflation weights**; relative average monthly expenditure of i on food and gasoline. All other weights equal 0.
$\mathbb{E}_t^i\,\pi_{t+1}^{1^{st}max}$	$\omega_k^i = 1 \forall k = m; \omega_k^i = 0 \forall k \neq m$ $\mathbb{E}_t^i\,\pi_{m,t+1} = 1^{st}\max(\{\mathbb{E}_t^i\,\pi_{k,t+1}\})$	**Max**; aggregate expectation equal to highest category expectation.
$\mathbb{E}_t^i\,\pi_{t+1}^{2^{nd}max}$	$\omega_k^i = 1 \forall k = m; \omega_k^i = 0 \forall k \neq m$ $\mathbb{E}_t^i\,\pi_{m,t+1} = 2^{nd}\max(\{\mathbb{E}_t^i\,\pi_{k,t+1}\})$	**Second max**; aggregate expectation equal to second highest category expectation.

Notes: The table describes the construction of aggregated inflation expectations, based on the category specific expectations as well as different sets of weights.

energy prices. In particular, Arora et al. (2013) find that household inflation expectations react excessively to non-core price changes. A fourth and fifth set of weights take the highest and second-highest category expectation of each survey participant, respectively, as the aggregated inflation expectations, setting all other weights to 0. The choice of these measures is motivated by Bruine de Bruin et al. (2011), who find that extreme inflation rates play an important role in household expectations.

5.2 Statistical Properties of Aggregated Inflation Expectations

Based on these aggregation schemes, the following characteristics of aggregated inflation expectations emerge: First, mean aggregate inflation expectation exceeds those of all three plausibly

Table 5: Summary Statistics

	Mean	Disagreement	Time Series Volatility
Aggregate expectation	6.39	7.53	2.53
Aggregated expectations			
Plausibly rational aggregation			
Expenditure weights	4.95	5.28	1.30
Importance weights	4.59	4.73	1.33
PCE weights	4.46	4.62	1.24
Behavioral aggregation			
Equal weights	4.49	4.59	1.34
Core inflation	4.72	5.21	1.25
Non-core inflation	5.72	6.26	1.67
Max	11.29	8.50	2.81
Second max	6.96	6.44	1.80

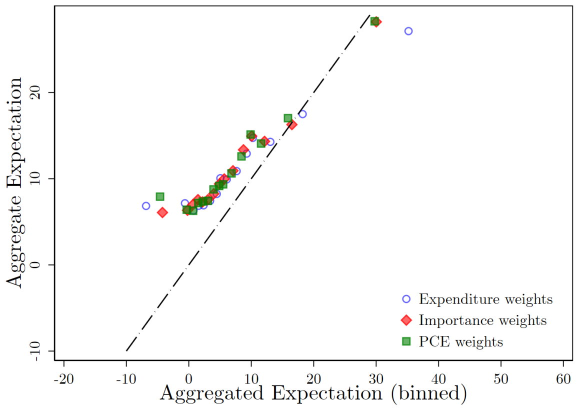
Notes: This table presents summary statistics on the mean on expectations, the standard deviation in the cross-section, and the standard deviation in the (daily mean) time series. Mean expectation: Time series mean of daily Huber-robust and survey-weighted mean expectations (see figure 3, upper row); Disagreement: Time series mean of daily Huber-robust and survey-weighted standard deviation of expectations (see figure 3, lower row); Time series volatility: Time series standard deviation of daily Huber-robust and survey-weighted mean expectations.

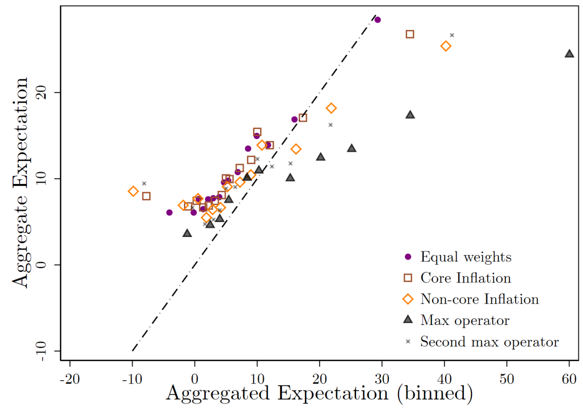
rational aggregations, as well as equal-weighted expectations and non-core- and core-inflation expectations; it is lower than those of both max operators. Second, in the cross-section, the standard deviation of aggregate inflation expectations is higher than that of all aggregations, except the max operator. Similarly, in the time-series dimension, aggregate inflation expectations and the max operator yield the two highest standard deviations. We note that fund managers in our auxiliary survey (A.13) also report aggregate inflation expectations higher than most aggregations (all except the max operator), but disagreement for aggregate expectations is consistently lower. Table 5 provides these summary statistics.

In the cross section, we illustrate these differences between aggregate inflation expectations and *aggregated* inflation expectations by means of a bin-scatter plot.[12] Two features stand out, as Figure 2 shows: First, almost all observations are above the 45°-line, indicating that aggregate inflation expectations tend to be higher than *aggregated* measures. This, however, does not hold for the highest levels of *aggregated* expectations, above a cut-off of 18 percent inflation over the next 12 months. Second, the relationship is nonlinear; beyond a certain upper threshold, more extreme *aggregated* expectations correspond to only slightly more extreme aggregate expectations while below a certain threshold, aggregate expectations diverge more. The same pattern holds

[12]In a related exercise, in Table 14 in the Appendix, we regress aggregate inflation expectations on *aggregated* expectations and a constant. For all measures of *aggregated* expectations, we find a positive, highly significant constant, as well as an *aggregated*-inflation-expectations coefficient smaller than one. The R^2 is largest for the equal-weights aggregation, showing that it explains the largest share of variation in reported aggregate expectations.

Figure 2: Aggregate vs. Aggregated Expectations





Notes: The figure divides aggregated expectations into 15 equal-sized bins and computes mean aggregate inflation expectations for each bin. Left panel: Blue circles: expectations aggregated using reported expenditure shares. Red diamonds: expectations aggregated using reported importance weights. Green squares: expectations aggregated using monthly PCE-weights. Right panel: Purple circles: expectations aggregated using equal weight. Brown squares: core-inflation expectations using reported expenditure shares. Orange diamonds: non-core-inflation expectations using reported expenditure shares. Dark grey triangles: max of category expectations. Light grey crosses: second max of category expectations.

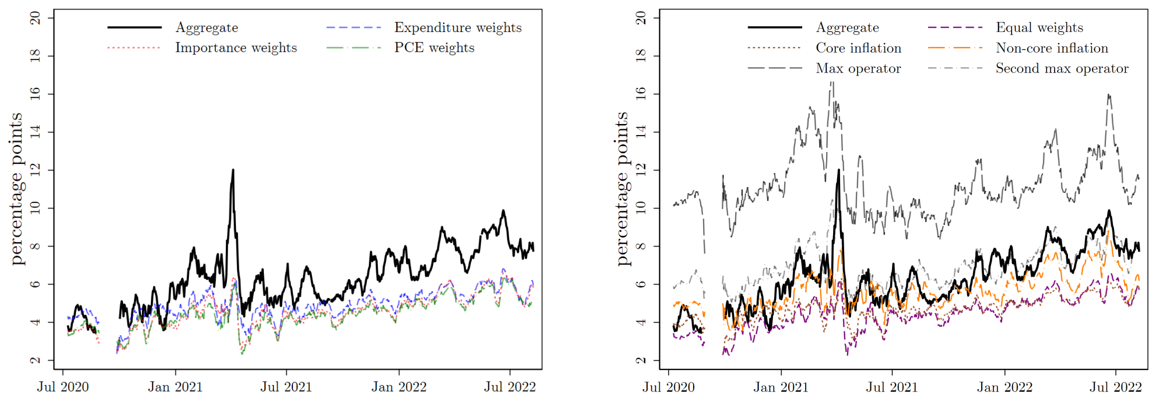
if the conventional, aggregate inflation expectations are binned on the horizontal axis. While for moderate responses there is a strong ordinal relationship, more extreme responses within the conventional measure of inflation expectations do not necessarily correspond to equally extreme *aggregated* expectations beyond a certain upper threshold.

Several time-series patterns emerge, as Figure 3 illustrates: Aggregate inflation expectations generally exceed the plausibly rational aggregations (top-left panel), the equal weights and core aggregations (top-right panel), but are exceeded by the max operator; the second-max and non-core aggregations appear to cluster near aggregate inflation expectations. The bottom row of Figure 3 shows that disagreement in aggregate inflation expectations, measured as the daily cross-sectional standard deviation of expectations, consistently exceeds that in the plausibly rational aggregations (bottom-left panel), equal aggregations (bottom-right panel), and, until about April 2021, that in core, non-core, and second-max aggregations—after which it roughly coincides with disagreement in the latter three aggregations.

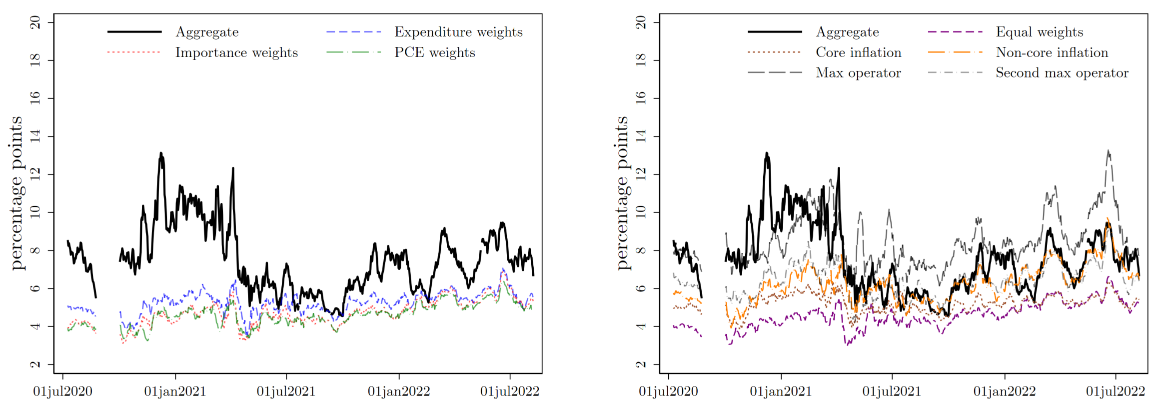
Two additional patterns are worth highlighting. First, the spike in aggregate inflation expectations around April 2021, contemporaneous with a surge in realized inflation and inflation news in the US, far exceeds those observed for plausibly rational aggregations (upper-left panel). Second, following the shift into a high-inflation regime in November 2021, the gap appears to widen between aggregate inflation expectations and plausibly rational aggregations.

Figure 3: Aggregate vs Aggregated Measures

Mean Time Series



Disagreement Time Series



Notes: The top row shows time-series for mean aggregate inflation expectations; the bottom the time-series for disagreement on aggregate inflation, as the daily cross-sectional standard deviation of expectations. The panels show an 11-day balanced moving average of daily observations. Underlying daily observations are Huber-robust and survey-weighted means. In each panel, aggregate inflation expectations are given by a black line, measures of *aggregated* inflation expectations by colored lines. Questions on inflation expectations were not part of the survey during September 2020.

5.3 Gap between Aggregate and Aggregated Inflation Expectations

This section shows that at the individual level, the relationship between aggregate and *aggregated* inflation expectations relates to socio-demographic characteristics, uncertainty of expectations and dispersion of beliefs over categories. To show these insights, we define the *aggregation gap* as the difference between the aggregate expectation and any aggregator of category-inflation expectations.

$$\Lambda_i = \mathbb{E}_t^i \, \pi_{t+1} - \mathbb{E}_t^i \, \pi_{t+1}^{aggregated}$$

Λ_i defines the aggregation gap for survey participant i as the difference between his or her aggregate forecast $\mathbb{E}_t^i \, \pi_{t+1}$ and an *aggregated* expectation measure $\mathbb{E}_t^i \, \pi_{t+1}^{aggregated}$. Table 6 presents Huber-robust and survey-weighted estimates, across all individuals in our sample, for the absolute

Table 6: Summary Statistics

	Absolute Aggregation Gap abs(Λ_i)
Plausibly rational aggregation	
Expenditure weights	5.64***
Importance weights	5.49***
PCE weights	5.33***
Behavioral aggregation	
Equal weights	5.34***
Core inflation	5.67***
Non-core inflation	6.06***
Max	9.09***
Second max	6.51***

Notes: This table presents Huber-robust and survey-weighted estimates for the mean absolute aggregation gap; Stars: significance level of a t-test that numbers are different from zero. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$;

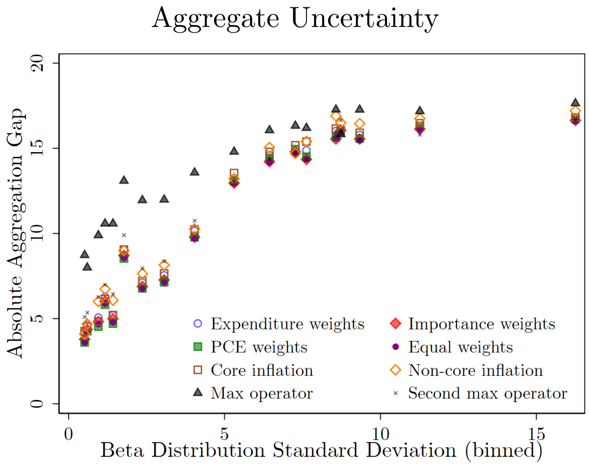
aggregation gap by *aggregated* measure. The absolute aggregation gap provides a measure of the discrepancy between aggregate and *aggregated* inflation expectations irrespective of sign. The max operator yields the largest gap by a clear margin, and the PCE-weights aggregation the smallest, with equal weights but marginally higher.

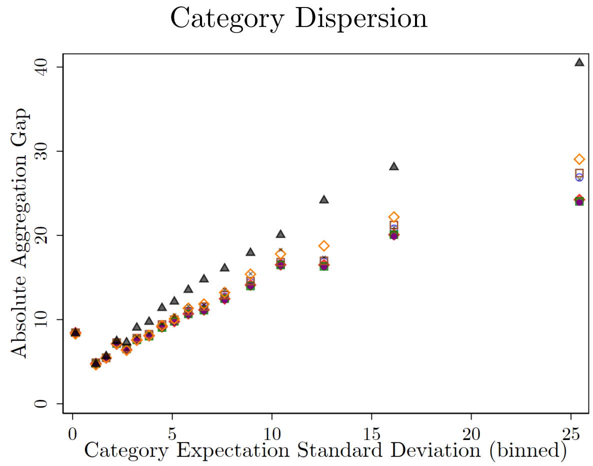
5.3.1 Demographics and the Aggregation Gap

When we regress the absolute aggregation gap on an array of demographic and socio-economic characteristics, we find that women tend to display a higher aggregation gap than do men, as do younger respondents relative to the older. Moreover, higher education is associated with a lower gap, consistent with the notion that responses to at least one of the two inflation-expectation measures—aggregate or *aggregated*—become noisier when the inflation questions are experienced as more complex or difficult to understand. Table 13 in the Appendix summarizes these findings.

These results align with D'Acunto et al. (2019, 2022), who find that cognitive abilities play an important role in forecast accuracy. Moreover, D'Acunto et al. (2022) show that the responses of lower-IQ survey respondents, for which educational attainment might serve as a proxy, are more likely to be rounded, consistent with our interpretation that expectations become noisier for less-educated respondents, thereby yielding a higher aggregation gap. Binder (2017) reports similar results for rounding in surveys, and Stanisławska et al. (2021) find congruent demographic patterns for the probability of consistent responses to questions eliciting expected changes in inflation numerically and qualitatively.

Figure 4: The Aggregation Gap and Uncertainty





Notes: The left panel shows the correlation between the absolute aggregation gap abs(Λ_i) and the individual standard deviation of aggregate inflation expectations obtained via a beta distribution over a probabilistic question; the right panel shows the correlation of the absolute aggregation gap with the individual standard deviation of category expectations.

5.3.2 Uncertainty and the Aggregation Gap

One way to probe the implications of question complexity is to consider the relationship between inflation uncertainty and the absolute aggregation gap. Presumably, elevated uncertainty about inflation expectations may indicate heightened perceived complexity. As a proxy for aggregate inflation-expectations uncertainty at the respondent-level, we take the standard deviation of aggregate inflation expectations reported in a density forecast (QDIST, Appendix C). To obtain this measure, we fit for each respondent an individual beta distribution over the reported probabilities of specific outcomes; the respondent-specific uncertainty can then be obtained as the standard deviation of the distribution fitted. This procedure follows the methodology of Armantier et al. (2017), developed for the SCE.

The root-square aggregation gap increases in a pronounced fashion with respondents' uncertainty about aggregate inflation, as the left panel of Figure 4 shows. A plausible explanation for this pattern is that the cognitive processes underlying aggregate inflation expectations differ from the combination of cognitive processes and aggregation procedures constituting *aggregated* inflation expectations. This could happen because individuals adapt the heuristics at play according to the demands of the task at hand (Payne et al., 1993), and those demands might become differentiated with greater uncertainty about aggregate inflation.

These results are also consistent with those of Ben-David et al. (2018), who find within the SCE that uncertainty about aggregate inflation represents an effective measure of individual confidence in the forecast. Following new information over time, updates in mean expectations are larger for respondents with higher uncertainty. Our results suggest that lower personal confidence in forecasts, as measured by uncertainty, corresponds to higher gaps possibly because the inflation concept respondents have in mind is less clear.

5.3.3 Category-Expectation Dispersion and the Aggregation Gap

Another aspect of complexity in inflation expectations pertains to variation between consumption categories. When an individual expresses greater dispersion in category expectations, this may reflect a more complex, differentiated view on the economy, rendering a judgment on future aggregate inflation inherently more difficult. Moreover, the mere mental computation of aggregate expectations also becomes more challenging.

We use the standard deviation across a respondent's category-inflation expectations as a proxy for the dispersion of category-inflation expectations. The right panel in Figure 4 shows that the absolute aggregation gap increases strongly with dispersion in category expectations.

Overall, we find that the aggregation gap is positively associated with proxies for the complexity of the aggregate inflation concept. In other words, the more complex the aggregate inflation concept, the greater the divergence between aggregate and *aggregated* inflation expectations.

5.3.4 The Directional Aggregation Gap

Results in Table 5, as well as figures 2 and 3, indicate that the reported aggregate inflation expectation exceeds the *aggregated* measures of inflation expectations (apart from max operators). We investigate this discrepancy in Appendix A.2, which reproduces statistics from the section prior, but for the directional aggregation gap rather than the mean root square.

Table 15 in the Appendix shows that all plausibly rational aggregations yield a positive aggregation gap, implying that aggregate inflation expectations on average exceed *aggregated* expectations. This result is noteworthy, especially for expenditure and PCE-weights, as it rejects the idea that the reported aggregate represents merely a mental process summing categories by either self-reported expenditure shares or official PCE-weights. While noise may account for $\Lambda_i > 0$ for an individual survey participant, noise cannot explained that the estimated mean for the cross-section is significantly different from zero.

The lowest gap, moreover, is obtained for the non-core aggregation, which is much lower than that for core expectations. This indicates that non-core expectations—gasoline, energy, and groceries—play an important role in aggregate inflation expectations, in line with the recent literature (e.g., Binder, 2018; D'Acunto et al., 2019; Dietrich, 2022; Trehan, 2011).

As for demographic patterns, the aggregation gap is higher for grocery shoppers, younger respondents, and the less educated. This demographic heterogeneity might point to promising directions for exploring why mean aggregate inflation expectations in major surveys of US consumers, such as the University of Michigan's Survey of Consumers, have been surprisingly high over the last decade, prior to the COVID pandemic. It raises the possibility that average aggregate inflation expectations for nationally representative samples have been inflated by reporting anomalies among specific demographic segments (such as the young with less education).

Interestingly, both measures of task complexity—inflation uncertainty and category expectation dispersion—are associated with a higher directional aggregation gap. That is, as the task complexity increases, consumers increasingly report aggregate inflation numbers greater than their category-based beliefs. This might also explain the visual pattern noted in section 5.2, for Figure 5.2, where we observe that the discrepancy between aggregate inflation expectations and plausibly rational aggregations is particularly pronounced in April 2021, coinciding with surging realized inflation and inflation news, and following November 2021, which brought a shift into the high-inflation regime.

6 Economic Implications

Our findings have important implications for the estimation of a central relationship in macroeconomics—the consumption Euler equation. Regardless of which aggregation of category expectations is chosen as a measure of expected inflation in the estimation of the Euler equation, *aggregated* inflation expectations appear to contain additional, relevant information about consumption plans relative to conventionally elicited inflation expectations. At the same time, estimation using *aggregated* expectations implies lower parameter estimates for the intertemporal elasticity of substitution, a key parameter in the main macroeconomic models. In a simple New Keynesian model as in Galí (2015), our preferred estimate of the intertemporal elasticity of substitution implies potentially higher economic volatility.

To show these results, we estimate a consumption Euler equation. We assume that consumers follow a standard Euler equation, such as

$$Q_{i,t} = \mathbb{E}_t^i \left[\beta_i \left(\frac{C_{i,t+1}}{C_{i,t}} \right)^{-\frac{1}{\sigma}} \frac{P_t}{P_{t+1}} \right] \tag{2}$$

This representation of the household Euler equation is widely used in modern macroeconomics (see, for example, Galí, 2015; Woodford, 2003). We adjust the conventional representative-agent version by allowing for individual i-specific levels of the discount factor β_i, as well as a nominal interest rate $r_{i,t} = -\log(Q_{i,t})$. $\mathbb{E}_t^i$ gives the expectations operator for respondent i. A log-linearized version of equation (2) reads as:

$$c_{i,t} = \mathbb{E}_t \, c_{i,t+1} - \sigma \left[r_{i,t} - \mathbb{E}_t^i \, \pi_{t+1} - \rho_i \right] \tag{3}$$

where $\pi_t = p_t - p_{t-1}$ denotes the inflation rate. While $\mathbb{E}_t \, c_{i,t+1}$ denotes expected log real consumption, questions Q5 to Q7 of our survey ask respondents about expected expenditure relative to the last month, that is, $\mathbb{E}_t^i \, \Delta s_{i,t+1} = \mathbb{E}_t^i \, (\Delta c_{i,t+1} + \pi_{t+1})$. ρ_i is the log discount factor, $\log \beta_i$. Inserting the expression for the expected change in nominal consumption spending into equation (3) yields a version of the Euler equation that links expected spending to expected inflation:

$$\mathbb{E}_t^i \Delta s_{i,t+1} - \mathbb{E}_t^i \pi_{t+1} = \sigma \left[r_{i,t} - \mathbb{E}_t^i \pi_{t+1} - \rho_i \right] \tag{4}$$

On the left-hand side, we have the expected change in spending, net of the expected rate of inflation. Building on the empirical approach by Crump et al. (2021), we can now estimate this equation in the following form:

$$\mathbb{E}_t^i \Delta s_{i,t+1} = \beta_0 + \beta_1 \mathbb{E}_t^i \pi_{t+1} + D_i + T_t + \epsilon_{i,t} \tag{5}$$

where D_i represents demographic fixed effects[13] as well as a control for income expectations, and T_t represents time fixed effects. Including both time and demographic fixed effects relies on the assumption that $r_{i,t} - \rho_i$ may be explained by both variation in time (for example, by changes in the nominal interest rate) and demographic factors, which can impact both the rate of time preference and the nominal interest rate faced by households (i.e., specific risk premia). The coefficient β_1 in the estimation equation is equal to $1 - \sigma$ in the model in equation (4).

Estimation of the consumption Euler equation using *aggregated* measures of inflation expectations has clear implications for the estimated intertemporal elasticity of substitution. Estimates based on aggregated expectations all come out lower than the estimate based on aggregate inflation expectations. Table 7 shows the estimation results—using our individual-level, cross-sectional data—for the full array of inflation expectation measures in the cross-section. Here, we report $1 - \hat{\beta}_1$, which is equal to the intertemporal elasticity of substitution σ. The fourth column gives the R^2 values, the fifth the Akaike information criterion, and the sixth the p-value of a likelihood ratio test, which compares the fit of the respective models to the aggregate inflation-expectation model. To control for possible reporting errors within inflation expectations, Table 18 in the Appendix reports estimated coefficients for an instrumental variable regression, which takes as an instrument for each measure of inflation expectations the individual mean inflation expectation from the probability distribution question (QDIST, Appendix C).

Two results are additionally of note: First, coefficients for inflation expectations are highly significant in all models. Notably, the AIC and the likelihood ratio test suggest improved fit for the *aggregated* measures over aggregate inflation expectations. Moreover, the latter model obtains the lowest R^2. That is, the proportion of variation explained in planned consumption one year ahead is lower for aggregate inflation expectations than for any other *aggregated* measure; *aggregated* measures of inflation expectations are more informative for future spending plans and can thus be said to better represent effective beliefs.

Second, a similar picture emerges when we repeat the estimation for one-year-ahead nondurable and services spending, respectively. The aggregate inflation-expectations model for nondurable

[13] Since we rely only on a cross-sectional sample without a panel dimension, we include demographic controls, instead of individual fixed effects.

Table 7: 1 Year Ahead Spending Plans

	$\hat{\sigma} = 1 - \hat{\beta}_1$	t-stat	R^2	AIC	LR	N
Aggregate	0.960***	7.69	0.057	168157	-	23682
Expenditure	0.821***	15.35	0.083	167499	0.000	23682
Importance	0.786***	16.79	0.087	167390	0.000	23682
PCE	0.788***	15.92	0.085	167439	0.000	23682
Equal	0.777***	16.57	0.088	167381	0.000	23682
Core inflation	0.842***	13.37	0.076	167674	0.000	23682
Non-core inflation	0.874***	14.52	0.076	167679	0.000	23682
Max	0.912***	14.58	0.074	167737	0.000	23682
Second max	0.870***	14.36	0.079	167598	0.000	23682
12-months-ahead nondurable spending						
Aggregate	0.957***	4.96	0.058	33103	-	4696
Expenditure	0.808***	9.34	0.084	32975	0.000	4696
Importance	0.747***	10.67	0.094	32922	0.000	4696
PCE	0.770***	9.71	0.085	32967	0.000	4696
Equal	0.732***	10.27	0.094	32919	0.000	4696
Core inflation	0.845***	8.07	0.073	33027	0.000	4696
Non-core inflation	0.842***	8.64	0.083	32980	0.000	4696
Max	0.907***	6.90	0.071	33039	0.000	4696
Second max	0.851***	8.37	0.086	32964	0.000	4696
12-months-ahead services spending						
Aggregate	0.967***	7.21	0.059	162468	-	23793
Expenditure	0.857***	14.48	0.081	161916	0.000	23793
Importance	0.824***	15.75	0.086	161764	0.000	23793
PCE	0.820***	15.17	0.087	161751	0.000	23793
Equal	0.813***	15.65	0.088	161722	0.000	23793
Core inflation	0.861***	14.07	0.079	161951	0.000	23793
Non-core inflation	0.904***	12.72	0.073	162116	0.000	23793
Max	0.929***	14.06	0.074	162096	0.000	23793
Second max	0.891***	13.82	0.080	161923	0.000	23793

Notes: Estimated Euler equations, relying on various measures of aggregate or aggregated inflation expectations; t statistics in third column, based on robust standard errors; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; regression adjusted with survey weights to ensure that sample is representative. Data for nondurable spending until 25.02.2021. LR gives the likelihood ratio for the reported aggregate expectations model to minimize the information loss.

spending obtains the highest AIC and the lowest R^2, and *aggregated* models are statistically distinct, according to the likelihood ratio test. Similarly, the aggregate inflation-expectations model for spending on services yields the highest AIC and the lowest R^2, although its performance is matched by the model using self-reported expenditure weights.

Our estimates based on *aggregated* expectations imply relatively higher economic volatility than do those based on conventional aggregate expectations. We demonstrate the economic significance of changes in the intertemporal elasticity of substitution in the context of monetary policy, but could also do so in other model contexts, such as forward guidance. We simulate productivity shocks in a simple New Keynesian textbook model, as in Galí (2015),[14] first using an estimate of the intertemporal elasticity of substitution based on an estimation that uses aggregate inflation expectations ($\sigma = 0.960$, see Table 4); and second, using an elasticity based on an estimation that uses an aggregation of equal weights ($\sigma = 0.777$, see Table 4). We leave all other parameters fixed to highlight the economic importance of the difference in our estimate. We then record two metrics of economic volatility: the variance of inflation and the variance of the output gap. We find large changes: The variance of inflation is 12.2% higher in the simulation that uses the elasticity based on (equal-weight) *aggregated* inflation expectations, relative to simulations using estimates based on aggregate expectations. Similarly, the variance of the output gap is 5.7% higher across theses specifications. In welfare analysis, these changes may be considered costly.

6.1 Aggregation Gap and Spending Plans

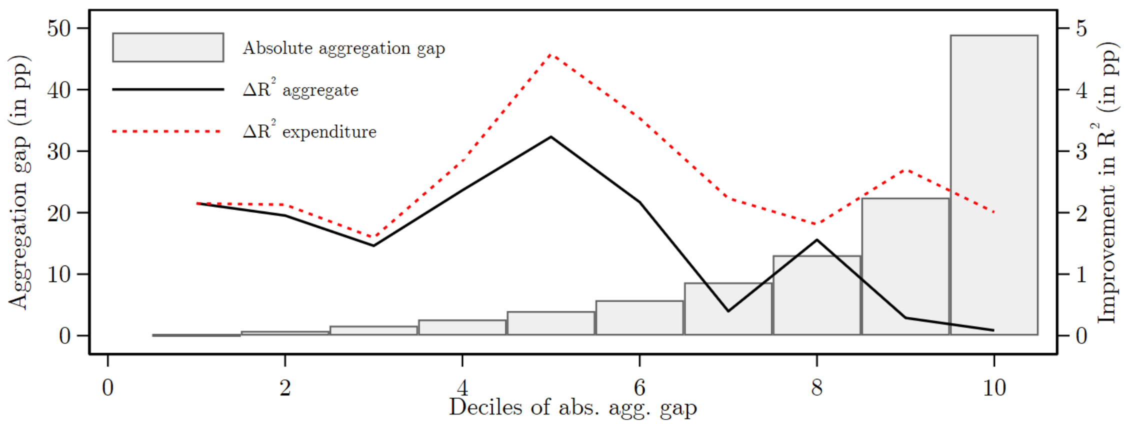
The estimation of the Euler equation can also be used to further substantiate the finding that all *aggregated* measures of inflation expectations contain superior information for explaining spending plans compared to the conventional aggregate measure of inflation expectations. Specificallly, *aggregated* measures of inflation expectations are more informative regardless of the aggregation gap, which, as shown in Section 5.3, relates systematically to heterogeneity in the population, namely socio-demographics and uncertainty.

To establish this insight, we split the sample by deciles of the absolute aggregation gap outlined in Section 5.3 and then repeat the estimation of the Euler equation. For each decile, we estimate the Euler equation for planned changes in total spending, as detailed in Equation 5. We are interested in the amount of variation (R^2) of total spending plans explained when we use either the aggregate or *aggregated* measure of inflation expectations as an explanatory variable, benchmarked against a restricted specification with only a constant. In Figure 5, the right axis indicates this difference between a model's R^2 and the benchmark. The dashed, red line shows the improvement for *aggregated* inflation expectations, and the black solid line for the conventional, aggregate measure of inflation expectations. As a background, the grey bars in Figure 5 display for each decile (left axis) the mean absolute aggregation gap between the conventional, aggregate inflation expectation and the expenditure-weighted, *aggregated* inflation expectation.

According to the definition of R^2, including an additional independent variable in the estimation improves the share of total variance explained. Thus, both lines are always above 0. By construction, the difference between the two measures is close to 0 for respondents with the smallest absolute aggregation gaps, as the measures necessarily differ only slightly. However, as the absolute aggregation gap grows, a clear pattern emerges for the conventional measure of aggregate inflation expectations: The improvement in R^2 from including the measure into the Euler-equation

[14] All parameters are identical to those in chapter 3 of Galí (2015).

Figure 5: Spending Plan regressions for deciles of the abs. agg. gap



Notes: The figure compares the improvement, for each decile of the aggregation gap, in R^2 achieved by adding a measure of inflation expectations to the estimation in equation (5), relative to an estimation without inflation expectations. Grey bars: Mean aggregation gap (left vertical axis) for each decile on horizontal axis. Black line, right vertical axis: improvement in R^2 by adding the conventional measure of inflation expectations. Red line, right vertical axis: improvement in R^2 by adding the *aggregated* measure of inflation expectations (expenditure-weighted).

regression declines substantially, approaching 0 for those with the largest aggregation gaps. When using the expenditure-weighted, *aggregated* expectations in the regression, on the other hand, the improvement in the R^2 does not appear to vary systematically with the gap, and it is also consistently higher than the R^2 achieved from using the aggregate measure. Against the backdrop of sociodemographic heterogeneity and uncertainty associated with the aggregation gap, this insight of superior explanatory power of aggregated inflation expectations for spending plans is highly relevant—for example, for policymakers—for measuring inflation expectations effectively across diverse parts of the population.

7 Conclusion

This paper presents novel survey evidence on disaggregated consumer inflation expectations by PCE categories. Four striking facts stand out. The first is that aggregate inflation expectations are higher than inflation expectations for any single category. For the representative agent, this rules out a linear mapping (with non-negative weights) of the category expectations into the aggregate inflation expectations. Moreover, disagreement among respondents over aggregate inflation expectations is higher than that over any category. Second, *aggregated* inflation expectations are lower than the aggregate expectations—the whole is greater than the sum of the parts. *Aggregated* inflation expectations are also less dispersed. Third, the respondent-specific gap between aggregate and *aggregated* inflation expectations rises with the subjective complexity of the aggregate inflation concept and correlates in a meaningful way with socioeconomic characteristics such as education.

Fourth, *aggregated* inflation expectations represent better predictors of planned consumer spending than do aggregate inflation expectations. Effective inflation expectations, it would therefore appear, are *not* best represented by explicit, conventionally reported aggregate inflation expectations, but by aggregations of category-specific inflation expectations. We find that this holds true regardless of socio-demographic heterogeneity and uncertainty faced by respondents.

These results provide a first step at disaggregating the object of inflation expectations, and studying the properties of the disaggregated expectations. Statistically, additional information emerges, as well as insights into the formation of inflation expectations with potential policy relevance. Our analysis opens up questions for future work - for example, what role heterogeneity plays for updating expectations, or what the optimal level of disaggregation is for eliciting inflation expectations.

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A Additional Tables

A.1 Demographic Summary Statistics

Table 8: Summary Statistics - Mean Demographics

	Gender		Grocery		Education		Income		
	Female	Male	Yes	No	High	Low	High	Middle	Low
Aggregate expectation	7.31	6.01	6.70	5.87	6.11	7.46	7.65	6.36	6.97
Category expectations									
Motor vehicles	5.68	5.41	5.54	5.67	5.71	5.35	5.82	5.51	5.37
Recreational goods	4.45	3.72	4.01	4.04	4.23	3.82	4.27	4.18	3.85
Other durable goods	4.32	3.96	4.15	3.80	4.32	3.94	4.62	4.21	3.90
Food and beverages	5.79	4.88	5.28	5.60	5.39	5.27	5.60	5.52	5.25
Gasoline	5.78	4.96	5.28	5.74	5.40	5.35	5.39	5.72	5.27
Other nondurable	4.41	3.95	4.20	3.97	4.33	4.05	4.58	4.28	3.94
Housing and util.	5.28	4.66	4.99	4.94	5.22	4.77	5.30	5.34	4.69
Health care	4.15	3.90	4.03	3.95	4.21	3.81	4.53	4.13	3.70
Transportation	5.26	4.46	4.87	4.73	4.89	4.82	4.78	5.09	4.87
Food services	5.02	4.57	4.81	4.92	5.05	4.56	5.23	4.87	4.52
Other services	4.58	4.07	4.37	4.22	4.39	4.27	4.56	4.51	4.23
Aggregated expectations									
Plausibly rational aggregation									
Expenditure weights	5.40	4.63	4.99	5.14	5.08	4.95	5.22	5.22	4.90
Importance weights	5.02	4.28	4.61	4.77	4.78	4.51	4.88	4.81	4.49
PCE weights	4.90	4.15	4.48	4.53	4.63	4.41	4.75	4.65	4.36
Behavioral aggregation									
Equal weights	4.89	4.21	4.52	4.60	4.69	4.42	4.75	4.65	4.41
Core inflation	5.10	4.47	4.77	4.71	4.88	4.68	4.96	4.92	4.61
Non-core inflation	6.30	5.25	5.72	6.27	5.68	5.86	5.83	6.00	5.85
Max	12.54	10.58	11.29	12.75	11.29	11.76	11.52	11.48	11.94
Second max	7.64	6.51	6.97	7.57	7.06	7.01	7.06	7.21	7.16

Notes: This table presents summary statistics on the Huber-robust and survey-weighted mean on expectations across demographics.

Table 9: Summary Statistics - Standard Deviation Demographics

	Gender		Grocery		Education		Income		
	Female	Male	Yes	No	High	Low	High	Middle	Low
Aggregate expectation	10.18	5.86	7.88	7.03	5.98	10.22	7.61	6.22	9.67
Category expectations									
Motor vehicles	6.51	5.26	5.92	5.98	5.44	6.22	5.34	5.38	6.29
Recreational goods	6.83	5.62	6.34	5.85	5.67	6.79	5.57	5.61	6.90
Other durable goods	6.73	5.43	6.21	5.51	5.49	6.56	5.57	5.45	6.82
Food and beverages	7.06	5.86	6.49	6.08	5.83	6.89	5.93	5.76	6.99
Gasoline	7.97	7.24	7.49	8.30	7.47	7.65	7.33	7.56	7.77
Other nondurable	6.55	5.33	6.03	5.67	5.34	6.50	5.31	5.43	6.48
Housing and util.	6.93	5.76	6.47	6.13	5.77	6.94	5.79	5.90	6.92
Health care	6.99	5.90	6.51	6.21	6.09	6.80	6.15	5.99	6.83
Transportation	6.80	5.50	6.21	5.97	5.63	6.69	5.55	5.60	6.83
Food services	6.87	5.85	6.49	6.03	6.03	6.70	6.04	5.80	6.88
Other services	6.20	4.98	5.70	5.31	5.01	6.12	5.11	5.04	6.13
Aggregated expectations									
Plausibly rational aggregation									
Expenditure weights	5.87	4.64	5.29	4.92	4.74	5.72	4.58	4.81	5.78
Importance weights	5.16	4.20	4.72	4.40	4.40	4.83	4.16	4.42	4.98
PCE weights	5.11	4.06	4.63	4.23	4.23	4.84	4.10	4.23	4.91
Behavioral aggregation									
Equal weights	5.00	4.06	4.59	4.26	4.28	4.68	4.00	4.29	4.84
Core inflation	5.76	4.56	5.22	4.76	4.66	5.69	4.40	4.70	5.67
Non-core inflation	6.78	5.65	6.26	6.02	5.78	6.64	5.87	5.77	6.77
Max	9.57	7.62	8.41	8.95	7.99	8.98	7.94	8.11	9.30
Second max	7.13	5.82	6.43	6.51	5.87	6.90	5.81	6.05	7.11

Notes: This table presents summary statistics on the Huber-robust and survey-weighted standard deviation on expectations across demographics.

Table 10: Summary Statistics - Age Groups

	Mean				Disagreement (SD)			
	18-34	35-44	45-54	above 55	18-34	35-44	45-54	above 55
Aggregate expectation	7.95	9.00	8.42	5.74	11.64	11.63	9.62	4.36
Category expectations								
Motor vehicles	4.62	5.89	5.98	6.35	6.38	6.26	6.04	4.97
Recreational goods	2.47	4.11	4.81	5.28	7.15	6.89	6.25	4.50
Other durable goods	2.82	4.25	4.77	5.23	6.76	6.87	6.13	4.64
Food and beverages	3.80	5.41	6.32	7.06	6.99	7.18	6.78	5.19
Gasoline	3.81	5.16	6.50	7.60	7.42	7.32	7.63	7.98
Other nondurable	2.85	4.26	5.11	5.25	7.00	6.57	6.00	4.34
Housing and util.	3.66	4.77	5.96	6.30	7.08	7.09	6.48	5.09
Health care	2.61	4.17	4.59	5.26	7.02	6.79	6.15	5.30
Transportation	3.51	4.80	5.59	6.27	6.86	6.74	6.41	4.95
Food services	3.06	4.65	5.55	6.62	6.94	6.77	6.32	5.32
Other services	3.37	4.24	5.06	5.20	6.35	6.26	5.56	4.08
Aggregated expectations								
Plausibly rational aggregation								
Expenditure weights	3.66	4.95	6.02	6.47	5.11	5.28	5.31	4.65
Importance weights	3.05	4.51	5.61	6.46	3.81	4.60	4.82	4.53
PCE weights	3.10	4.36	5.37	6.17	4.02	4.75	4.66	4.14
Behavioral aggregation								
Equal weights	2.99	4.42	5.42	6.32	3.68	4.54	4.69	4.32
Core inflation	3.63	4.68	5.64	5.96	5.32	5.26	5.13	4.42
Non-core inflation	4.16	5.66	6.73	7.36	6.36	6.43	6.41	5.66
Max	10.63	11.61	12.23	13.22	8.09	8.51	9.19	8.89
Second max	6.13	7.27	7.47	8.50	6.65	6.64	7.01	5.88

Notes: This table presents summary statistics on the Huber-robust and survey-weighted mean and standard deviation on expectations across age groups.

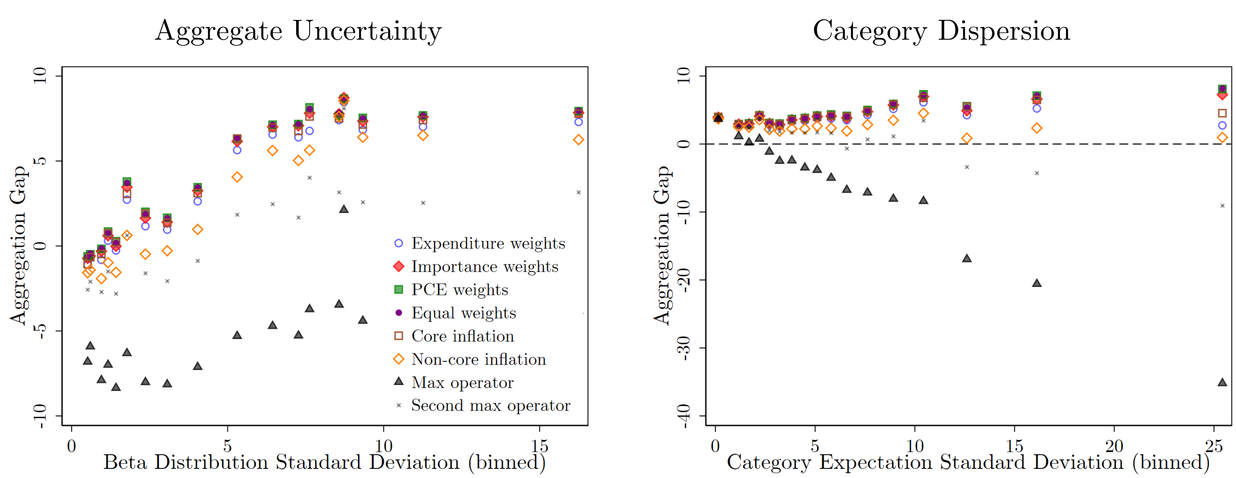
A.2 The Directional Aggregation Gap

Table 11: Summary Statistics

	Mean Aggregation Gap (Λ_i)	Mean Absolute Aggregation Gap abs(Λ_i)
Plausibly rational aggregation		
Expenditure weights	1.33***	5.64***
Importance weights	1.55***	5.49***
PCE weights	1.62***	5.33***
Behavioral aggregation		
Equal weights	1.64***	5.34***
Core inflation	1.62***	5.67***
Non-core inflation	0.68***	6.06***
Max	-3.97***	9.09***
Second max	-0.42***	6.51***

Notes: This table presents Huber-robust and survey-weighted estimates for the mean aggregation gap and mean root square aggregation gap; Stars: significance level of a t-test that numbers are different from zero. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$;

Figure 6: The Aggregation Gap and Uncertainty



Notes: The left panel shows the correlation between the aggregation gap Λ_i^{exp} and the individual aggregate inflation expectations obtained via a beta distribution over a probabilistic question; the right panel shows the correlation with the individual standard deviation of category expectations.

A.3 Demographic Effects: The Aggregation Gap

Table 12: Demographics and the Aggregation Gap

	(1) Expenditure	(2) Importance	(3) PCE	(4) Equal	(5) Core	(6) Non-core	(7) 1^{st}max	(8) 2^{nd} max
Female	-0.0288	-0.0639	-0.0523	-0.0378	0.146	-0.239**	-0.808***	-0.349***
	(-0.37)	(-0.86)	(-0.72)	(-0.52)	(1.87)	(-2.68)	(-8.04)	(-4.12)
Grocery Shopper	0.895***	0.909***	0.898***	0.867***	0.825***	0.908***	1.721***	1.293***
	(7.57)	(8.07)	(8.08)	(7.85)	(6.95)	(6.64)	(11.00)	(9.84)
35 to 44 years	-0.219*	-0.376***	-0.289**	-0.377***	-0.148	-0.661***	-0.111	-0.0852
	(-2.10)	(-3.75)	(-2.92)	(-3.83)	(-1.39)	(-5.37)	(-0.86)	(-0.76)
45 to 54 years	-1.174***	-1.257***	-1.182***	-1.212***	-1.013***	-1.695***	-0.774***	-0.744***
	(-9.57)	(-10.59)	(-10.02)	(-10.40)	(-8.13)	(-11.99)	(-4.90)	(-5.50)
above 55 years	-2.798***	-3.047***	-2.749***	-2.952***	-2.453***	-3.802***	-3.847***	-3.032***
	(-33.48)	(-37.95)	(-34.90)	(-37.53)	(-29.04)	(-38.00)	(-34.77)	(-32.88)
High Educated	-0.673***	-0.705***	-0.722***	-0.711***	-0.699***	-0.581***	-0.873***	-0.830***
	(-7.80)	(-8.49)	(-8.83)	(-8.73)	(-7.99)	(-5.84)	(-7.61)	(-8.68)
Middle Income	0.0624	0.142	0.188*	0.175*	0.112	-0.201*	0.110	0.188
	(0.70)	(1.64)	(2.20)	(2.07)	(1.25)	(-1.99)	(0.93)	(1.88)
High Income	0.110	0.0624	0.0902	0.103	0.0815	0.0826	0.433**	0.205
	(0.96)	(0.57)	(0.83)	(0.96)	(0.71)	(0.64)	(2.88)	(1.64)
Constant	2.098***	2.430***	2.358***	2.474***	2.201***	2.307***	-3.242***	0.198
	(15.49)	(18.74)	(18.43)	(19.42)	(16.08)	(14.36)	(-18.47)	(1.33)
N	54453	54183	52857	54205	53152	49216	55995	55009
r2	0.0346	0.0430	0.0389	0.0421	0.0289	0.0471	0.0377	0.0353

Notes: This table presents Huber-robust and survey-weighted regressions of the aggregation gap on several demographic characteristics. The headers for each column represent the aggregation mechanism. For details on aggregated expectations, see Table 4. t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 13: Demographics and the Absolute Aggregation Gap

	(1) Expenditure	(2) Importance	(3) PCE	(4) Equal	(5) Core	(6) Non-core	(7) 1^{st}max	(8) 2^{nd} max
Female	0.764***	0.658***	0.734***	0.687***	0.819***	0.602***	0.923***	0.593***
	(12.40)	(11.41)	(12.74)	(12.09)	(12.92)	(8.52)	(9.64)	(8.47)
Grocery Shopper	-0.0469	0.00631	-0.0275	-0.0189	-0.0474	-0.227*	-0.551***	-0.230*
	(-0.51)	(0.07)	(-0.32)	(-0.22)	(-0.50)	(-2.16)	(-3.74)	(-2.20)
35 to 44 years	-0.276***	-0.272***	-0.206**	-0.272***	-0.211*	-0.408***	-0.321**	-0.384***
	(-3.31)	(-3.45)	(-2.62)	(-3.50)	(-2.43)	(-4.15)	(-2.59)	(-4.12)
45 to 54 years	-0.906***	-0.908***	-0.850***	-0.912***	-0.947***	-1.210***	-0.706***	-0.692***
	(-9.34)	(-9.98)	(-9.26)	(-10.14)	(-9.44)	(-10.98)	(-4.86)	(-6.34)
above 55 years	-2.001***	-1.993***	-2.068***	-2.022***	-2.140***	-2.007***	-0.721***	-1.689***
	(-30.31)	(-32.19)	(-33.64)	(-33.18)	(-31.62)	(-25.44)	(-6.90)	(-22.47)
High Educated	-0.591***	-0.624***	-0.724***	-0.663***	-0.651***	-0.477***	-0.164	-0.605***
	(-8.54)	(-9.65)	(-11.19)	(-10.43)	(-9.15)	(-6.01)	(-1.49)	(-7.65)
Middle Income	-0.284***	-0.205**	-0.192**	-0.217**	-0.284***	-0.310***	-0.376***	-0.189*
	(-3.97)	(-3.05)	(-2.85)	(-3.28)	(-3.87)	(-3.86)	(-3.41)	(-2.32)
High Income	-0.0311	-0.0785	-0.0265	-0.0668	-0.0254	-0.0936	0.218	0.0174
	(-0.34)	(-0.93)	(-0.31)	(-0.80)	(-0.27)	(-0.92)	(1.52)	(0.17)
Constant	6.492***	6.314***	6.201***	6.258***	6.602***	7.363***	9.387***	7.244***
	(60.79)	(63.81)	(62.91)	(63.93)	(60.17)	(59.05)	(56.49)	(60.23)
N	54348	54034	52846	54172	53175	49148	57473	55146
r2	0.0368	0.0401	0.0465	0.0430	0.0415	0.0277	0.00469	0.0197

Notes: This table presents Huber-robust and survey-weighted regressions of the absolute aggregation gap on several demographic characteristics. The headers for each column represent the aggregation mechanism. For details on aggregated expectations, see Table 4. t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

A.4 Aggregate vs. Aggregated Inflation Expectations

Table 14: Aggregate vs. Aggregated Inflation Expectations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Expenditure	0.557***								0.116
	(34.72)								(1.61)
Importance		0.650***							-0.220*
		(37.02)							(-2.15)
PCE			0.639***						-0.378***
			(35.12)						(-4.48)
Equal				0.685***					1.042***
				(38.07)					(8.44)
Core Inflation					0.514***				-0.0122
					(31.32)				(-0.22)
Non-core Inflation						0.389***			-0.0429
						(30.63)			(-1.40)
Max							0.314***		0.126***
							(33.93)		(7.01)
Second max								0.411***	0.00485
								(31.63)	(0.17)
Constant	7.589***	7.174***	7.370***	7.067***	8.123***	8.464***	6.446***	7.440***	6.187***
	(48.97)	(45.39)	(46.10)	(44.83)	(53.66)	(55.85)	(38.32)	(44.68)	(37.39)
N	50701	50701	50701	50701	50701	50701	50701	50701	50701
R2	0.0721	0.0807	0.0756	0.0840	0.0621	0.0560	0.0668	0.0652	0.0906
AIC	441745	441270	441551	441088	442285	442618	442033	442117	440735

Notes: The table presents estimates on a micro level for a linear regression of reported aggregate on one (column 1 to 8) or multiple (column 9) aggregated, category-based measures of inflation. t statistics in parentheses, based on robust standard errors; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; regression adjusted with survey weights to ensure that sample is representative.

A.5 The Aggregation Gap - Time Series

Table 15: The Aggregation Gap - Time Series

	Mean Aggregation Gap (Λ_i)	Mean Absolute Aggregation Gap abs(Λ_i)
Plausibly rational aggregation		
Expenditure weights	1.30***	1.69***
Importance weights	1.63***	1.85***
PCE weights	1.74***	1.94***
Behavioral aggregation		
Equal weights	1.72***	1.89***
Core inflation	1.56***	1.87***
Non-core inflation	0.56***	1.40***
Max	-4.75***	4.78***
Second max	-0.64***	1.45***

Notes: This table presents Huber-robust estimates for the mean difference between daily aggregate and aggregated expectations in the time series, as well as the mean absolute gap; Stars: significance level of a t-test that numbers are different from zero. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$;

A.6 Category Expectations

Table 16: Categories with 1^{st} and 2^{nd} highest expectation

Category	1st max	2nd max
Motor vehicles	35.9%	36.5%
Recreational goods	29.3%	35.5%
Other durable goods	29.4%	35.9%
Food and beverages	35.0%	40.1%
Gasoline	41.6%	35.9%
Other nondurable goods	28.8%	36.5%
Housing and utilities	34.4%	37.3%
Health care	30.8%	36.1%
Transportation services	33.9%	38.5%
Food services	32.0%	39.1%
Other services	29.6%	35.8%

Notes: The table shows the frequency for each category of being a survey participant's largest or second-largest expectation in the cross-section. Note that numbers need not add up to 1 as a respondent might have the same expectation for multiple categories.

A.7 Second-Order Approximation to the Price Index

A second-order log-linear approximation for conventional price indices, such as

$$
\begin{aligned}
1 &= \int_0^1 \left(\frac{P(i)}{P}\right)^{1-\epsilon} di && (6)\\
&= \int_0^1 e^{(1-\epsilon)(p(i)-p)} di && (7)\\
&\approx 1+(1-\epsilon)\int_0^1 (p(i)-p)di + \frac{(1-\epsilon)^2}{2}\int_0^1 (p(i)-p)^2 di && (8)
\end{aligned}
$$

where $p(i)$ and p denote logs of the respective prices.

As a result,

$$
\begin{aligned}
p_t &\approx \bar{p}_{i,t} + \frac{1-\epsilon}{2}\int_0^1 (p(i)-p)^2 di && (9)\\
&= \bar{p}_{i,t} + \frac{1-\epsilon}{2}\mathrm{var}(p(i)) && (10)
\end{aligned}
$$

where $\bar{p}_{i,t}$ denotes the average of log prices.

A.8 Time Series - Persistence

Table 17: AR(1) persistence

	AR(1), daily	AR(1), weekly
Aggregate expectation	0.39	0.80
Category expectations		
Motor vehicles	0.47	0.79
Recreational goods	0.28	0.66
Other durable goods	0.36	0.73
Food and beverages	0.27	0.59
Gasoline	0.41	0.63
Other nondurable goods	0.28	0.68
Housing and utilities	0.14	0.48
Health care	0.36	0.68
Transportation services	0.36	0.69
Food services	0.33	0.58
Other services	0.24	0.67
Aggregated expectation		
Plausibly rational aggregation		
Expenditure	0.25	0.62
Importance	0.30	0.72
PCE	0.37	0.74
Behavioral aggregation		
Equal	0.26	0.68
Core inflation	0.33	0.51
Non-core inflation	0.34	0.72
Max	0.11	0.60
Second max	0.30	0.57

Notes: This table presents estimated persistence (AR(1) process) of expectations in the time series, both for a daily and weekly aggregation. Huber-robust regressions used to make estimated coefficient insensitive to outliers.

A.9 Model Fit

In order to compare the model fit of different expectations measures, we rely on the Akaike Information Criterion (AIC). This is equal to:

$$AIC = 2k - 2\ln(\hat{L})$$

Where k is the number of estimated parameter sin the model and $\hat{L}$ represents the maximized value of the likelihood function.

Similarly, to study the statistical significance of differences in the model fit between various measures of expectations, we compute the likelihood ratio of models. Specifically assume that the AIC is lower for model 2 than for model 1, $AIC_1 > AIC_2$. Then, the likelihood ratio is defined as:

$$\begin{aligned} LR &= \frac{\hat{L}_1}{\hat{L}_2} \\ &= \exp\left(\frac{AIC_2 - AIC_1}{2}\right) \text{ if } k_1 = k_2 \end{aligned}$$

where the second line links the likelihood ratio to the AIC, given that both models estimate the same number of parameters. The likelihood ratio $LR \in [0, 1]$ then shows how probable model 1 is to minimize the information loss, relative to model 2.

A.10 Spending Plans - Instrumental Variable Regression

Table 18: Instrumental Variable regression: 1 Year Ahead Spending Plans

	$\hat{\sigma} = 1 - \hat{\beta}_{OLS}$ (OLS)	$\hat{\sigma} = 1 - \hat{\beta}_{IV}$ (IV)	t-stat	F-stat (first stage)	N
12-month-ahead aggregate spending					
Aggregate	0.960***	0.863***	7.34	478	23053
Expenditure	0.821***	0.700***	7.55	364	23053
Importance	0.786***	0.696***	7.63	445	23053
PCE	0.788***	0.673***	7.60	410	23053
Equal	0.777***	0.684***	7.63	463	23053
Core inflation	0.842***	0.667***	7.38	279	23053
Non-core inflation	0.874***	0.758***	7.45	364	23053
Max	0.912***	0.748***	7.29	198	23053
Second max	0.870***	0.717***	7.44	261	23053
12-month-ahead nondurable spending					
Aggregate	0.957***	0.889***	4.12	144	4567
Expenditure	0.808***	0.551***	3.99	42	4567
Importance	0.747***	0.492***	3.96	38	4567
PCE	0.770***	0.490***	3.99	43	4567
Equal	0.732***	0.479***	4.00	45	4567
Core inflation	0.845***	0.590***	3.93	47	4567
Non-core inflation	0.842***	0.468***	3.58	21	4567
Max	0.907***	0.523***	3.14	14	4567
Second max	0.851***	0.552***	3.70	26	4567
12-month-ahead services spending					
Aggregate	0.967***	0.927***	4.90	503	23168
Expenditure	0.857***	0.838***	5.01	372	23168
Importance	0.824***	0.837***	5.01	445	23168
PCE	0.820***	0.824***	5.02	412	23168
Equal	0.813***	0.831***	5.03	464	23168
Core inflation	0.861***	0.818***	4.96	286	23168
Non-core inflation	0.904***	0.871***	4.97	374	23168
Max	0.929***	0.869***	4.92	215	23168
Second max	0.891***	0.850***	4.98	275	23168

Notes: Estimated Euler equations, based on cross-sectional data; measures of inflation expectations in first column instrumented with the mean inflation expectation from the distribution question; see Table **??** for details on OLS results. t statistics in third column, based on robust standard errors; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$;

A.11 Aggregate Inflation Measure

Table 19: Replication Study - Wording of Aggregate Inflation Question

	Mean	Std. Dev. (Disagreement)
Aggregate expectation		
"Inflation"	9.54	8.20
"PCE Inflation"	9.86	7.35
"CPI Inflation"	10.17	7.08
Category expectations		
Motor vehicles	6.60	5.13
Recreational goods	5.05	7.01
Other durable goods	5.31	6.50
Food and beverages	7.00	7.19
Gasoline	5.62	7.87
Other nondurable goods	5.13	6.67
Housing and utilities	6.01	6.12
Health care	5.52	6.59
Transportation services	6.28	6.92
Food services	6.62	5.93
Other services	5.55	6.49
Aggregated expectation		
Plausibly rational aggregation		
Expenditure	6.28	5.78
Importance	5.99	5.49
PCE	5.97	5.39
Behavioral aggregation		
Equal	6.01	5.39
Core inflation	6.02	5.80
Non-core inflation	7.07	7.82
Max	12.68	9.00
Second max	8.63	6.64

Notes: This table presents the cross section mean and disagreement for a replication survey conducted between July 5 and July 28 2022. The survey uses three different wordings ("Inflation", "PCE Inflation", "CPI Inflation") for aggregate inflation, randomly assigned to respondents. Other questions are identical to the main survey. Answers to "CPI Inflation" are significantly higher, after controlling for socio-demographic factors (t-stat=2.02).

A.12 Question Ordering

Table 20: Robustness - Ordering of Inflation Questions

	Mean		p-val
First inflation question	Aggregate	Category	
Aggregate expectation	6.52	6.86	0.086
Category expectations			
Motor vehicles	6.38	6.35	0.707
Recreational goods	4.80	4.35	0.008
Other durable goods	4.73	4.83	0.357
Food and beverages	6.03	5.60	0.025
Gasoline	5.70	5.63	0.299
Other nondurable goods	4.84	4.71	0.855
Housing and utilities	4.92	5.17	0.297
Health care	4.55	4.36	0.320
Transportation services	5.14	5.21	0.982
Food services	5.30	4.97	0.075
Other services	4.53	4.59	0.896
Aggregated expectation			
Plausibly rational aggregation			
Expenditure	5.38	5.19	0.175
Importance	5.07	5.04	0.794
PCE	4.95	4.92	0.935
Behavioral aggregation			
Equal	5.08	4.97	0.539
Core inflation	5.11	4.88	0.143
Non-core inflation	5.91	5.91	0.047
Max	11.1	10.52	0.588
Second max	7.5	7.16	0.620

Notes: This table presents the cross section mean for survey respondents asked between January 19 and March 03, 2022, dependent on weather they received the question on aggregate inflation expectations first or after the question on category inflation expectations. The third column shows the p-value for a difference in cross-sectional Huber-robust and survey-weighted means, controlling for time and demographic fixed effects.

A.13 Replication: Financial Experts

Table 21: Replication Study - Financial Experts Panel

	Mean	Std. Dev. (Disagreement)	N
Aggregate expectations	5.81	1.38	35
Category expectations			
Motor vehicles	1.77	5.11	35
Recreational goods	3.13	3.11	35
Other durable goods	3.54	3.05	35
Food and beverages	6.04	4.22	35
Gasoline	2.99	6.41	35
Other nondurable goods	3.91	1.72	35
Housing and utilities	5.38	3.69	35
Health care	2.88	5.33	35
Transportation services	4.18	5.20	35
Food services	5.45	5.13	35
Other services	3.68	3.01	35
Aggregated expectation			
Plausibly rational aggregation			
Expenditure	4.93	3.80	34
PCE	4.08	3.68	35
Behavioral aggregation			
Equal	3.63	3.49	35
Core inflation	4.85	3.89	34
Non-core inflation	5.39	4.51	34
Max	7.89	3.26	35
Second max	5.45	2.98	35

Notes: This table presents the cross section mean and disagreement (Huber-robust estimates) for a replication survey conducted between November 4 and November 9 2022, with a group of financial market experts (fund managers).

B Low and High Inflation Environment

We split the sample in November 2021 and define the period from June 2020 to October 2021 as the "low inflation environment." The period after November 2021 (until August 2022) is defined as a "high inflation environment." We reproduce key statistics from the paper for both periods, to check for consistency.

B.1 Summary Statistics

Table 22: Summary Statistics - Low and High Inflation Environment

	Mean		Std. Dev. (Disagreement)		Time Series Volatility	
Inflation environment	Low	High	Low	High	Low	High
Aggregate expectation	5.62	7.62	7.60	7.41	2.70	1.61
Category expectations						
Motor vehicles	4.88	6.46	5.86	6.11	1.90	0.97
Recreational goods	3.53	4.74	6.15	6.63	1.75	0.99
Other durable goods	3.60	4.93	5.97	6.42	1.83	1.00
Food and beverages	4.85	5.93	6.28	6.80	1.86	1.18
Gasoline	4.95	5.79	7.15	8.24	2.19	1.64
Other nondurable goods	3.71	4.85	5.83	6.32	1.48	0.94
Housing and utilities	4.73	5.25	6.42	6.53	1.76	0.88
Health care	3.43	4.81	6.53	6.51	1.62	1.08
Transportation services	4.36	5.53	5.89	6.68	1.60	1.06
Food services	4.36	5.45	6.42	6.53	1.68	1.01
Other services	3.95	4.91	5.48	5.90	1.39	0.85
Aggregated expectation						
Plausibly rational aggregation						
Expenditure	4.58	5.53	5.07	5.61	1.38	0.93
Importance	4.13	5.32	4.37	5.31	1.31	0.98
PCE	4.03	5.15	4.29	5.14	1.23	0.91
Behavioral aggregation						
Equal	4.00	5.28	4.20	5.19	1.31	0.96
Core inflation	4.39	5.23	5.10	5.38	1.36	0.83
Non-core inflation	5.30	6.38	5.80	6.98	1.72	1.35
Max	11.01	11.73	8.17	9.04	3.14	2.13
Second max	6.58	7.56	6.20	6.83	1.95	1.34

Notes: This table presents summary statistics on the demographic distribution of expectations. Statistics based on averages of Huber-robust and survey-weighted daily means on expectations across demographics.

B.1.1 Gender

Table 23: Summary Statistics - Gender - High and Low Inflation Environment

	Male				Female			
	Mean		Disagreement		Mean		Disagreement	
Inflation environment	Low	High	Low	High	Low	High	Low	High
Aggregate expectation	5.41	6.97	5.84	5.90	6.23	9.00	10.28	10.01
Category expectations								
Motor vehicles	4.96	6.11	5.20	5.35	4.88	6.94	6.27	6.89
Recreational goods	3.34	4.32	5.41	5.95	3.89	5.32	6.70	7.03
Other durable goods	3.51	4.67	5.27	5.69	3.70	5.30	6.58	6.96
Food and beverages	4.56	5.38	5.67	6.17	5.19	6.71	6.72	7.60
Gasoline	4.87	5.10	6.81	7.92	5.15	6.76	7.37	8.92
Other nondurable	3.59	4.52	5.20	5.52	3.85	5.28	6.36	6.84
Housing and util.	4.43	5.02	5.73	5.82	5.08	5.60	6.90	6.99
Health care	3.51	4.52	5.92	5.87	3.47	5.20	7.03	6.91
Transportation	4.08	5.06	5.18	5.98	4.59	6.31	6.41	7.40
Food services	4.23	5.10	5.78	5.96	4.48	5.88	6.82	6.97
Other services	3.76	4.57	4.81	5.25	4.12	5.31	6.11	6.35
Aggregated expectations								
Plausibly rational aggregation								
Expenditure weights	4.35	5.09	4.42	5.00	4.90	6.19	5.61	6.30
Importance weights	3.95	4.80	3.90	4.68	4.40	5.99	4.72	5.87
PCE weights	3.82	4.69	3.77	4.54	4.35	5.77	4.73	5.74
Behavioral aggregation								
Equal weights	3.85	4.78	3.72	4.59	4.23	5.94	4.53	5.75
Core inflation	4.19	4.91	4.41	4.79	4.70	5.73	5.59	6.01
Non-core inflation	4.97	5.69	5.18	6.40	5.66	7.31	6.23	7.65
Max	10.55	10.62	7.47	7.84	11.81	13.69	8.76	10.84
Second max	6.27	6.90	5.68	6.06	6.99	8.65	6.63	7.93

Notes: This table presents summary statistics on the demographic distribution of expectations. Statistics based on averages of Huber-robust and survey-weighted daily means on expectations across demographics.

B.1.2 Grocery Shopper

Table 24: Summary Statistics - Grocery Shopper - High and Low Inflation Environment

	Grocery Shopper				Not Grocery Shopper			
	Mean		Disagreement		Mean		Disagreement	
Inflation environment	Low	High	Low	High	Low	High	Low	High
Aggregate expectation	5.29	6.66	7.14	6.89	5.95	7.88	8.04	7.64
Category expectations								
Motor vehicles	4.88	6.71	5.54	6.57	4.96	6.45	5.86	6.01
Recreational goods	3.46	4.83	5.48	6.34	3.54	4.75	6.18	6.60
Other durable goods	2.88	5.01	5.21	5.91	3.63	4.95	6.08	6.41
Food and beverages	4.92	6.48	5.56	6.75	4.88	5.92	6.32	6.77
Gasoline	5.40	6.18	7.63	9.19	4.96	5.78	7.09	8.13
Other nondurable	3.35	4.78	5.48	5.92	3.77	4.88	5.85	6.31
Housing and util.	4.53	5.48	6.00	6.32	4.84	5.22	6.46	6.48
Health care	3.27	4.83	6.28	6.14	3.52	4.82	6.53	6.47
Transportation	3.82	5.95	5.46	6.67	4.45	5.53	5.94	6.64
Food services	4.29	5.76	5.71	6.46	4.41	5.44	6.47	6.51
Other services	3.75	4.81	4.98	5.75	4.04	4.91	5.59	5.87
Aggregated expectations								
Plausibly rational aggregation								
Expenditure weights	4.60	5.89	4.35	5.72	4.66	5.52	5.11	5.58
Importance weights	4.24	5.51	3.83	5.17	4.17	5.31	4.37	5.27
PCE weights	3.86	5.43	3.71	4.94	4.09	5.13	4.33	5.11
Behavioral aggregation								
Equal weights	3.92	5.47	3.67	5.03	4.03	5.27	4.22	5.17
Core inflation	4.11	5.50	4.29	5.39	4.48	5.23	5.15	5.34
Non-core inflation	5.48	7.28	5.02	7.31	5.31	6.37	5.82	6.96
Max	12.40	13.22	8.63	9.38	11.04	11.68	8.07	8.95
Second max	7.07	8.26	5.99	7.21	6.59	7.56	6.17	6.84

Notes: This table presents summary statistics on the demographic distribution of expectations. Statistics based on averages of Huber-robust and survey-weighted daily means on expectations across demographics.

B.1.3 Education

Table 25: Summary Statistics - Education - High and Low Inflation Environment

	Low Education				High Education			
	Mean		Disagreement		Mean		Disagreement	
Inflation environment	Low	High	Low	High	Low	High	Low	High
Aggregate expectation	6.59	8.83	10.25	10.19	5.46	7.15	6.12	5.76
Category expectations								
Motor vehicles	4.74	6.31	6.07	6.47	5.07	6.72	5.35	5.59
Recreational goods	3.41	4.49	6.62	7.04	3.68	5.09	5.54	5.89
Other durable goods	3.49	4.62	6.37	6.85	3.68	5.33	5.44	5.57
Food and beverages	4.86	5.90	6.60	7.34	4.89	6.16	5.61	6.18
Gasoline	5.03	5.85	7.18	8.39	5.00	6.02	6.93	8.32
Other nondurable	3.67	4.65	6.32	6.78	3.84	5.08	5.24	5.49
Housing and util.	4.62	5.01	6.95	6.94	4.98	5.58	5.80	5.74
Health care	3.35	4.54	6.83	6.77	3.61	5.15	6.21	5.90
Transportation	4.38	5.51	6.36	7.21	4.33	5.75	5.40	5.99
Food services	4.16	5.18	6.61	6.85	4.54	5.83	6.06	5.96
Other services	3.96	4.75	5.95	6.40	3.95	5.08	4.97	5.08
Aggregated expectations								
Plausibly rational aggregation								
Expenditure weights	4.62	5.49	5.57	5.97	4.68	5.72	4.48	5.14
Importance weights	4.08	5.18	4.46	5.41	4.27	5.60	4.03	5.00
PCE weights	4.05	5.00	4.54	5.32	4.13	5.44	3.89	4.77
Behavioral aggregation								
Equal weights	3.98	5.13	4.30	5.28	4.14	5.55	3.90	4.88
Core inflation	4.40	5.12	5.64	5.76	4.50	5.47	4.52	4.88
Non-core inflation	5.40	6.57	6.18	7.35	5.24	6.36	5.28	6.56
Max	11.50	12.18	8.53	9.69	10.96	11.80	7.64	8.55
Second max	6.63	7.62	6.54	7.46	6.58	7.82	5.61	6.27

Notes: This table presents summary statistics on the demographic distribution of expectations. Statistics based on averages of Huber-robust and survey-weighted daily means on expectations across demographics.

B.1.4 Income

Table 26: Summary Statistics - Income - High and Low Inflation Environment

	Low Income				Middle Income				High Income			
	Mean		Disag.		Mean		Disag.		Mean		Disag.	
Inflation environment	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High
Aggregate expectation	6.24	8.11	9.94	9.27	5.67	7.41	6.40	5.96	7.09	8.50	7.61	7.62
Category expectations												
Motor vehicles	4.72	6.39	6.11	6.57	4.95	6.32	5.16	5.70	5.20	6.75	5.35	5.33
Recreational goods	3.42	4.53	6.83	7.03	3.58	5.07	5.38	5.94	3.80	4.95	5.42	5.79
Other durable goods	3.37	4.73	6.77	6.89	3.69	4.99	5.27	5.73	4.12	5.37	5.68	5.41
Food and beverages	4.83	5.91	6.69	7.47	5.13	6.13	5.36	6.37	5.32	6.03	5.90	6.00
Gasoline	4.86	5.92	7.27	8.55	5.40	6.20	6.93	8.50	5.10	5.82	6.90	7.96
Other nondurable	3.46	4.69	6.29	6.78	3.85	4.93	5.32	5.58	4.26	5.06	5.23	5.42
Housing and util.	4.48	5.03	6.92	6.91	5.29	5.42	5.88	5.93	5.06	5.65	5.85	5.71
Health care	3.17	4.54	6.83	6.83	3.60	4.93	6.03	5.93	4.15	5.11	6.33	5.89
Transportation	4.37	5.65	6.57	7.23	4.71	5.65	5.23	6.15	4.30	5.46	5.30	5.92
Food services	4.09	5.22	6.83	6.96	4.38	5.61	5.65	6.03	4.83	5.82	6.21	5.80
Other services	3.90	4.75	5.98	6.35	4.22	4.94	4.89	5.24	4.14	5.18	5.15	5.05
Aggregated expectations												
Plausibly rational aggregation												
Expenditure weights	4.48	5.55	5.57	6.10	4.95	5.63	4.50	5.28	4.96	5.63	4.38	4.88
Importance weights	4.00	5.28	4.59	5.60	4.40	5.45	3.98	5.10	4.54	5.40	3.83	4.67
PCE weights	3.89	5.13	4.54	5.50	4.26	5.26	3.82	4.89	4.40	5.29	3.84	4.51
Behavioral aggregation												
Equal weights	3.87	5.25	4.42	5.49	4.16	5.39	3.83	4.98	4.35	5.35	3.66	4.52
Core inflation	4.25	5.18	5.54	5.88	4.69	5.28	4.53	4.95	4.64	5.44	4.22	4.68
Non-core inflation	5.34	6.65	6.27	7.53	5.62	6.58	5.16	6.70	5.61	6.15	5.62	6.24
Max	11.54	12.58	8.73	10.21	11.15	11.97	7.54	8.98	11.66	11.32	8.09	7.73
Second max	6.70	7.87	6.73	7.70	6.87	7.73	5.70	6.59	6.78	7.47	5.72	5.95

Notes: This table presents summary statistics on the demographic distribution of expectations. Statistics based on averages of Huber-robust and survey-weighted daily means on expectations across demographics.

B.1.5 Age

Table 27: Summary Statistics - Age (mean) - High and Low Inflation Environment

	Below 35		35 to 44		45 to 54		Above 55	
Inflation environment	Low	High	Low	High	Low	High	Low	High
Aggregate expectation	7.12	9.23	8.69	9.49	7.05	10.29	4.83	7.12
Category expectations								
Motor vehicles	4.11	5.39	5.69	6.20	5.03	7.23	5.26	7.99
Recreational goods	2.14	2.97	3.88	4.45	3.92	6.02	4.45	6.54
Other durable goods	2.49	3.33	3.95	4.71	3.92	5.89	4.35	6.56
Food and beverages	3.63	4.04	5.30	5.59	5.41	7.53	6.14	8.45
Gasoline	3.65	4.06	4.87	5.59	5.81	7.41	6.76	8.90
Other nondurable	2.55	3.31	3.99	4.68	4.40	6.07	4.59	6.26
Housing and util.	3.62	3.74	4.66	4.94	5.56	6.50	5.92	6.88
Health care	2.14	3.34	3.81	4.73	3.92	5.50	4.52	6.40
Transportation	3.30	3.80	4.49	5.26	4.50	7.01	5.36	7.65
Food services	2.66	3.69	4.45	4.95	4.89	6.45	5.94	7.67
Other services	3.17	3.66	3.72	5.02	4.51	5.79	4.67	6.01
Aggregated expectations								
Plausibly rational aggregation								
Expenditure weights	3.51	3.90	4.78	5.21	5.39	6.90	5.76	7.60
Importance weights	2.81	3.43	4.28	4.87	4.85	6.66	5.65	7.72
PCE weights	2.92	3.38	4.11	4.76	4.57	6.46	5.41	7.38
Behavioral aggregation								
Equal weights	2.71	3.41	4.13	4.86	4.56	6.56	5.48	7.62
Core inflation	3.48	3.86	4.51	4.93	5.04	6.42	5.35	6.90
Non-core inflation	3.97	4.44	5.46	5.95	5.78	7.94	6.48	8.74
Max	11.02	10.01	12.02	11.01	11.34	13.42	12.04	15.05

Notes: This table presents summary statistics on the demographic distribution of expectations. Statistics based on averages of Huber-robust and survey-weighted daily means on expectations across demographics.

Table 28: Summary Statistics - Age (disagreement) - High and Low Inflation Environment

	Below 35		35 to 44		45 to 54		Above 55	
Inflation environment	Low	High	Low	High	Low	High	Low	High
Aggregate expectation	11.60	11.72	11.86	11.30	9.45	9.85	4.45	4.24
Category expectations								
Motor vehicles	6.76	5.79	6.47	5.95	5.79	6.37	4.36	5.89
Recreational goods	7.24	7.03	6.94	6.83	5.97	6.64	4.21	4.93
Other durable goods	6.80	6.70	7.10	6.54	6.04	6.26	4.37	5.06
Food and beverages	7.08	6.85	7.36	6.89	6.04	7.76	4.56	6.15
Gasoline	7.52	7.26	7.27	7.39	6.84	8.69	6.57	10.12
Other nondurable	7.09	6.86	6.67	6.41	5.70	6.42	4.03	4.80
Housing and util.	7.31	6.71	7.36	6.70	6.33	6.69	4.89	5.39
Health care	7.26	6.64	7.04	6.40	5.97	6.42	5.19	5.47
Transportation	6.87	6.84	6.79	6.67	5.90	7.07	4.37	5.84
Food services	7.19	6.54	7.03	6.39	6.07	6.66	5.06	5.70
Other services	6.40	6.28	6.38	6.08	5.31	5.90	3.83	4.47
Aggregated expectations								
Plausibly rational aggregation								
Expenditure weights	5.24	4.90	5.25	5.32	4.75	6.09	4.15	5.43
Importance weights	3.70	3.98	4.46	4.83	4.14	5.78	3.92	5.47
PCE weights	3.95	4.13	4.68	4.85	4.02	5.54	3.63	4.96
Behavioral aggregation								
Equal weights	3.54	3.90	4.38	4.77	4.02	5.59	3.73	5.25
Core inflation	5.55	4.96	5.33	5.14	4.72	5.68	4.10	4.92
Non-core inflation	6.39	6.30	6.31	6.60	5.42	7.68	4.74	7.08
Max	8.32	7.75	8.76	8.16	8.56	10.04	7.83	10.52
Second max	6.83	6.36	6.73	6.51	6.55	7.63	5.16	6.99

Notes: This table presents summary statistics on the demographic distribution of expectations. Statistics based on averages of Huber-robust and survey-weighted daily means on expectations across demographics.

Table 29: Aggregate vs. Aggregated Inflation Expectations - Before November 2021

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Expenditure	0.444***								0.0227
	(14.75)								(0.18)
Importance		0.567***							-0.0461
		(16.22)							(-0.28)
PCE			0.533***						-0.442***
			(14.89)						(-3.43)
Equal				0.605***					0.930***
				(16.56)					(5.09)
Core Inflation					0.388***				-0.00417
					(13.67)				(-0.04)
Non-core Inflation						0.321***			-0.0209
						(12.42)			(-0.38)
Max							0.281***		0.179***
							(16.52)		(5.68)
Second max								0.327***	-0.0643
								(13.24)	(-1.34)
Constant	6.287***	5.843***	6.088***	5.794***	6.734***	6.891***	4.885***	6.180***	4.696***
	(24.88)	(22.67)	(23.42)	(22.68)	(28.05)	(27.26)	(17.63)	(22.77)	(16.88)
N	20685	20685	20685	20685	20685	20685	20685	20685	20685
R2	0.0383	0.0476	0.0416	0.0499	0.0326	0.0291	0.0426	0.0345	0.0586
AIC	180209.6	180008.8	180139.3	179957.3	180331.9	180407.3	180116.8	180289.9	179783.1

Notes: The table presents estimates on a micro level for a linear regression of reported aggregate on one (column 1 to 8) or multiple (column 9) aggregated, category-based measures of inflation. t statistics in parentheses, based on robust standard errors; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; regression adjusted with survey weights and Huber-robust weights to ensure that sample is representative and independent of outliers, respectively.

Table 30: Aggregate vs. Aggregated Inflation Expectations - After November 2021

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Expenditure	0.590***								0.168
	(31.64)								(1.94)
Importance		0.657***							-0.283*
		(32.64)							(-2.37)
PCE			0.658***						-0.241*
			(31.49)						(-2.17)
Equal				0.688***					0.883***
				(33.58)					(5.23)
Core					0.565***				0.0171
					(28.49)				(0.25)
Non core						0.399***			-0.0417
						(27.73)			(-1.13)
First max							0.316***		0.0956***
							(28.34)		(4.43)
Second max								0.434***	0.0471
								(28.61)	(1.29)
Constant	8.737***	8.383***	8.542***	8.241***	9.249***	9.800***	7.858***	8.595***	7.452***
	(44.84)	(41.89)	(42.17)	(41.05)	(47.78)	(51.94)	(36.85)	(40.88)	(35.64)
N	29936	29936	29936	29936	29936	29936	29936	29936	29936
r2	0.0901	0.0948	0.0915	0.0977	0.0797	0.0684	0.0772	0.0807	0.104
AIC	260403.5	260247.5	260355.8	260151.8	260742.0	261110.2	260823.7	260709.9	259956.8

Notes: The table presents estimates on a micro level for a linear regression of reported aggregate on one (column 1 to 8) or multiple (column 9) aggregated, category-based measures of inflation. t statistics in parentheses, based on robust standard errors; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; regression adjusted with survey weights and Huber-robust weights to ensure that sample is representative and independent of outliers, respectively.

B.2 The Aggregation Gap

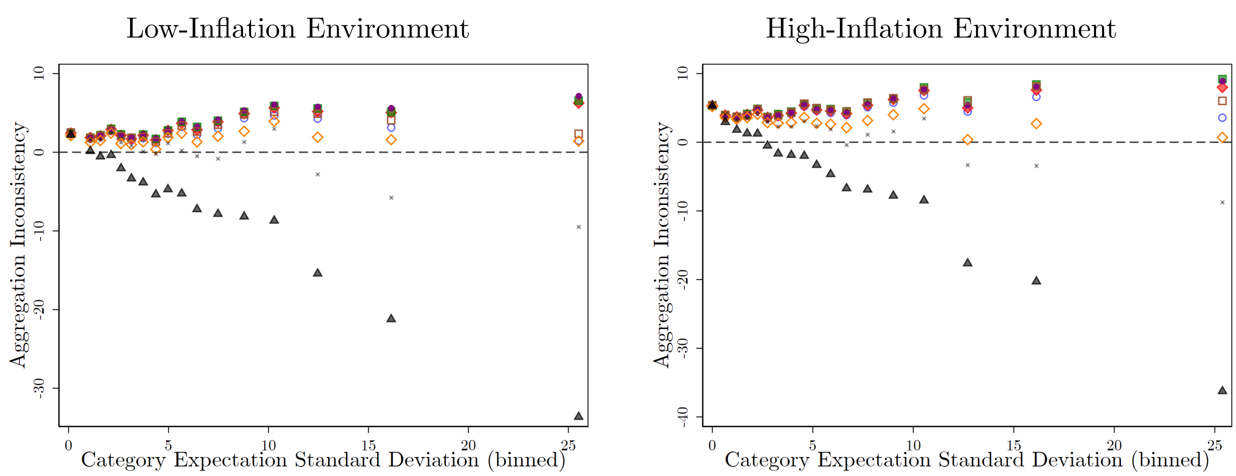
B.3 The Signed Aggregation Gap

Table 31: Summary Statistics

	Mean Aggregation Gap (Λ_i)		Mean Root Square Aggregation Gap $\left(\sqrt{\Lambda_i^2}\right)$	
Inflation environment	Low	High	Low	High
Plausibly rational aggregation				
Expenditure	0.65***	1.77***	5.62***	5.65***
Importance	1.01***	1.91***	5.35***	5.55***
PCE	1.17***	1.95***	5.16***	5.49***
Behavioral aggregation				
Equal	1.07***	1.99***	5.18***	5.42***
Core inflation	-4.26***	-3.61***	9.20***	9.03***
Non-core inflation	-0.78***	-0.17***	6.52***	6.51***
Max	0.63***	1.36***	6.02***	6.16***
Second max	0.83***	2.07***	5.72***	5.64***

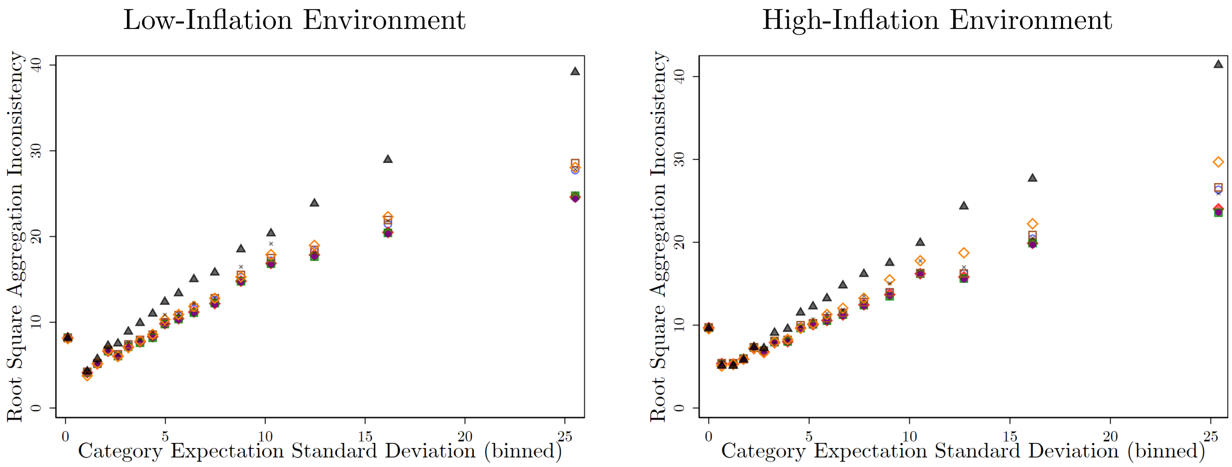
Notes: This table presents Huber-robust and survey-weighted estimates for the mean aggregation gap and mean root square aggregation gap; Stars: significance level of a t-test that numbers are different from zero. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$;

Figure 7: Absolute Aggregation Gap and Category Dispersion



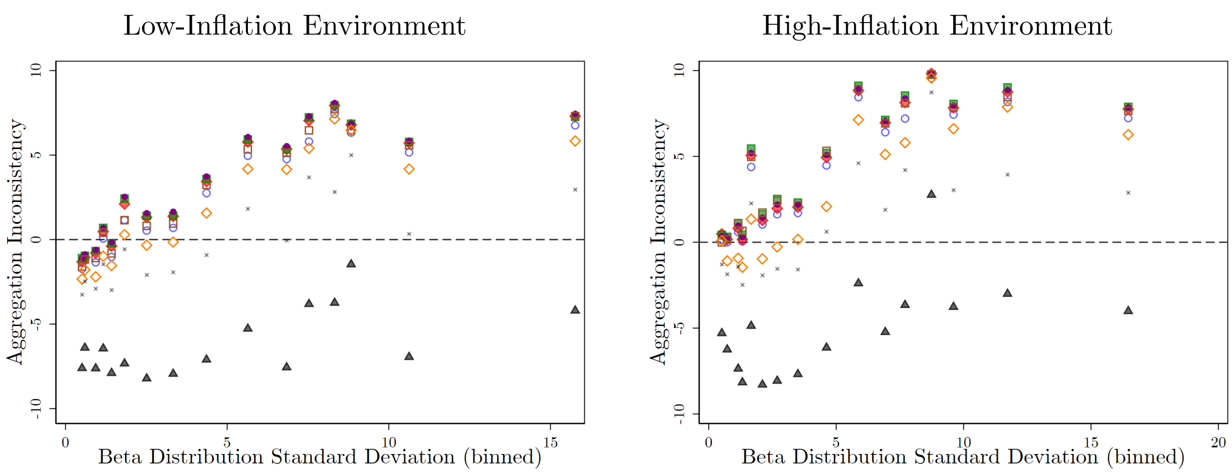
Notes:

Figure 8: The Aggregation Gap and Category Dispersion



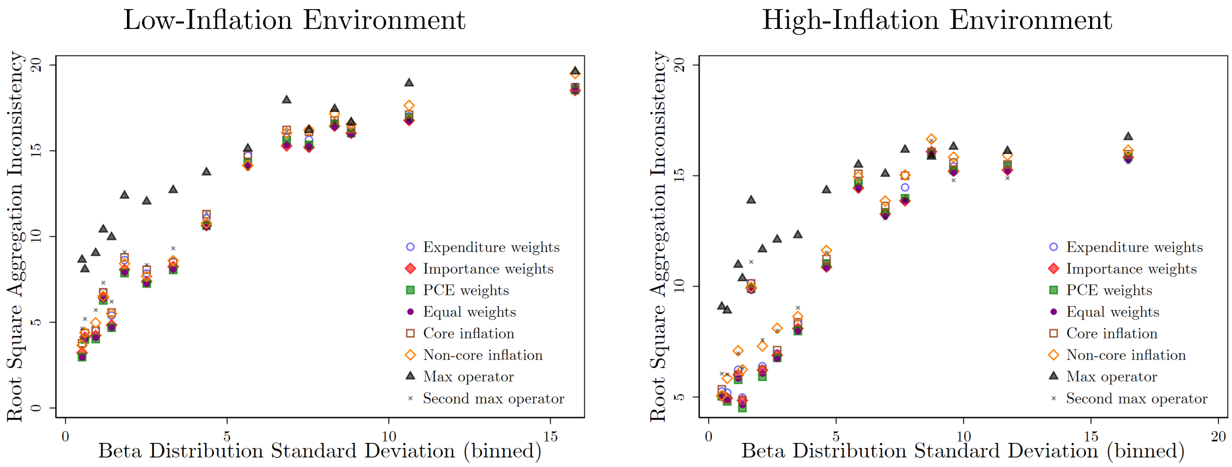
Notes:

Figure 9: The Absolute Aggregation Gap and Aggregate Uncertainty



Notes:

Figure 10: The Aggregation Gap and Aggregate Uncertainty



Notes:

B.4 Spending Plans

Table 32: 1 Year Ahead Spending Plans

	$\hat{\sigma} = 1 - \hat{\beta}_1$	t-stat	R^2	AIC	p-val (LR)	N
June 2020 - October 2021						
Aggregate	0.956***	5.90	0.071	76485	-	10767
Expenditure	0.826***	9.67	0.090	76271	0	10767
Importance	0.778***	10.84	0.095	76204	0	10767
PCE	0.781***	10.22	0.094	76221	0	10767
Equal	0.765***	10.83	0.096	76196	0	10767
Core inflation	0.847***	8.68	0.086	76317	0	10767
Non-core inflation	0.884***	8.28	0.080	76387	0	10767
Max	0.916***	8.52	0.080	76381	0	10767
Second max	0.865***	9.72	0.090	76261	0	10767
November 2021 - August 2022						
Aggregate	0.964***	4.91	0.047	91488	-	12889
Expenditure	0.818***	11.84	0.079	91052	0	12889
Importance	0.792***	12.82	0.082	91012	0	12889
PCE	0.793***	12.20	0.080	91042	0	12889
Equal	0.785***	12.57	0.082	91010	0	12889
Core inflation	0.839***	10.12	0.070	91178	0	12889
Non-core inflation	0.869***	11.86	0.075	91116	0	12889
Max	0.910***	11.85	0.070	91178	0	12889
Second max	0.874***	10.61	0.071	91159	0	12889

Notes: Estimated Euler equations, relying on various measures of aggregate or aggregated inflation expectations; t statistics in third column, based on robust standard errors; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; regression adjusted with survey weights to ensure that sample is representative.

Table 33: 1 Year Ahead Services Spending Plans

	$\hat{\sigma} = 1 - \hat{\beta}_1$	t-stat	R^2	AIC	p-val (LR)	N
June 2020 - October 2021						
Aggregate	0.970***	5.03	0.071	73966	-	10809
Expenditure	0.866***	9.24	0.086	73783	0	10809
Importance	0.825***	10.66	0.092	73711	0	10809
PCE	0.823***	9.97	0.093	73710	0	10809
Equal	0.812***	10.55	0.094	73693	0	10809
Core inflation	0.878***	8.64	0.084	73809	0	10809
Non-core inflation	0.904***	7.87	0.081	73846	0	10809
Max	0.925***	9.53	0.084	73808	0	10809
Second max	0.885***	9.85	0.092	73711	0	10809
November 2021 - August 2022						
Aggregate	0.965***	5.25	0.052	88318	-	12958
Expenditure	0.851***	11.18	0.079	87952	0	12958
Importance	0.823***	11.84	0.084	87873	0	12958
PCE	0.818***	11.54	0.085	87862	0	12958
Equal	0.814***	11.79	0.086	87851	0	12958
Core inflation	0.848***	11.09	0.078	87955	0	12958
Non-core inflation	0.904***	10.03	0.069	88091	0	12958
Max	0.931***	10.48	0.067	88109	0	12958
Second max	0.896***	9.92	0.073	88033	0	12958

Notes: Estimated Euler equations, relying on various measures of aggregate or aggregated inflation expectations; t statistics in third column, based on robust standard errors; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; regression adjusted with survey weights and Huber-robust weights to ensure that sample is representative and independent of outliers, respectively.

C Survey Appendix

This section lists relevant survey questions used within the paper.

C.1 Survey Overview

The survey was administered on the Qualtrics Research Core Platform, and Qualtrics Research Services recruited participants to provide responses. Survey data used in this paper spans the time from July 9, 2020 to September 9, 2021. Participants were asked for their expectations and behavior regarding COVID-19. While the survey also contains other blocks with various questions, these are not reported here, since they are asked after the questions on COVID-19 and thus do not affect the answers.

C.2 Sample

Invitations went out to residents of the US Respondents were pre-screened for residence status, English language fluency, and age. All respondents who failed to meet the screening criteria were discontinued from the survey. Only respondents who confirmed residence in the US, who professed English language fluency, and who reported to be of ages 18 or above, were brought into to the survey proper. Once respondents met these criteria, we screened responses by removing any participants who took less than five minutes to complete the survey or had at least one gibberish response (e.g., "$sd - \$rt2$").

C.3 Aggregate Expectations

To learn about respondents' expectations of future inflation and income, we use the following set of questions. Note that we first ask about participants' point estimates and then collect additional data on the individual distribution of expectations. By this approach, we can gain insights into individual uncertainty.
Survey participants are shown the following introductory text:

In some of the following questions, we will ask you to think about the percent chance of something happening in the future. Your answers can range from 0 to 100, where 0 means there is absolutely no chance, and 100 means that it is absolutely certain. For example, numbers like: 2 and 5 percent may indicate "almost no chance" 18 percent or so may mean "not much chance" 47 or 52 percent chance may be a "pretty even chance" 83 percent or so may mean a "very good chance" 95 or 98 percent chance may be "almost certain".

Q1: Inflation Point Prediction
The next few questions are about inflation. Over the next 12 months do you think there will be inflation or deflation?

O Inflation
O Deflation (opposite of inflation)

Depending on the answer given on the previous question, the participant is shown the next question:

*What do you expect the rate of **inflation/deflation** to be over the next 12 months? Please give your best guess.*
*I expect the rate of **inflation/deflation** to be _____ percent over the next 12 months.*

We choose to ask about point estimates in this twofold manner in order to avoid issues about the correct sign of the numerical answer, i.e. that respondents intend to answer −3 percent but just put 3 in the answer field.

We then ask about the distribution of an individuals' inflation expectation:

QDIST: Inflation Distribution

Now we would like you to think about what may happen to inflation over the next 12 months. We realize that this question may take a little more effort. In your view, what would you say is the percent chance that, over the next 12 months. . .

the rate of inflation will be 12% or higher _____
the rate of inflation will be between 8% and 12% _____
the rate of inflation will be between 4% and 8% _____
the rate of inflation will be between 2% and 4% _____
the rate of inflation will be between 0% and 2% _____
the rate of deflation (opposite of inflation) will be between 0% and 2% _____
the rate of deflation (opposite of inflation) will be between 2% and 4% _____
the rate of deflation (opposite of inflation) will be between 4% and 8% _____
the rate of deflation (opposite of inflation) will be between 8% and 12% _____
the rate of deflation (opposite of inflation) will be 12% or higher _____

We then start with questions about the expected change in personal household income for the 12-month horizon:

QPHI: Personal Household Income Point Prediction

In your view, will the total income of all members of your household (including you), after taxes and deductions, increase or decrease over the next 12 months?

O Positive
O Negative

By how much do you expect total income of all members of your household to increase over the next 12 months? Please give your best guess.
*Over the next 12 months, I expect total income of all members of my household to **increase/ decrease** by _____ percent.*

C.4 Category Expectations and Weights

To elicit participants' category-specific inflation expectations and expenditure weights, we ask the following questions:

Q2: Importance weights
Which of the following broad consumption categories matter the most to you right now in your daily life? Please move the slider to indicate the importance for each of them, with 0 indicating no importance and 100 indicating highest importance.

Motor vehicles and parts (such as cars and SUVs)	0_____|_____100
Recreational goods and vehicles (such as sports equipment and laptops)	0_____|_____100
Other durable goods (such as furniture, appliances, jewelry, luggage)	0_____|_____100
Food and beverages for off-premises consumption (such as food from grocery stores)	0_____|_____100
Gasoline and other energy goods	0_____|_____100
Other nondurable goods (such as clothing, medicine and personal care products)	0_____|_____100
Housing and utilities (such as rent and utility bills)	0_____|_____100
Health care	0_____|_____100
Transportation services (such as public transit tickets and airfare)	0_____|_____100
Food services and accommodations (such as restaurants and hotels)	0_____|_____100
Other services (such as internet/phone service, education, financial services, hairdressers)	0_____|_____100

Q3: Expenditure weights
In terms of consumption spending, how much money did you spend on each of the following broad consumption categories during the last month? Please indicate an approximate dollar amount in each field.

Motor vehicles and parts (such as cars and SUVs)	_____
Recreational goods and vehicles (such as sports equipment and laptops)	_____
Other durable goods (such as furniture, appliances, jewelry, luggage)	_____
Food and beverages for off-premises consumption (such as food from grocery stores)	_____
Gasoline and other energy goods	_____
Other nondurable goods (such as clothing, medicine and personal care products)	_____
Housing and utilities (such as rent and utility bills)	_____
Health care	_____
Transportation services (such as public transit tickets and airfare)	_____
Food services and accommodations (such as restaurants and hotels)	_____
Other services (such as internet/phone service, education, financial services, hairdressers)	_____

Q4: Category Inflation

Twelve months from now, what do you think will have happened to the price of the following items?

I expect the price of ...

Motor vehicles and parts (such as cars and SUVs)	to [increase/decrease]	by	______
Recreational goods and vehicles (such as sports equipment and laptops)	to [increase/decrease]	by	______
Other durable goods (such as furniture, appliances, jewelry, luggage)	to [increase/decrease]	by	______
Food and beverages for off-premises consumption (such as food from grocery stores)	to [increase/decrease]	by	______
Gasoline and other energy goods	to [increase/decrease]	by	______
Other nondurable goods (such as clothing, medicine and personal care products)	to [increase/decrease]	by	______
Housing and utilities (such as rent and utility bills)	to [increase/decrease]	by	______
Transportation services (such as public transit tickets and airfare)	to [increase/decrease]	by	______
Food services and accommodations (such as restaurants and hotels)	to [increase/decrease]	by	______
Other services (such as internet/phone service, education, financial services, hairdressers)	to [increase/decrease]	by	______

C.5 Expected Spending

We ask respondents about their expected spending in 12 months, relative to last month with the following questions:

Q4: Total Spending

Compared with your spending last month, how do you expect your total spending to change in the next . . .

	Go Down	No Change	Go Up	By %
. . . month?	O	O	O	_____
. . . two months?	O	O	O	_____
. . . year?	O	O	O	_____
. . . two years?	O	O	O	_____

Q5: Services Spending

Compared with your spending last month, how do you expect your spending on services — such as medical and dental care, haircuts, and restaurant meals — to change in the next. . .

	Go Down	No Change	Go Up	By %
. . . month?	O	O	O	_____
. . . two months?	O	O	O	_____
. . . year?	O	O	O	_____
. . . two years?	O	O	O	_____

Q6: Nondurable Spending

Compared with last month, how do you expect your spending on nondurable goods—such as clothes, medicine, food at grocery stores, or personal care products—to change in the next. . .

	Go Down by	No Change	Go Up	By %
. . . month?	O	O	O	_____
. . . two months?	O	O	O	_____
. . . year?	O	O	O	_____
. . . two years?	O	O	O	_____

C.6 Demographics

To check for demographics and to make the survey representative, we checked for certain demographic characteristics. These include age, gender, ethnicity, state of residence, the highest educational level, personal income, and the personal savings rate.