

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

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Abstract

This paper introduces a novel measure of consumer inflation expectations: We elicit and combine inflation forecasts across categories of personal consumption expenditure to form an *aggregated* measure of inflation expectations. Drawing on nearly 60,000 respondents, our data comprise the early low-inflation environment of the COVID pandemic and the 2021 inflation surge. Conventionally elicited inflation expectations consistently exceed aggregated measures constructed under plausible weighting schemes. Aggregated measures display less disagreement and volatility and are stronger predictors of consumers' spending plans. The relative informational value of aggregated measures rises with the individual-level gap between conventional and aggregated inflation expectations. Our results chart a new course for designing the measurement of inflation expectations.

Keywords: Household expectations, Survey, Sectoral expectations, Inflation expectations
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1 Introduction

Inflation expectations are a decisive factor for charting the course of monetary policy, and central banks “spend a lot of time watching them” (Powell, 2021). Policymakers pay special attention to consumer expectations because they affect households’ consumption-savings decisions and wage-price spirals.¹ Consumer inflation expectations, however, are notoriously difficult to capture accurately with prevailing survey methods. Many consumers struggle to grasp the concept of inflation; they rely on salient cues when reporting forecasts; and survey responses are vulnerable to a host of cognitive biases.²

These challenges inherent to the measurement of inflation expectations resonate with the canonical work by Tversky and Kahneman (1974) on heuristics and biases in judgment under uncertainty and the literature on the psychology of human judgment (Fischhoff and Broomell, 2020), and they point to a potential mismatch between human cognition and the demands of conventional elicitation techniques. Conventional techniques aim to elicit aggregate inflation, which is a concept comprising price changes across categories of personal consumption expenditures (PCE). Because the cognitive complexity of decisions is likely to increase in the number of relevant components (Gabaix and Graeber, 2023), one might surmise that it would be harder for an individual to produce an expectation for aggregate inflation than for its category-specific constituent parts.

Our paper, therefore, proposes an alternative approach to measuring inflation expectations, by decomposing aggregate inflation into its more tangible components—price changes for disaggregated categories of goods and services. Accordingly, we develop a survey that elicits inflation forecasts for the full range of PCE categories. This granular elicitation allows us to construct a novel measure of *aggregated* consumer inflation expectations, by combining category-specific forecasts. We find that aggregated inflation expectations are not only less noisy than the conventional measure of aggregate inflation expectations, but they also predict planned consumer spending better. These properties hold consistently across respondents in the population. Arguably, therefore, *aggregated* inflation expectations yield a more informative 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 policymakers who aim to elicit decision-relevant beliefs across the population.

We collected these expectations from almost 60,000 US consumers in a nationally representative

¹For consumption-savings decisions, see Bachmann et al. (2015), Crump et al. (2022), and Ryngaert (2022); for wage-price spirals, see Blanchard (1986) and Lorenzoni and Werning (2023).

²D’Acunto et al. (2022) find that low-IQ respondents, especially, seem to have 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. Potential salient cues include extreme price movements (Bruine de Bruin et al., 2011), changes in grocery and gas prices (Binder, 2018; Cavallo et al., 2017; D’Acunto et al., 2021), weighting consumption categories with the frequency of purchases (Georganas et al., 2014), and, under conditions with rapid price increases in specific categories, the category-specific inflation rates (Niu and Harvey, 2023).

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 consumption categories, covering the entire range of PCE. In doing so, 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 data set of comprehensive category-specific inflation expectations. In addition, we also ask survey participants about their own personal consumption expenditures and the relative importance of the consumption categories, along with their consumption plans.

We derive aggregated inflation expectations measures by combining the disaggregated category responses, and we compare them with the conventional aggregate inflation expectations. In particular, we evaluate eight different procedures for aggregating category-specific inflation expectations, across two conceptual 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 salient 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 allow for insensitivity to category weights, the heavy weighting of salient categories, and attention to salient price changes, respectively.

When we compare conventionally elicited aggregate inflation expectations to *aggregated* measures in the cross-section, we find 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.³ Moreover, subjective uncertainty about aggregate inflation expectations correlates strongly with the absolute aggregation gap. One interpretation is that the more uncertain consumers are about their aggregate forecast, the more the complexity of the aggregation task bears on consumers’

³Several other papers have investigated inconsistencies in consumer surveys between responses to questions in different formats asking about aggregate inflation expectations (Stanislawska et al., 2021) or consumer spending (Winter, 2004). Similar to our findings, their results show that 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).

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 using the official PCE weights should align with the conventional aggregate forecast—but it does not.⁴ This finding complements those of Coibion and Gorodnichenko (2012), who reject the hypothesis of full-information rational expectations (FIRE) by examining expectations and realizations. The internal inconsistency that we document between expectations at the individual level reveals another departure from FIRE.

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). 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 planning, and thus more informative for monetary policy, during both the COVID-19 pandemic and the 2021 inflation surge. Moreover, the relative benefit of using expenditure-weighted, aggregated inflation expectations over the more conventional 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 policymakers 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, especially in the context 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 on expenditure. Others have documented that consumers form aggregate inflation expectations by extrapolating from gasoline prices (e.g., Armantier et al., 2016; Binder and Makridis, 2022; Binder, 2018; Coibion and Gorodnichenko, 2015) or relying on recalled price changes (Cavallo et al., 2017; D’Acunto and Weber, 2022). Arora et al. (2013) and Trehan (2011) find that aggregate inflation expectations react excessively to non-core price changes, and Dietrich (2024) shows that consumers are relatively more attentive to their internal food and energy inflation forecasts. This literature highlights that particular pieces of information may carry

⁴Likewise, 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.

significant weight in the formation of inflation expectations—in line with our findings. Ironically, despite the evidence that they are relevant for inflation expectations, neither groceries nor gasoline are part of core inflation on which monetary policymakers often focus attention.

Beyond the domain of inflation expectations, specifically, past experiences may play a more general role in belief formation (Malmendier and Nagel, 2016), including expectations about future macroeconomic conditions or house prices (Kuchler and Zafar, 2019). The recent framework of selective recall and memory by Bordalo et al. (2022, 2023) posits a theory of belief formation in this context that provides a nuanced view of the role of experiences. To assess the probability of a scenario, individuals compare the similarity of a scenario at hand with the experiences they recall following a cue; such recall either facilitates the probability assessment or interferes with it. Our results accord with this class of models: Recall may prove easier in the context of concrete consumption categories than in the case of abstract aggregate inflation, which may offer more interference and thereby lead to noisier expectations.⁵ Our finding that category-specific expectations are less dispersed and less volatile over time than aggregate inflation expectations is consistent with this interpretation. Likewise, that subjective uncertainty about aggregate inflation expectations correlates positively with the absolute aggregation gap—the difference between aggregate and *aggregated* inflation expectations—could reflect the increased difficulties in mapping recalled experiences to the aggregate inflation forecast. Appendix E presents a version of the Bordalo et al. (2023) framework that explicitly rationalizes our findings.

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 sub-questions. 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 (2009, 2012), moreover, 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 level.

Our paper proceeds as follows: Section 2 describes our novel survey data. Section 3 examines

⁵Several papers have documented a strong link between recall and inflation expectations (e.g., Jonung, 1981; Weber et al., 2022).

category-specific inflation expectations and compares them to aggregate inflation expectations. Section 4 investigates procedures for aggregating category-specific inflation expectations and explores the gap between aggregate and *aggregated* inflation expectations. Section 5 relates aggregate and *aggregated* expectations to household spending plans in Euler equation estimations. A final section concludes.

2 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 nonsensical answers for at least one response or who complete the survey in less than five minutes, and reCAPTCHA tests to reduce the likelihood that bots would interfere.⁶

Our sampling criteria generated a sample roughly representative of the US population along the targeted dimensions, as seen in Table 1. To improve the fit further, we compute survey weights 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—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.⁷ Our approach to eliciting aggregate inflation forecasts is methodologically similar to that of other influential household surveys, such

⁶Qualtrics Research Services provides the filtered data. The daily sample size refers to the number of respondents after filtering. Survey respondents receive monetary compensation for their time.

⁷On a subset of the data, we switched the ordering, asking about disaggregated category expectations first. We did not find a significant order effect.

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			Household Income		
female	49.9%	50.8%	less than 50k\$	47.8%	37.8%
male	49.7%	49.2%	50k\$ - 100k\$	29.5%	28.6%
other	0.4%	-%	more than 100k\$	22.7%	33.6%
Region			Education		
Midwest	20.6%	20.7%	some college or less	50.6%	58.3%
Northeast	21.9%	17.3%	bachelor’s degree or more	49.4%	41.7%
South	39.5%	38.3%			
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).

as the University of Michigan’s Surveys of Consumers (SoC) and the New York Fed’s Survey of Consumer Expectations (SCE).⁸ Subsequently, we elicit inflation expectations for 11 PCE categories (Q2 in Table 2) using a format closely aligned with 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 3 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.⁹

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.¹⁰ The principal reason is that point forecasts prove more tractable in the present survey framework,

⁸The SoC has collected data on household inflation expectations since 1978; the SCE started in 2013. Both ask directly about aggregate inflation or the expected change in *aggregate* prices, at a monthly frequency, and they include some kind of panel structure; while the SoC asks a subset of participants to respond to the survey again, half a year later, the SCE has a rolling panel structure, with respondents answering 12 consecutive monthly surveys. Our survey does not feature a panel structure, but is conducted at a higher frequency (daily).

⁹We 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.

¹⁰We 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 [<i>category</i>] 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 F.

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 on goods and services in the respective category during the last month (Q3 in Table 2) and how important they consider the category to be 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.

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	2.04
Other nondurable goods	4.15	6.02	1.41
Housing and utilities	4.82	6.19	1.53
Health care	4.93	6.46	1.50
Transportation services	3.96	6.52	1.58
Food services	4.78	6.46	1.54
Other services	4.32	5.65	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.

Subsequently, we asked respondents to indicate their expected spending 12 months ahead, relative to that in the month prior to the survey. We also repeated the question 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 F.

3 Category-Specific Inflation Expectations

This section presents the statistical properties of aggregate and category-specific inflation expectations (Q1 and Q2 in Table 2, respectively). 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.

Between July 2020 and August 2022, survey participants expected on average aggregate inflation over the next 12 months to be 6.39 percent (see Table 3). The table reports the mean expectation and disagreement among households (cross-sectional standard deviation) in the first and second columns, with displayed statistics representing the average over the daily Huber-robust and survey-

weighted mean and standard deviation, respectively.¹¹ Strikingly, every category-specific inflation rate is expected to be lower than the aggregate rate: from 3.96 percent for “Health care services” to 5.49 percent for “Motor vehicles.”

An agent with views mirroring those of the cross-section, therefore, expected that aggregate inflation would exceed inflation expectations in *any* category. This pattern is driven by respondents reporting aggregate expectations outside the range of their own individual category-specific expectations: About 26 percent of respondents state an aggregate expectation greater than their expectation for any category. 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 in isolation could be explained by random reporting errors on the part of the individual respondents (Bertrand and Mullainathan, 2001), white-noise reporting errors cannot account for 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, which— following the statistical methodology of the PCE price index reported by the BEA—form the basis for aggregate inflation. In theory, therefore, a linear combination of weights should exist for the representative agent, summing up to unity, such that the weighted category-specific expectations equate to the aggregate inflation expectation. This, however, is clearly not the case in the data.

A potential explanation for this gap might be that respondents interpret the aggregate inflation question as referring to a macroeconomic variable, whereas 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’s SCE, aggregate expectations ask about “inflation/deflation,” while category-specific expectations refer to changes in “the price of” a category, with no suggestion that only one question type applies specifically to subjective personal 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 could be at play when respondents report aggregate versus category-specific inflation expectations. That is, respondents might adapt the heuristics used ac-

¹¹In order to minimize the sensitivity of reported statistics to outliers in the survey, the top and bottom 1 percent of responses for the aggregate and category inflation expectations are truncated. Huber-robust weights are applied to further reduce the sensitivity of reported statistics to outliers Huber (1964).

ording to the demands of the task at hand (i.e., Payne et al., 1993). We run a series of robustness checks that provide further insight into this pattern.

First, in a separate survey, we asked respondents about specific aggregate inflation indices, namely, PCE or CPI inflation (see Table B.1 in the Appendix). Our main findings hold up qualitatively; aggregate inflation expectations exceed inflation expectations for any category. In fact, 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 artifact, we randomized the order of aggregate and category-specific inflation questions for a subset of the sample (see Table B.2 in the Appendix); the mean aggregate expectation exceeds any category-specific expectation, irrespective of whether we first elicit aggregate or category-specific expectations.

Third, to explore whether the patterns in the cross-section extend beyond the typical consumer, we administered an abridged version of our survey to 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 B.3, 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 we obtain for consumers (Table 3), but a notable contrast arises for the disagreement in aggregate inflation expectations. While smaller than that of any category for fund managers, it is larger for consumers. This result could be explained by the potentially differential memory base held by fund managers and according to the framework of selective recall and memory in belief formation (Bordalo et al., 2022, 2023), which we discuss below.

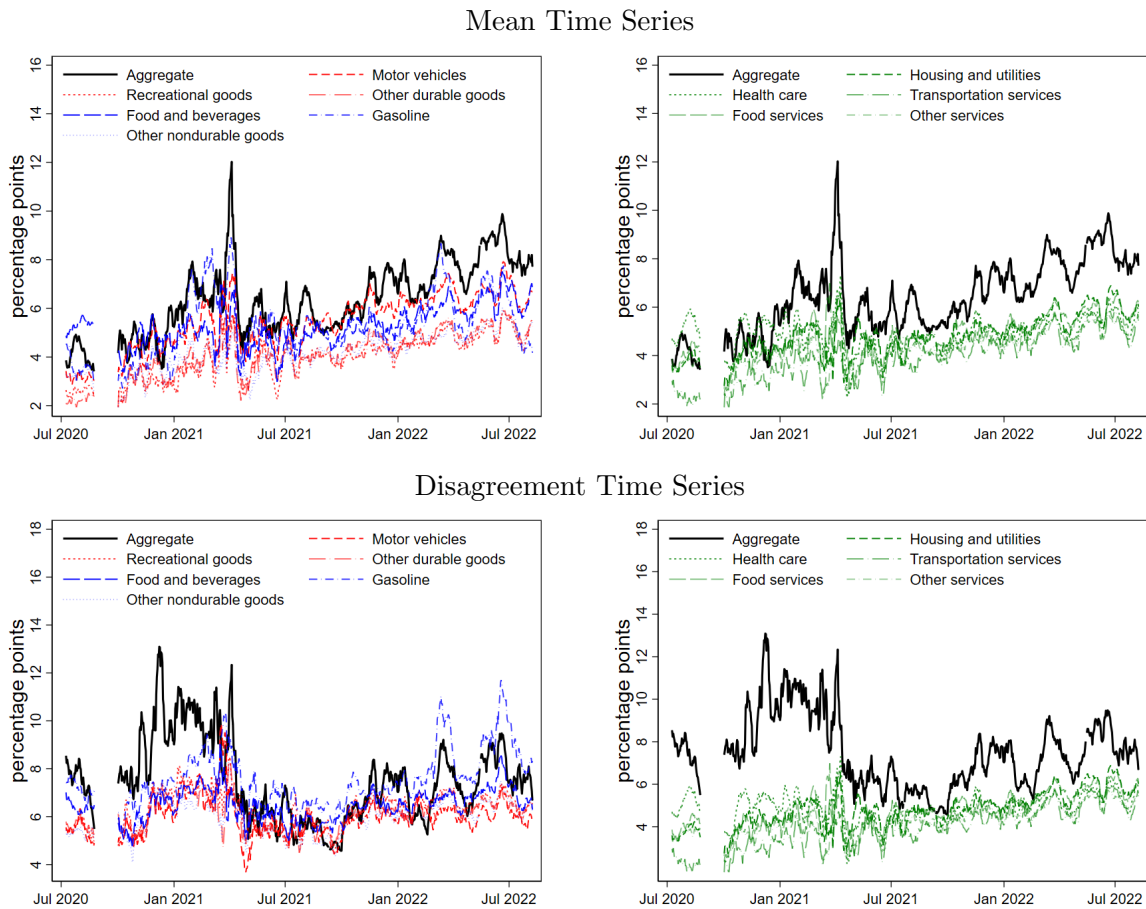
Fourth, we gauge the stability of our results over time. The upper row of Figure 1 shows the time series, daily means, for aggregate and mean category-specific inflation expectations during the survey period. The left panel displays category-specific expectations for the durable (red lines) and nondurable (blue lines) consumption goods, whereas the right panel shows services categories (green lines). All time series are centered 11-day moving averages.¹² 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.¹³ Consequently, for a representative agent, there is no possible linear combination of category-specific expectations with non-negative aggregation weights that maps category-specific expectations into aggregate expectations.

Time-series volatility (of expectations) is an important moment in economic analysis because it conveys information about cyclical dynamics, such as the role of rising economic uncertainty embodied in expectations (Dietrich et al., 2022). We find that volatility over time is higher for

¹²The centered moving average constructs for each day the average of the mean from the respective day and the five days before and after.

¹³The 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



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 centered 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.

aggregate inflation expectations than it is for category-specific expectations (see Column 3 in Table 3). 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 across survey respondents. 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 sample period, disagreement is much higher for aggregate expectations than it is for category-specific expectations (see also Table 3). This pattern could be interpreted within the framework of selective recall and memory in belief formation by Bordalo et al. (2022, 2023); recall may be facilitated in the context of concrete consumption categories relative to the case of abstract aggregate inflation, which may trigger more interference and thereby lead to noisier expectations.

This mechanism could explain why category-specific expectations are less dispersed and less volatile over time than aggregate inflation expectations.

Finally, we consider the pattern of demographic heterogeneity in inflation expectations (see Tables A.1 and A.2 in the Appendix). 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 levels and, where they are not, do not diverge in a consistent fashion. Across almost all categories, women report higher inflation expectations and greater disagreement; this pattern holds also for aggregate inflation expectations, generally consistent with demographic patterns reported by Bruine de Bruin et al. (2010). A paradoxical pattern, however, arises with age (see Table A.3 in the Appendix). For the oldest age group in our sample (older than 55), aggregate inflation expectations are lower than those of younger respondents—but for expectations by category, the pattern is reversed: older respondents report higher expectations.

4 Aggregate vs. Aggregated Inflation Expectations

Next, we show that aggregate inflation expectations differ significantly from *aggregated* measures, which describe overall inflation expectations by aggregating category-specific expectations. *Aggregated* inflation expectations tend to be lower than aggregate expectations, and disagreement among survey participants is higher for the latter. A statistically significant, positive gap between aggregate inflation expectations and both expenditure- and PCE-weighted aggregations is especially noteworthy as it reflects internally inconsistent beliefs about inflation. The gap increases with uncertainty and varies in a meaningful way with socioeconomic and demographic characteristics. Section 4.1 introduces the aggregation methods, Section 4.2 the statistical properties of *aggregated* inflation expectations relative to aggregate expectations, and Section 4.3 the relationship between aggregate inflation expectations and the *aggregated* measures.

4.1 Aggregated Inflation Expectations

We build multiple measures of *aggregated* inflation expectations, relying on category-specific expectations and sets of weights ω_k . For every set of weights, we assume the *aggregated* inflation expectation is a weighted average of categories in the sense that $\omega_k \geq 0$ and that $\sum_{k=1}^N \omega_k = 1$. Thus,

$$\mathbb{E}_t^i \pi_{t+1}^{aggregated} = \sum_{k=1}^N [\omega_k^i \mathbb{E}_t^i \pi_{k,t+1}], \quad (1)$$

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

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 the 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 expenditure of i on category k during last month.
$\mathbb{E}_t^i \pi_{t+1}^{imp}$	$\omega_k^i = \frac{Imp_{k,t}^i}{\sum_{k=1}^N Imp_{k,t}^i} \quad \forall k$	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.
$\mathbb{E}_t^i \pi_{t+1}^{1stmax}$	$\omega_k^i = 1 \forall k = m; \omega_k^i = 0 \forall k \neq m$ $\mathbb{E}_t^i \pi_{m,t+1} = 1^{st} \max(\{\mathbb{E}_t^i \pi_{k,t+1}\})$	Max ; aggregate expectation equal to highest category expectation.
$\mathbb{E}_t^i \pi_{t+1}^{2ndmax}$	$\omega_k^i = 1 \forall k = m; \omega_k^i = 0 \forall k \neq m$ $\mathbb{E}_t^i \pi_{m,t+1} = 2^{nd} \max(\{\mathbb{E}_t^i \pi_{k,t+1}\})$	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.

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.¹⁴ A second set of weights aggregates category inflation expectations with self-reported

¹⁴Up to second order, aggregate inflation—and, analogously, its expectation—is given by the (appropriately weighted) mean of category inflation $\bar{\pi}_{k,t}$ and a second-order variance term, related to the dispersion of prices: $\pi_t \approx \bar{\pi}_{k,t} + \frac{1}{2}C[\text{var}(\pi_{k,t}) - \text{var}(\pi_{k,t-1})]$, where C denotes a constant. This result follows directly from a Taylor approximation to common price aggregators. Appendix D.1 provides an example. Our analysis focuses on the first-order

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 respondents who aggregate category-specific expectations according to personal consumption baskets. 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 forms of “behavioral” expectations formation. A first assigns 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 opposite of the aforementioned, reflecting an agent who pays attention to non-core inflation. 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 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.

4.2 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 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, aggregate inflation expectations and the max operator yield the two highest standard deviations. Table 5 provides summary statistics. Fund managers in our auxiliary survey (Table B.3 in the Appendix) also report aggregate inflation expectations higher than most aggregations (all except the max operator), but disagreement for aggregate expectations is consistently lower.

For the cross-section, we illustrate these differences between aggregate inflation expectations and *aggregated* inflation expectations by means of a bin-scatter plot in Figure 2.¹⁵ Two features

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 report aggregate expectations either above or below the category range. We can thus rule out that a systematic one-sided approximation error drives our results.

¹⁵In a related exercise, in Table A.8 in the Appendix, we regress aggregate inflation expectations on *aggregated*

Table 5: Summary Statistics

	Mean	Disagreement	Time Series Volatility
Aggregate expectation	6.39	7.53	2.53
Aggregated expectations			
<i>Plausibly rational aggregation</i>			
Expenditure weights	4.99	5.32	1.39
Importance weights	4.69	4.78	1.35
PCE weights	4.30	4.59	1.30
<i>Behavioral aggregation</i>			
Equal weights	4.49	4.59	1.34
Core inflation	4.79	5.19	1.34
Non-core inflation	5.72	6.26	1.67
Max	11.29	8.51	2.82
Second max	6.96	6.45	1.80

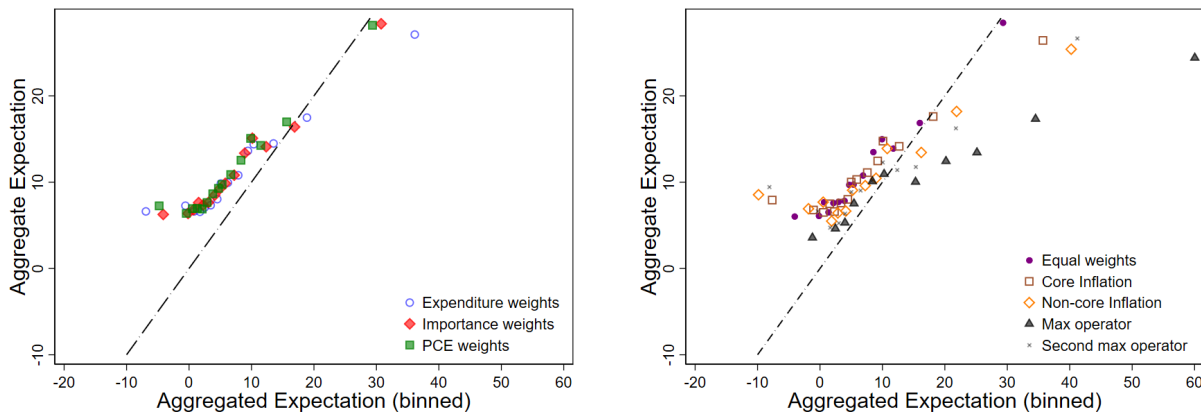
Notes: This table presents summary statistics on the mean on expectations, the standard deviation in the cross-section, and the standard deviation in the (daily mean) time series. Mean expectation: Time series mean of daily Huber-robust and survey-weighted mean expectations (see Figure 3, upper row);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

stand out: First, almost all observations lie above the 45°-line, indicating that aggregate inflation expectations tend to be higher than *aggregated* measures. This pattern, 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, whereas below a certain lower threshold, aggregate expectations diverge more. The same pattern holds if the conventional aggregate inflation expectations are binned on the horizontal axis. While a strong ordinal relationship exists for moderate responses, 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 well. Figure 3 shows that 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 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 aggrega-

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 behavioral, equal-weights aggregation, showing that it explains the largest share of variation in reported aggregate expectations. The subsequent section shows which factors correlate with the gap between the two measures.

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.

tions (bottom-left panel), equal-weight 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 time-series 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.

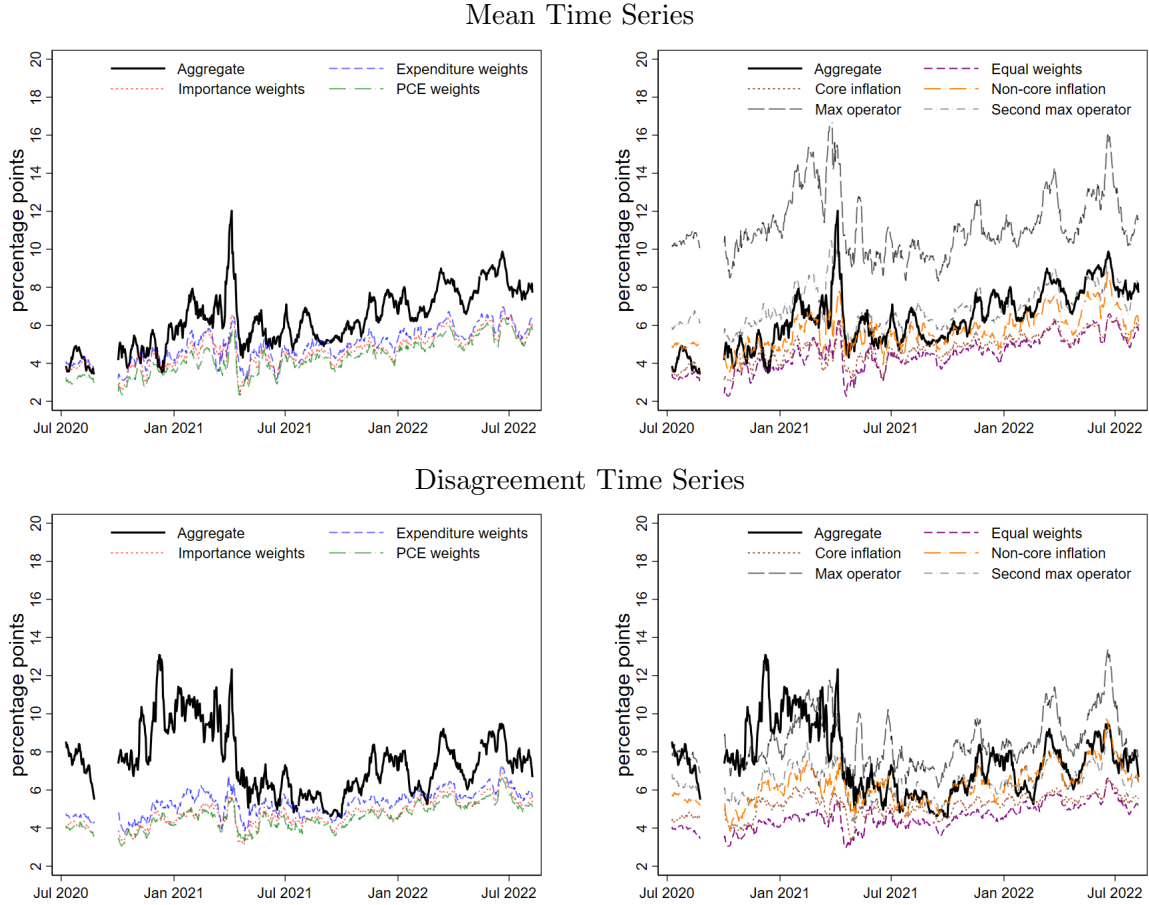
4.3 Gap between Aggregate and Aggregated Inflation Expectations

This section shows that the relationship between aggregate and *aggregated* inflation expectations, at the individual level, is linked to socio-demographic characteristics and the uncertainty of aggregate inflation expectations. For this purpose, we define the *aggregation gap* as the difference between the aggregate expectation and any aggregator of category-specific 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 the 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 aggregation

Figure 3: Aggregate vs Aggregated Measures



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 centered 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.

gap by *aggregated* measures. 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, whereas the PCE-weighted aggregation yields the smallest.

4.3.1 Demographics and the Aggregation Gap

When regressing 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 men, as do younger relative to older respondents. 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

Table 6: Summary Statistics

	Absolute Aggregation Gap $\text{abs}(\Lambda_i)$
<i>Plausibly rational aggregation</i>	
Expenditure weights	5.68***
Importance weights	5.50***
PCE weights	5.32***
<i>Behavioral aggregation</i>	
Equal weights	5.34***
Core inflation	5.69***
Non-core inflation	6.06***
Max	9.10***
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; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

complex or difficult to understand. Table A.6 in the Appendix summarizes these findings.

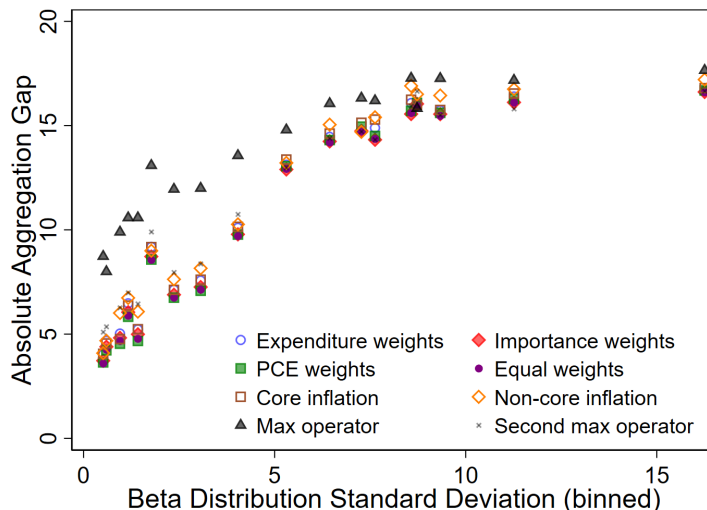
These results align with D’Acunto et al. (2019, 2022), who find that cognitive abilities play an important role in forecast accuracy. Moreover, D’Acunto et al. (2022) show that the responses of lower-IQ survey respondents, for which educational attainment might serve as a proxy, are more likely to be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

4.3.2 Uncertainty and the Aggregation Gap

One way to probe the implications of forecast 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 F). To obtain this measure, we fit for each respondent an individual beta distribution over the probabilities reported of specific outcomes; the respondent-specific uncertainty is the standard deviation of the distribution fitted. This procedure follows the methodology of Armantier et al. (2017) developed for the SCE.

The absolute aggregation gap increases with respondents’ uncertainty about aggregate inflation, as 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 pattern could arise because individuals adapt the heuristics at play according to the demands of the task at hand (Payne et al.,

Figure 4: The Aggregation Gap and Uncertainty



Notes: The figure shows the correlation between the absolute aggregation gap $\text{abs}(\Lambda_i)$ and the individual standard deviation of aggregate inflation expectations obtained via a beta distribution over a probabilistic question.

1993), and those demands might become differentiated with greater uncertainty about aggregate inflation. Alternatively, the absolute aggregation gap could be interpreted within the framework of Bordalo et al. (2022, 2023), given the role of selective recall and memory in belief formation (see also Appendix E). If recall, given the question cue, proves easier in the context of specific consumption categories than in the case of aggregate inflation, for which there is more interference, then elevated uncertainty about aggregate inflation expectations should be a reflection of the relative difficulty. This, in turn, could render aggregate inflation expectations noisier, which would increase the absolute aggregation gap.

Our 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 show that lower personal confidence in forecasts, as measured by uncertainty, corresponds to higher gaps, conceivably because the inflation concept respondents have in mind is less clear.

4.3.3 The Directional Aggregation Gap

The directional aggregation gap is important as it can reveal whether discrepancies between the two measures of inflation expectations wash out *on average*; the absence of a statistically significant directional gap would suggest that the measures are internally consistent. This subsection demonstrates that the directional aggregation gap is positive and substantial, even when taking into account demographic and economic factors.

All plausibly rational aggregations, including expenditure and PCE weights, yield a positive gap, as Table A.4 in the Appendix shows. This result rejects the idea that the reported aggregate reduces to a mental process summing categories by either self-reported expenditure shares or official PCE weights, as the FIRE hypothesis might suggest. While noise may account for $\Lambda_i > 0$ for any individual survey participant, noise cannot explain 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 result 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, 2024; 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 households, 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 low education).

Interestingly, our measure of task complexity—inflation uncertainty—is 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 result might also explain the visual pattern noted in Section 4.2, for Figure 3, 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 to a high-inflation regime.

One might wonder whether another systematic factor explains the aggregation gap in a manner not captured by the above regressors. Respondents, for example, may have a particular variable in mind, the growth rate of which they incorporate into their inflation calculation, but not fully into their consumption basket. This procedure would create an apparent gap between our aggregate and *aggregated* inflation expectations. However, any such variable or omitted category would have to be characterized by extremely high expected inflation rates all the time, both in our low- and high-inflation periods, in order to explain the large, persistent bias—despite representing a small or zero share of the comprehensive PCE basket. While one candidate—house prices—is included in our 11 categories through the housing costs category, another candidate, with no weight in the measured consumption basket, might be asset-price inflation more generally. However, when we consider as a proxy for asset prices the return or lagged return on the S&P 500, we do not see any significant relationship with the aggregation gap. This result likely arises from the fact that asset prices are very volatile and often decline (especially during part of our sample period), and hence

cannot consistently explain a (positive) gap. Appendix Table A.7 shows this result.

5 Model

Among the several facts documented above, two main facts about individual-level inflation expectations stand out for the average respondent: (i) Aggregate inflation expectations exceed *aggregated* inflation expectations but are significantly below the highest category expectation (max operator); and (ii) uncertainty about aggregate inflation expectations and the aggregation gap correlate positively. A behaviorally motivated, stylized framework can account for these facts whereas conventional models do not readily match these empirical regularities without further extensions or assumptions that are unlikely to hold empirically.

5.1 Setup

Suppose inflation π_k in consumption categories $k = 1, 2$ takes on two values: high inflation π^H or low inflation π^L , which a representative survey respondent believes occur with probability p_H and $p_L = 1 - p_H$. Categories have fixed consumption weights ω_k with $\sum_{k \in (1,2)} \omega_k = 1$. Aggregate inflation is given by the sum of the category inflation rates, that is, $\pi^{aggregate} = \omega\pi_1 + (1 - \omega)\pi_2$. Without loss of generality, assume $\pi_H > \pi_L = 0$. Also, high inflation does not represent the median inflation experience, that is, $p_H < 0.5$.

Category inflation expectations, $E[\pi_k]$, form the basis of the analysis. Category k inflation expectations are given by $E[\pi_k] = p_H\pi_H + p_L \cdot 0 = p_H \cdot \pi_H$. They are identical across categories and increasing in p_H , the probability of the high inflation event. Uncertainty at the category level is characterized by the variance over the different outcomes: $var(\pi_k) = p_H \cdot (1 - p_H) \cdot (\pi_H)^2$. Note that as long as $p_H < .5$, an increase in p_H will increase category dispersion. Given these category-level expectations, aggregated inflation expectations, $E[\pi^{aggregated}]$, are given by a linear aggregation over categories:

$$E[\pi^{aggregated}] = \sum \omega_k E[\pi_k] = \omega \cdot p_H \cdot \pi_H + (1 - \omega) \cdot p_H \cdot \pi_H = p_H \cdot \pi_H \quad (2)$$

which is identical to category expectations which are the same across categories.

Aggregate inflation expectations, $E[\pi^{aggregate}]$, are formed very differently. In their computation, respondents overweight the high-inflation event in each category. That is, the probability for a high-inflation event is multiplied with a probability adjustment factor, $\delta > 1$. As a result, the probabilities for high and low-inflation events, respectively, become $\tilde{p}_H = \frac{\delta p_H}{\Delta} > p_H$ and $\tilde{p}_L = \frac{p_L}{\Delta} < p_L$ where $\delta p_H + 1 - p_H = \Delta > 1$ denotes the appropriate normalization constant that ensures these probabilities add up to 1.

This assumption of higher probabilities attached to high-inflation events in an aggregate context ($\tilde{p}_H > p_H$) captures the tendency individuals have to over-weight rare, salient events (Lichtenstein et al., 2018). Because high inflation in aggregate is generated by a conjunction of high-inflation events at the category level, the former is necessarily rarer than individual instances of the latter. Moreover, individuals tend to overweight highly rare events more than less rare events (Lichtenstein et al., 1978). Thus, the likelihood of high inflation in aggregate is likely to be over-weighted more than high-inflation events at the category level. This justifies the probability adjustment factor, $\delta > 1$, for high-inflation events in an aggregate context.

Our proposed mechanism yields a type of probability assessment reminiscent of the conjunction fallacy (Tversky and Kahneman, 1983), which is a violation of the conjunction rule from basic statistics whereby the probability of two or more combined events cannot exceed that of any constituent single event. Indeed, the mechanism behind the conjunction fallacy may provide a compatible, close alternative to ours because the combined events that produce a “cost-of-living crisis” may prove more retrievable and imaginable than high inflation within a specific category. Relying on ease of retrieval and imaginability as a judgmental heuristic, an individual may judge high aggregate inflation—and thereby high inflation in most or all categories—as more likely than high inflation for most if not all of its constituent categories judged individually. At a deeper level, both this and our mechanism can be formalized and micro-founded using a theory of memory and recall (Kahana 2012, Bordalo et al. 2023).¹⁶

5.2 Results

This setup delivers two propositions that rationalize our main empirical findings: There is an aggregation gap, and uncertainty is correlated with the aggregation gap.

Proposition 1 (Aggregation Gap). *Aggregate inflation expectations, $E[\pi^{aggregate}]$, exceed aggregated inflation expectations, $E[\pi^{aggregated}]$, creating a positive aggregation gap $\Lambda \forall p_H \in (0, 1)$:*

$$\Lambda = E[\pi^{aggregate}] - E[\pi^{aggregated}] = p_H \pi_H \left(\frac{\delta}{\Delta} - 1 \right) > 0 \quad (3)$$

Proof. This result follows from $\delta > 1$ which implies $\frac{\delta}{\Delta} > 1$. See appendix for details. \square

The intuition for this result is as follows: When assessing aggregate inflation expectations, respondents overweight high-inflation outcomes relative to a category-specific inflation expectations assessment, inducing a positive aggregation gap.

The second proposition, below, also follows naturally from features of the underlying binomial probability distribution of the model: Holding the behavioral parameter δ constant, increases in

¹⁶Additional mechanisms compatible with our model may also exist. While we remain agnostic about them, we discuss below how we may rule out two conventional approaches.

π_H , and under mild conditions p_H , are associated with increases in the levels of uncertainty, and the aggregation gap. Hence, both co-vary positively with the variation in these model primitives π_H , and p_H under mild conditions.

Proposition 2 (Positive Correlation Uncertainty and Aggregation Gap). *The correlation of individual-level uncertainty $\text{var}(\pi_k)$ and the aggregation gap Λ is always positive when originating from increases in π_H , and also positive for all $p_H < \frac{1}{1+\delta}$:*

$$\text{corr}(\text{var}(\pi_k), \Lambda) > 0 \tag{4}$$

Proof. See appendix. □

The intuition for the result is the following: First, regarding variation in π_H , the properties of the underlying binomial distribution ensure that an increase in π_H scales up the gap while convexity in the calculation of the variance simultaneously increases the variance. Regarding variation in p_H , it is well known that the variance of a binomial peaks at 0.5. Because the adjustment factor δ raises the probability \tilde{p}_H , the threshold for the variance to increase, in p_H , is adjusted down to $1/(1+\delta)$. In terms of the gap, the intuition is likewise straight-forward: There cannot be a gap when all mass is on one event only, that is, $\Lambda(p_H = 1) = \Lambda(p_H = 0) = 0$. But Λ is also a downwards-sloping parabola with a maximum for some $p_H \in (0, 1)$ so that an increase in p_H raises the gap up to this point. It turns out that $1/(1+\delta)$ is to the left of it as we show in the appendix. Hence, both variance and gap are also increasing for low enough p_H .

5.3 Alternative Setups

Recurring to the behavioral over-weighting paradigm in the context of inflation expectations aggregation is a useful modeling step: It allows our stylized framework to match the empirical regularities we observe for the aggregation process. Conventional models do not readily match these empirical regularities without further extensions or assumptions that are unlikely to hold empirically.

For example, one might conjecture that higher-order terms in the approximation to the price aggregator may add a systematically positive bias missed by the linear aggregation of category beliefs. However, this is only the case if one assumes that consumption categories are complements as we show in Appendix E, which is likely not the case for most categories. Likewise, a stylized model of rational inattention implies that respondents should over-weight relatively more volatile inflation category (see for example Dietrich (2024)). Such overweighting, however, does not necessarily imply a positive aggregation bias in the aggregate.¹⁷

¹⁷In a related literature on real exchange rate persistence, Imbs et al. (2005) show that aggregation may also introduce higher persistence into more aggregate processes. Such higher persistence may then imply an aggregation gap for a given shock, compared to the less persistent category level which more quickly reverts to zero deviations. The sign of the gap will, however, be tied to the sign of the underlying shocks and thus does not generate a systematically signed aggregation bias.

6 Economic Implications

Thus far, we have established that ordinary consumers think differently about aggregate versus category-specific inflation expectations. To gauge the importance of this wedge, we first focus on a central relationship in macroeconomics—the consumption Euler equation. By estimating the Euler equation, we show that aggregated measures of inflation expectations carry superior information for explaining spending plans compared to the conventional aggregate measure of inflation expectations, and that this relative informational advantage increases with the aggregation gap, which—as we show in Section 4.3—is related to heterogeneity in the population, namely, socio-demographics and uncertainty. *Aggregated* inflation expectations, moreover, appear to carry additional information regardless of the aggregation chosen as a measure for estimating the Euler equation. At the same time, 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 consumers follow a standard Euler equation

$$Q_{i,t} = \mathbb{E}_t^i \left[\beta_i \left(\frac{C_{i,t+1}}{C_{i,t}} \right)^{-\frac{1}{\sigma}} \frac{P_t}{P_{t+1}} \right]. \quad (5)$$

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 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 represents the expectations operator for respondent i . A log-linearized version of equation (5) is

$$c_{i,t} = \mathbb{E}_t c_{i,t+1} - \sigma [r_{i,t} - \mathbb{E}_t^i \pi_{t+1} - \rho_i], \quad (6)$$

where $\pi_t = p_t - p_{t-1}$ denotes the inflation rate. Whereas $\mathbb{E}_t c_{i,t+1}$ 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 into equation (6) the expression for the expected change in nominal consumption spending yields a version of the Euler equation that links expected spending to expected inflation

$$\mathbb{E}_t^i \Delta s_{i,t+1} - \mathbb{E}_t^i \pi_{t+1} = \sigma [r_{i,t} - \mathbb{E}_t^i \pi_{t+1} - \rho_i]. \quad (7)$$

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. (2022), we then estimate this equation through the following specification

$$\mathbb{E}_t^i \Delta s_{i,t+1} = \gamma_0 + \gamma_1 \mathbb{E}_t^i \pi_{t+1} + D_i + T_t + \epsilon_{i,t}, \quad (8)$$

where D_i represents demographic fixed effects¹⁸ 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 individuals face. The coefficient γ_1 in the estimation equation is equal to $1 - \sigma$ in the model in equation (7).

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. The table reports $1 - \hat{\gamma}_1$, which is equal to the intertemporal elasticity of substitution σ . The third column gives the R^2 values, the fourth the Akaike information criterion, and the fifth the p-value of a likelihood ratio test, which compares the fit of the respective models to the aggregate inflation-expectation model.

Two results stand out. 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 of the *aggregated* measures; *aggregated* measures of inflation expectations are more informative for future spending plans and can thus 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 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 . As a robustness exercise to control for possible reporting errors within inflation expectations, Table A.9 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 F).

As with the dispersion of aggregate inflation expectations relative to category-specific expectations, and the absolute aggregation gap between aggregate and *aggregated* inflation expectations, the results can be interpreted through the lens of the model of Bordalo et al. (2022, 2023) on the role of selective recall and memory in belief formation. If recall proves easier in the context of specific consumption categories than in the case of aggregate inflation, for which more interference

¹⁸Since we rely only on a cross-sectional sample without a panel dimension, we include demographic controls, instead of individual fixed effects.

Table 7: 1 One-Year-Ahead Spending Plans

	$\hat{\sigma} = 1 - \hat{\gamma}_1$	t-stat	R^2	AIC	LR	N
Aggregate	0.959***	7.88	0.057	171354	-	24143
Expenditure	0.825***	15.28	0.083	170693	0.000	24143
Importance	0.784***	17.00	0.088	170555	0.000	24143
PCE	0.787***	15.89	0.084	170647	0.000	24143
Equal	0.774***	16.72	0.088	170560	0.000	24143
Core inflation	0.845***	13.57	0.076	170857	0.000	24143
Non-core inflation	0.872***	14.68	0.076	170865	0.000	24143
Max	0.912***	14.72	0.074	170931	0.000	24143
Second max	0.870***	14.47	0.079	170791	0.000	24143
12-months-ahead nondurable spending						
Aggregate	0.956***	5.12	0.061	33236	-	4719
Expenditure	0.793***	9.39	0.088	33094	0.000	4719
Importance	0.754***	10.27	0.093	33071	0.000	4719
PCE	0.757***	9.90	0.089	33092	0.000	4719
Equal	0.733***	10.13	0.095	33060	0.000	4719
Core inflation	0.822***	8.57	0.081	33135	0.000	4719
Non-core inflation	0.844***	8.58	0.083	33121	0.000	4719
Max	0.905***	7.03	0.073	33172	0.000	4719
Second max	0.851***	8.43	0.087	33099	0.000	4719
12-months-ahead services spending						
Aggregate	0.965***	7.73	0.061	165534	-	24260
Expenditure	0.859***	14.71	0.082	164981	0.000	24260
Importance	0.828***	15.42	0.086	164870	0.000	24260
PCE	0.825***	14.63	0.085	164900	0.000	24260
Equal	0.815***	15.44	0.088	164829	0.000	24260
Core inflation	0.861***	14.72	0.082	164981	0.000	24260
Non-core inflation	0.906***	12.34	0.073	165232	0.000	24260
Max	0.929***	14.11	0.074	165182	0.000	24260
Second max	0.892***	13.83	0.081	165014	0.000	24260

Notes: Estimated Euler equations, relying on various measures of aggregate or aggregated inflation expectations; t statistics in second 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.

occurs, then the measure of aggregate inflation expectations should be noisier, yielding a weaker fit in models that predict spending plans based on aggregate inflation expectations.

Our estimates based on *aggregated* expectations, moreover, 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),¹⁹ first using an estimate of the intertemporal elasticity of substitution based on an estimation that uses aggregate inflation expectations ($\sigma = 0.960$; see Table 7) and, second, using an elasticity based on an estimation that uses an aggregation of equal weights ($\sigma = 0.777$; see Table 7). We leave all other parameters fixed to highlight the economic importance of the difference in our estimates. 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 percent higher in the simulation that uses the elasticity based on (equal-weight) *aggregated* inflation expectations, relative to simulations using estimates based on conventional aggregate expectations. Similarly, the variance of the output gap is 5.7 percent higher across these specifications. In welfare analysis, these changes may be considered costly.

6.1 Superior Information of Aggregated Expectations

The estimation of the Euler equation can also be used to further substantiate the finding that *aggregated* measures of inflation expectations contain superior information for explaining spending plans compared to the conventional aggregate measure of inflation expectations. Specifically, the relative informational advantage of *aggregated* measures of inflation expectations increases with the aggregation gap, which, as shown in Section 4.3, is related to heterogeneity in the population, namely, socio-demographics and uncertainty.

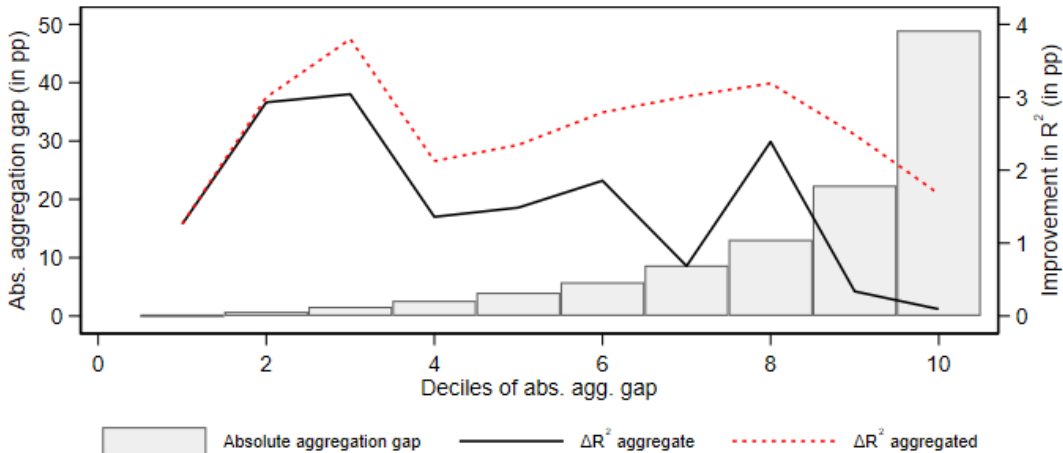
To establish this insight, we split the sample by deciles of the absolute aggregation gap outlined in Section 4.3 and then repeat the estimation of the Euler equation. For each decile, we estimate the Euler equation for planned changes in total spending, as detailed in equation 8. We are interested in the amount of variation (R^2) of total spending plans explained when we use either the aggregate or the *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 that of 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 expectations and the expenditure-weighted, *aggregated* inflation expectations.²⁰

By construction, both lines are always above zero because including an additional independent variable in the estimation improves the share of total variance explained. Moreover, because the measures differ only slightly for respondents with the smallest absolute aggregation gaps, the difference between the two measures in this region is close to zero. However, as the absolute aggregation gap grows, a clear pattern emerges for the conventional measure of aggregate inflation

¹⁹All parameters are identical to those in Chapter 3 of Galí (2015).

²⁰We use the expenditure-weighted aggregation as an example. Similar patterns emerge for each of the other aggregations, as Figure A.2 in the Appendix shows.

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 (8), 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).

expectations: The improvement in R^2 from including the measure in the Euler-equation regression declines substantially, approaching zero for those with the largest aggregation gaps. When using the expenditure-weighted, *aggregated* expectations in the regression, on the other hand, improvement in R^2 does not drop to zero, and the R^2 is also consistently higher than that obtained with aggregate inflation expectations. Against the backdrop of socio-demographic heterogeneity and uncertainty associated with the aggregation gap, this relative informational advantage of aggregated inflation expectations is highly relevant—especially for policymakers—for measuring inflation expectations effectively across diverse parts of the population.

7 Conclusion

Motivated by evidence that consumers struggle to grasp the concept of inflation, we introduce an alternative approach to measuring consumer inflation expectations. Rather than asking consumers outright about aggregate inflation expectations, as conventional measures do, we elicit their expectations for the underlying parts, the full range of personal consumption expenditures, which we then aggregate. Our results indicate that *aggregated* measures, across all of our aggregation procedures, yield more information about consumer spending plans compared to the conventional measure. We obtained this finding in a daily consumer survey of close to 60,000 respondents over two years, extending from the low-inflation environment of the COVID pandemic to the 2021 inflation surge.

In addition, four striking facts stand out. The first is that aggregate inflation expectations are

higher than inflation expectations for any single category. For a representative agent, this finding rules out a linear mapping (with non-negative weights) of the category-specific expectations into aggregate inflation expectations. Moreover, disagreement among respondents over aggregate inflation expectations is higher than that over any category. Second, *aggregated* inflation expectations, unsurprisingly with the exception of the max operators, are lower than 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, at higher levels of the respondent-specific gap between aggregate and *aggregated* inflation expectations, the information about consumer spending plans provided by *aggregated* expectations is higher in both absolute and relative terms than that provided by aggregate expectations. In other words, when the two measures differ substantially, the *aggregated* measure becomes more informative.

We conclude, therefore, that effective inflation expectations—the expectations on which consumers act—appear to be *not* best represented by explicit, conventionally reported aggregate inflation expectations, but by aggregations of category-specific inflation expectations. This holds true irrespective of socio-demographic heterogeneity and the uncertainty faced by respondents.

Clearly, alternative procedures for decomposing the aggregate inflation concept are worth exploring, as are alternative aggregation mechanisms and measures of consumer planning and behavior. We regard our paper as a first step in this direction, a proof of concept that lays out foundations for future work aimed at improving the measurement of a key macroeconomic aggregate, a vital input to monetary policy that is notoriously difficult to capture.

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A Additional Tables

A.1 Socio-Demographic Summary Statistics

Table A.1: Summary Statistics - Mean Demographics

	Gender		Grocery		Education		Income		
	Female	Male	Yes	No	High	Low	High	Middle	Low
Aggregate expectation	7.31	6.00	6.69	5.84	6.11	7.45	7.64	6.36	6.96
Category expectations									
Motor vehicles	5.68	5.41	5.53	5.66	5.71	5.35	5.82	5.51	5.37
Recreational goods	4.45	3.72	4.01	4.04	4.22	3.83	4.26	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	5.61	5.52	5.25
Gasoline	5.78	4.96	5.28	5.72	5.40	5.35	5.39	5.72	5.27
Other nondurable	4.41	3.95	4.20	3.96	4.32	4.05	4.58	4.28	3.94
Housing and util.	5.26	4.46	4.87	4.73	4.88	4.82	4.77	5.09	4.87
Health care	5.28	4.65	4.99	4.92	5.22	4.76	5.30	5.34	4.68
Transportation	4.15	3.90	4.03	3.94	4.21	3.81	4.53	4.13	3.70
Food services	5.02	4.56	4.80	4.92	5.04	4.56	5.22	4.87	4.52
Other services	4.59	4.07	4.38	4.21	4.39	4.27	4.56	4.51	4.23
Aggregated expectations									
<i>Plausibly rational aggregation</i>									
Expenditure weights	5.44	4.67	5.02	5.15	5.13	5.03	5.20	5.26	5.04
Importance weights	5.16	4.34	4.71	4.89	4.87	4.60	4.95	4.91	4.60
PCE weights	4.73	4.00	4.34	4.44	4.48	4.24	4.63	4.51	4.23
<i>Behavioral aggregation</i>									
Equal weights	4.90	4.20	4.52	4.65	4.68	4.42	4.79	4.69	4.41
Core inflation	5.18	4.53	4.84	4.86	4.96	4.79	4.98	5.03	4.82
Non-core inflation	6.30	5.25	5.72	6.29	5.68	5.84	5.93	6.00	5.84
Max	12.54	10.58	11.29	12.72	11.29	11.76	11.51	11.48	11.95
Second max	7.64	6.51	6.97	7.56	7.06	7.02	7.05	7.21	7.16

Notes: This table presents summary statistics on the Huber-robust and survey-weighted mean on expectations across demographics. “Grocery” refers to whether a respondent indicates being the main grocery shopper in the household.

Table A.2: 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	7.05	5.98	10.22	7.61	6.23	9.67
Category expectations									
Motor vehicles	6.51	5.26	5.92	5.96	5.44	6.22	5.34	5.38	6.28
Recreational goods	6.83	5.62	6.34	5.85	5.67	6.79	5.58	5.61	6.91
Other durable goods	6.73	5.43	6.21	5.52	5.49	6.56	5.57	5.45	6.82
Food and beverages	7.06	5.87	6.50	6.09	5.83	6.89	5.94	5.76	7.00
Gasoline	7.97	7.24	7.49	8.30	7.48	7.65	7.33	7.55	7.77
Other nondurable	6.55	5.33	6.03	5.67	5.34	6.50	5.30	5.43	6.48
Housing and util.	6.80	5.50	6.21	5.96	5.63	6.69	5.56	5.60	6.83
Health care	6.93	5.77	6.47	6.13	5.77	6.95	5.80	5.90	6.92
Transportation	6.99	5.90	6.51	6.22	6.09	6.80	6.14	5.99	6.82
Food services	6.87	5.86	6.49	6.03	6.03	6.70	6.05	5.80	6.88
Other services	6.20	4.98	5.70	5.31	5.01	6.13	5.11	5.03	6.13
Aggregated expectations									
<i>Plausibly rational aggregation</i>									
Expenditure weights	5.93	4.65	5.31	5.05	4.77	5.74	4.54	4.93	5.83
Importance weights	5.23	4.22	4.77	4.48	4.42	4.89	4.15	4.42	5.06
PCE weights	5.08	4.03	4.61	4.18	4.27	4.71	4.11	4.27	4.87
<i>Behavioral aggregation</i>									
Equal weights	5.00	4.06	4.59	4.21	4.28	4.68	4.03	4.30	4.84
Core inflation	5.80	4.52	5.21	4.82	4.69	5.62	4.43	4.80	5.72
Non-core inflation	6.77	5.66	6.26	6.02	5.78	6.62	5.88	5.76	6.77
Max	9.57	7.62	8.41	8.98	8.00	8.99	7.94	8.12	9.30
Second max	7.13	5.83	6.43	6.52	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. “Grocery” refers to whether a respondent indicates being the main grocery shopper in the household.

Table A.3: 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	7.94	8.98	8.40	5.73	11.64	11.62	9.62	4.36
Category expectations								
Motor vehicles	4.61	5.89	5.98	6.35	6.37	6.26	6.02	4.97
Recreational goods	2.47	4.11	4.80	5.28	7.15	6.89	6.24	4.49
Other durable goods	2.82	4.25	4.77	5.22	6.76	6.87	6.12	4.64
Food and beverages	3.79	5.41	6.32	7.06	7.00	7.17	6.78	5.19
Gasoline	3.81	5.16	6.49	7.60	7.42	7.32	7.62	7.97
Other nondurable	2.85	4.26	5.11	5.25	6.99	6.56	5.99	4.34
Housing and util.	3.50	4.80	5.58	6.27	6.86	6.74	6.40	4.96
Health care	3.66	4.77	5.95	6.30	7.08	7.09	6.47	5.09
Transportation	2.61	4.17	4.59	5.26	7.02	6.79	6.15	5.30
Food services	3.07	4.66	5.54	6.62	6.94	6.77	6.32	5.32
Other services	3.36	4.24	5.06	5.20	6.35	6.26	5.54	4.09
Aggregated expectations								
<i>Plausibly rational aggregation</i>								
Expenditure weights	3.65	5.03	6.06	6.67	5.08	5.37	5.41	4.73
Importance weights	3.12	4.61	5.67	6.60	3.86	4.67	4.90	4.54
PCE weights	2.87	4.23	5.26	6.01	3.83	4.64	4.66	4.17
<i>Behavioral aggregation</i>								
Equal weights	2.98	4.41	5.42	6.31	3.68	4.53	4.66	4.32
Core inflation	3.63	4.86	5.71	6.19	5.23	5.27	5.26	4.47
Non-core inflation	4.17	5.67	6.77	7.36	6.33	6.40	6.38	5.65
Max	10.63	11.60	12.21	13.22	8.10	8.51	9.17	8.89
Second max	6.13	7.26	7.46	8.50	6.64	6.64	7.00	5.89

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

A.2 Aggregation Gap

A.2.1 The Directional Aggregation Gap

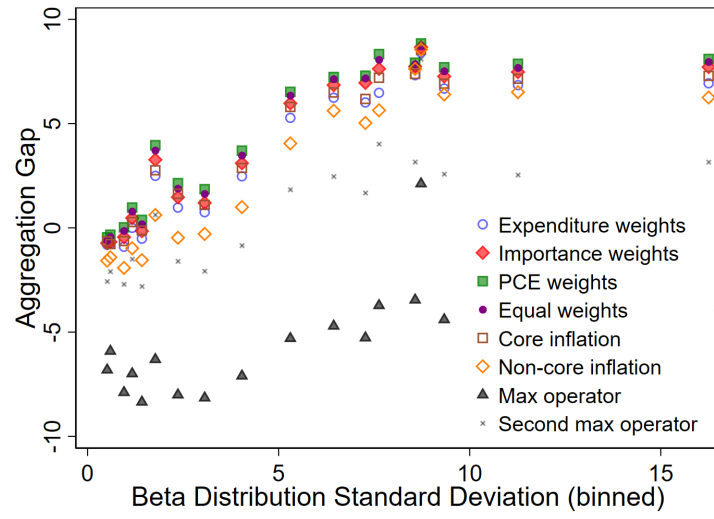
In this section we report results for the aggregation gap between aggregate and aggregated inflation expectations per respondent, without taking the absolute value of the gap. Table A.4 displays the mean aggregation gap, as compared to the mean absolute aggregation gap (see also Table 6 in the main text). While the absolute aggregation gap provides a measure of the discrepancy between aggregate and aggregated inflation expectations irrespective of sign, the aggregation gap indicates the direction of the gap.

Table A.4: Summary Statistics

	Mean Aggregation Gap (Λ_i)	Mean Absolute Aggregation Gap $\text{abs}(\Lambda_i)$
<i>Plausibly rational aggregation</i>		
Expenditure weights	1.23***	5.68***
Importance weights	1.45***	5.50***
PCE weights	1.72***	5.32***
<i>Behavioral aggregation</i>		
Equal weights	1.63***	5.34***
Core inflation	1.47***	5.69***
Non-core inflation	0.68***	6.06***
Max	-3.98***	9.10***
Second max	-0.43***	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 A.1: The Aggregation Gap and Uncertainty



Notes: The figure shows the correlation between the aggregation gap Λ_i and the subjective uncertainty over aggregate inflation expectations obtained via a beta distribution over a probabilistic question.

A.2.2 Aggregation Gap - Socio-Demographic Effects

Tables A.5 and A.6 link the (absolute) aggregation gap to socio-demographic factors as well as respondents' grocery shopping habits.

Table A.5: Demographics and the Aggregation Gap

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Expenditure	Importance	PCE	Equal	Core	Non-core	1 st max	2 nd max
Female	0.00275 (0.03)	0.0780 (1.00)	0.129 (1.70)	0.147 (1.92)	0.140 (1.71)	-0.191* (-2.12)	-0.544*** (-5.00)	-0.0231 (-0.26)
Grocery Shopper	0.715*** (5.74)	0.770*** (6.50)	0.593*** (5.12)	0.640*** (5.48)	0.614*** (4.95)	0.915*** (6.62)	1.641*** (9.78)	1.064*** (7.75)
35 to 44 years	-0.430*** (-3.76)	-0.437*** (-3.95)	-0.418*** (-3.85)	-0.432*** (-3.96)	-0.420*** (-3.65)	-0.670*** (-5.32)	-0.0574 (-0.39)	-0.0653 (-0.53)
45 to 54 years	-1.354*** (-10.21)	-1.464*** (-11.50)	-1.312*** (-10.59)	-1.380*** (-11.03)	-1.206*** (-9.00)	-1.721*** (-11.95)	-0.885*** (-5.12)	-0.849*** (-5.89)
above 55 years	-3.136*** (-34.39)	-3.164*** (-36.10)	-2.862*** (-33.40)	-3.031*** (-35.09)	-2.859*** (-31.31)	-3.851*** (-37.91)	-3.723*** (-30.59)	-2.928*** (-29.33)
High Educated	-0.807*** (-8.96)	-0.784*** (-9.10)	-0.761*** (-9.02)	-0.794*** (-9.34)	-0.859*** (-9.48)	-0.568*** (-5.64)	-0.919*** (-7.45)	-0.813*** (-8.20)
Middle Income	0.0101 (0.11)	-0.0118 (-0.13)	0.0324 (0.37)	0.00289 (0.03)	0.0571 (0.61)	-0.200 (-1.95)	0.0420 (0.34)	0.0183 (0.18)
High Income	0.237* (2.05)	0.0497 (0.45)	0.0385 (0.35)	0.0480 (0.44)	0.216 (1.85)	0.125 (0.96)	0.430** (2.70)	0.161 (1.26)
Constant	2.328*** (15.78)	2.477*** (17.61)	2.768*** (19.98)	2.699*** (19.34)	2.507*** (17.02)	2.264*** (13.91)	-3.477*** (-17.93)	0.134 (0.83)
N	47575	47402	47159	47309	47468	48020	49010	47990
r2	0.0442	0.0496	0.0439	0.0479	0.0386	0.0483	0.0365	0.0359

Notes: This table presents HUber-robust and survey-weighted regressions of the aggregation gap on several demographic characteristics. For reasons of comparison, we only use data from respondents where all aggregated expectations are defined. Number of observations differs between columns, as some observations receive a Huber weight of 0. 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 A.6: Demographics and the Absolute Aggregation Gap

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Expenditure	Importance	PCE	Equal	Core	Non-core	1 st max	2 nd max
Female	0.665*** (3.31)	0.718*** (11.94)	0.729*** (12.38)	0.734*** (12.42)	0.839*** (12.92)	0.595*** (8.32)	0.856*** (8.36)	0.655*** (8.98)
Grocery Shopper	0.750** (2.63)	-0.159 (-1.77)	-0.175* (-2.02)	-0.164 (-1.87)	-0.170 (-1.77)	-0.217* (-2.04)	-0.639*** (-4.05)	-0.332** (-3.02)
35 to 44 years	-1.237*** (-4.36)	-0.344*** (-3.99)	-0.375*** (-4.40)	-0.376*** (-4.42)	-0.311*** (-3.35)	-0.387*** (-3.85)	-0.388** (-2.83)	-0.371*** (-3.64)
45 to 54 years	-3.554*** (-11.12)	-1.105*** (-11.37)	-1.187*** (-12.48)	-1.147*** (-11.97)	-0.970*** (-9.15)	-1.248*** (-11.14)	-0.949*** (-6.01)	-0.864*** (-7.41)
above 55 years	-7.795*** (-36.01)	-2.065*** (-30.63)	-2.255*** (-34.14)	-2.156*** (-32.55)	-2.195*** (-30.33)	-2.058*** (-25.73)	-1.004*** (-8.77)	-1.781*** (-21.92)
High Educated	-0.680** (-2.79)	-0.595*** (-8.91)	-0.694*** (-10.57)	-0.650*** (-9.92)	-0.681*** (-9.40)	-0.471*** (-5.87)	-0.192 (-1.65)	-0.507*** (-6.22)
Middle Income	-1.361*** (-6.40)	-0.370*** (-5.37)	-0.371*** (-5.49)	-0.372*** (-5.48)	-0.344*** (-4.60)	-0.319*** (-3.93)	-0.451*** (-3.88)	-0.366*** (-4.43)
High Income	0.814** (2.62)	-0.213* (-2.47)	-0.169* (-2.00)	-0.192* (-2.27)	-0.140 (-1.49)	-0.0989 (-0.96)	0.0599 (0.40)	-0.172 (-1.63)
Constant	14.43*** (43.33)	6.527*** (61.26)	6.516*** (62.77)	6.489*** (61.93)	6.777*** (58.89)	7.393*** (58.78)	9.877*** (54.07)	7.433*** (56.78)
N	52035	47321	47102	47237	47494	47979	50199	48238
r2	0.0519	0.0470	0.0574	0.0527	0.0477	0.0288	0.00590	0.0234

Notes: This table presents Huber-robust and survey-weighted regressions of the absolute aggregation gap on several demographic characteristics. For reasons of comparison, we only use data from respondents where all aggregated expectations are defined. Number of observations differs between columns, as some observations receive a Huber weight of 0. 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 A.7: Aggregation Gap and Asset Price Changes

<i>Absolute aggregation gap</i> (<i>expenditure weighted</i>)	(1) $ \Lambda_i^{exp} $	(2) $ \Lambda_i^{exp} $	(3) $ \Lambda_i^{exp} $	(4) $ \Lambda_i^{exp} $
$\Delta_{t,t-1} \ln(\text{S\&P 500})$	-1.176 (-0.54)			
$\Delta_{t-1,t-2} \ln(\text{S\&P 500})$		0.560 (0.56)		
$\Delta_{t,t-365} \ln(\text{S\&P 500})$			0.0430 (0.53)	
$\Delta_{t-1,t-366} \ln(\text{S\&P 500})$				0.0421 (0.55)
Constant	6.995*** (9.88)	7.225*** (15.60)	7.398*** (14.23)	7.422*** (14.81)
Time + Demographic FE	yes	yes	yes	yes
N	35911	35952	36641	36864
R^2	0.0752	0.0729	0.0751	0.0748
<i>Directed aggregation gap</i> (<i>expenditure weighted</i>)	(5) Λ_i^{exp}	(6) Λ_i^{exp}	(7) Λ_i^{exp}	(8) Λ_i^{exp}
$\Delta_{t,t-1} \ln(\text{S\&P 500})$	0.811 (0.29)			
$\Delta_{t-1,t-2} \ln(\text{S\&P 500})$		-0.407 (-0.31)		
$\Delta_{t,t-365} \ln(\text{S\&P 500})$			-0.0301 (-0.28)	
$\Delta_{t-1,t-366} \ln(\text{S\&P 500})$				-0.0298 (-0.30)
Constant	2.285* (2.19)	2.076** (3.04)	2.036** (3.07)	1.958** (3.02)
Time + Demographic FE	yes	yes	yes	yes
N	35899	35946	36630	36862
R^2	0.0673	0.0672	0.0678	0.0672

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table presents Huber-robust and survey-weighted regressions of the absolute aggregation gap (expenditure weighted) on daily asset price changes (S&P 500). Time (daily) and demographic fixed effects used. For details on aggregated expectations, see Table 4. *t* statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

A.3 Aggregate vs. Aggregated Inflation Expectations

Table A.8: Aggregate vs. Aggregated Inflation Expectations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Expenditure	0.545*** (35.40)								0.117 (1.64)
Importance		0.639*** (37.00)							-0.414*** (-4.38)
PCE			0.649*** (35.91)						-0.273** (-2.88)
Equal				0.688*** (38.80)					1.127*** (8.79)
Core Inflation					0.506*** (32.13)				-0.0221 (-0.39)
Non-core Inflation						0.390*** (31.15)			-0.0295 (-0.98)
Max							0.316*** (34.59)		0.128*** (7.05)
Second max								0.415*** (32.33)	0.00751 (0.26)
Constant	7.583*** (49.52)	7.158*** (45.58)	7.424*** (47.65)	7.044*** (45.33)	8.049*** (53.33)	8.466*** (56.76)	6.422*** (38.79)	7.410*** (45.12)	6.139*** (37.77)
N	52035	52035	52035	52035	52035	52035	52035	52035	52035
r2	0.0723	0.0797	0.0773	0.0847	0.0636	0.0560	0.0675	0.0661	0.0915
aic	453151	452739	452872	452455	453640	454057	453423	453500	452081

Notes: The table presents micro-level estimates for a linear regression of the reported aggregate inflation expectations on one (columns 1 to 8) or multiple (column 9) aggregated, category-based measures of inflation. For reasons of comparison, we only use data from respondents where all aggregated expectations are defined. 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.4 Spending Plans - Instrumental Variable Regression

Table A.9 reports results on an estimation of the Euler equation, using measures of inflation expectations in the first column instrumented with the mean inflation expectation from the distribution question (QDIST; see Appendix F).

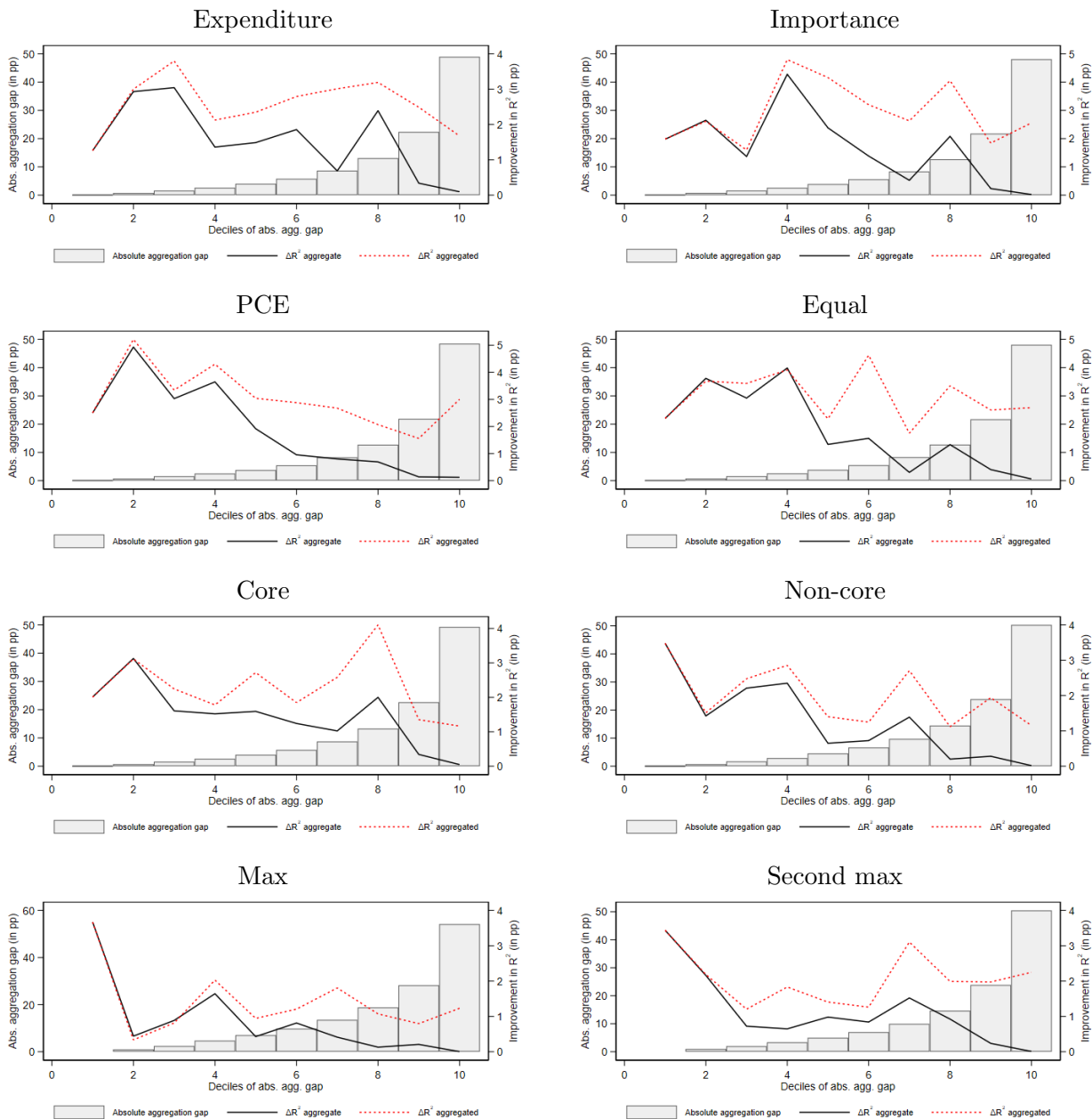
Table A.9: Instrumental Variable regression: One-Year-Ahead Spending Plans

	$\hat{\sigma} = 1 - \hat{\gamma}_{OLS}$ (OLS)	$\hat{\sigma} = 1 - \hat{\gamma}_{IV}$ (IV)	t-stat	F-stat (first stage)	N
Aggregate	0.959***	0.859***	7.60	486	23510
Expenditure	0.825***	0.714***	7.93	411	23510
Importance	0.784***	0.699***	7.91	485	23510
PCE	0.787***	0.664***	7.89	434	23510
Equal	0.774***	0.679***	7.92	479	23510
Core inflation	0.845***	0.696***	7.90	375	23510
Non-core inflation	0.872***	0.752***	7.73	376	23510
Max	0.912***	0.743***	7.55	205	23510
Second max	0.870***	0.711***	7.71	269	23510
12-months-ahead nondurable spending					
Aggregate	0.956***	0.889***	4.12	145	4591
Expenditure	0.793***	0.497***	3.97	36	4591
Importance	0.754***	0.499***	3.98	42	4591
PCE	0.757***	0.435***	3.85	37	4591
Equal	0.733***	0.48***	4.00	45	4591
Core inflation	0.822***	0.533***	3.92	38	4591
Non-core inflation	0.844***	0.467***	3.58	21	4591
Max	0.905***	0.52***	3.13	14	4591
Second max	0.851***	0.549***	3.69	26	4591
12-months-ahead services spending					
Aggregate	0.965***	0.927***	4.92	511	23630
Expenditure	0.859***	0.850***	5.06	412	23630
Importance	0.828***	0.844***	5.04	487	23630
PCE	0.825***	0.824***	5.05	426	23630
Equal	0.815***	0.833***	5.05	480	23630
Core inflation	0.861***	0.839***	5.06	374	23630
Non-core inflation	0.906***	0.872***	5.00	387	23630
Max	0.929***	0.871***	4.95	222	23630
Second max	0.892***	0.852***	5.01	283	23630

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 7 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.5 Spending Plan Regressions - Deciles of Absolute Aggregation Gaps

Figure A.2: Spending Plan Regressions - Deciles of Absolute Aggregation Gaps



Notes: The figure reproduces Figure 5 from the main text for different aggregated inflation expectations. Each panel 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 (8), 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.

B Robustness

We performed a number of robustness exercises to ensure that our findings, especially as reported in section 3, are not unduly influenced by framing artefacts. Table B.1 reports results on an additional survey that asked respondents about more specific concepts of aggregate inflation, such as PCE or CPI inflation. Table B.2 reports results on a subset of respondents from the main survey that were asked about category-specific inflation expectations before the question on aggregate expectations. In addition, Table B.3 reports results from a replication study with fund managers.

Table B.1: Robustness - 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		
<i>Plausibly rational aggregation</i>		
Expenditure	6.28	5.78
Importance	5.99	5.49
PCE	5.97	5.39
<i>Behavioral aggregation</i>		
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-sectional mean and disagreement for a replication survey conducted between July 5 and July 28, 2022. The survey assigns respondents randomly to one of three different descriptions of aggregate inflation (“Inflation,” “PCE Inflation,” and “CPI Inflation”). Other questions are identical to those in the main survey. Answers to “CPI Inflation” are significantly higher after controlling for socio-demographic factors (t-stat = 2.02).

Table B.2: Robustness - Ordering of Inflation Questions

	Aggregate First	Category First	
		Mean	p-val
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			
<i>Plausibly rational aggregation</i>			
Expenditure	5.38	5.19	0.175
Importance	5.07	5.04	0.794
PCE	4.95	4.92	0.935
<i>Behavioral aggregation</i>			
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-sectional mean for survey respondents asked between January 19 and March 3, 2022, dependent on whether they received the question about aggregate inflation expectations before or after the question about 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.

Table B.3: 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			
<i>Plausibly rational aggregation</i>			
Expenditure	4.93	3.80	34
PCE	4.08	3.68	35
<i>Behavioral aggregation</i>			
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-sectional 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).

We performed three additional robustness exercises, aligning the wording of the aggregate and category specific questions.

Aggregate For the first robustness exercise, we kept the question on aggregate inflation expectations, but changed the question on category-specific expectations to a comparable wording:

Over the next 12 months, do you think that there will be inflation or deflation for the following items? What do you expect the rates of inflation or deflation to be over the next 12 months? I expect the rate of [inflation/deflation] for [...] to be ...

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

Table B.4: Replication Study - Aggregate Question Wording

	Mean	Std. Dev. (Disagreement)	Λ_i	N
Aggregate expectations	6.06	7.36		3286
Category expectations				
Motor vehicles	5.52	5.53		3286
Recreational goods	4.18	6.71		3286
Other durable goods	4.40	6.00		3286
Food and beverages	5.33	6.89		3286
Gasoline	5.37	6.80		3286
Other nondurable goods	4.26	5.86		3286
Housing and utilities	5.30	6.55		3286
Health care	5.09	6.61		3286
Transportation services	3.93	5.67		3286
Food services	4.98	5.77		3286
Other services	4.56	5.61		3286
Aggregated expectations				
Expenditure	3.88	4.03	1.29***	3286
Importance	3.69	3.50	1.73***	3286
PCE				
Equal	4.67	4.33	0.88***	3286
Core inflation	3.46	3.73	1.62***	3286
Non-core inflation	5.46	5.93	0.31*	3041
Max	10.13	7.12	-3.47***	3286
Second max	6.79	5.86	-0.61***	3286

Notes: This table presents the cross-sectional mean and disagreement (Huber-robust estimates) for a replication survey conducted between February 14 and May 28, 2024.

Category For the second robustness exercise, we kept the question on category-specific inflation expectations, but changed the question on aggregate inflation expectations to a comparable wording:

The next few questions are about inflation. Twelve months from now, what do you think will have happened to prices in general in the US economy? I expect prices in general to

- O Increase*
- O Decrease*

I expect prices in general to [increase/decrease] by — percent.

Table B.5: Replication Study - Category Question Wording

	Mean	Std. Dev. (Disagreement)	Λ_i	N
Aggregate expectations	6.87	7.32		3272
Category expectations				
Motor vehicles	5.92	5.34		3272
Recreational goods	4.58	5.57		3272
Other durable goods	4.61	5.66		3272
Food and beverages	5.79	6.63		3272
Gasoline	5.23	6.71		3272
Other nondurable goods	4.74	5.53		3272
Housing and utilities	5.75	5.80		3272
Health care	5.22	5.80		3272
Transportation services	4.27	5.60		3272
Food services	5.55	5.67		3272
Other services	4.97	5.43		3272
Aggregated expectations				
Expenditure	4.13	4.14	2.08***	3272
Importance	3.90	3.54	2.50***	3272
PCE				
Equal	4.93	4.34	1.47***	3272
Core inflation	3.69	3.82	2.47***	3272
Non-core inflation	5.58	5.64	0.88***	3032
Max	10.42	6.95	-3.16***	3272
Second max	6.82	4.72	-0.01	3272

Notes: This table presents the cross-sectional mean and disagreement (Huber-robust estimates) for a replication survey conducted between February 14 and April 7, 2024.

Category For the third robustness exercise, we compare inflation expectations for a distributional question on aggregate inflation to responses for distributional questions on category-specific inflation expectations:

Table B.6: Replication Study - Distributional Questions

	Subj. mean (mean)	Disag.	Subj. median (mean)	Subj. mode (mean)	Subj. uncert. (mean)	N
Aggregate expectations	2.68	4.43	2.60	1.98	5.54	3006
Category expectations						
Motor vehicles	2.79	4.29	2.74	2.07	5.19	555
Recreational goods	2.36	4.39	2.33	1.44	5.38	537
Other durable goods	2.18	4.27	2.21	1.52	5.34	529
Food and beverages	2.51	4.18	2.36	1.46	5.25	544
Gasoline	2.38	4.44	2.33	1.11	5.18	549
Other nondurable goods	2.65	4.17	2.59	1.81	5.29	548
Housing and utilities	2.84	4.50	2.69	2.18	5.19	541
Health care	2.28	3.83	2.18	1.22	4.30	553
Transportation services	2.42	4.25	2.37	1.77	5.19	542
Food services	2.83	4.31	2.76	1.76	4.76	555
Other services	2.08	3.42	2.08	1.04	4.83	543

Notes: This table presents the cross-sectional mean and disagreement (Huber-robust estimates) for a replication survey conducted between February 14 and April 7, 2024.

Table B.7: Replication Study - Aggregate vs Category UPDATE

	Aggregate			Category			Distribution		
	$\pi - \pi^k$	t-stat	N	$\pi - \pi^k$	t-stat	N	$\pi - \pi^k$	t-stat	N
Motor vehicles	1.08***	6.16	1620	1.42***	7.99	1621	-0.05	-0.35	229
Recreational goods	1.82***	10.24	1605	2.27***	12.16	1606	0.28*	2.27	229
Other durable goods	2.03***	9.82	1649	2.70***	14.36	1616	0.27*	2.39	225
Food and beverages	0.60***	3.38	1627	0.98***	5.30	1626	0.22	1.16	248
Gasoline	0.88***	4.79	1619	2.10***	11.36	1613	-0.19	-1.07	244
Other nondurable goods	1.77***	9.73	1621	2.55***	13.87	1610	-0.12	-1.20	233
Housing and utilities	0.93***	4.93	1613	1.55***	7.26	1671	-0.05	-0.41	224
Health care	1.87***	10.36	1606	2.58***	13.48	1602	0.42*	2.65	246
Transportation services	0.76***	4.24	1607	1.38***	6.34	1670	0.21	1.32	241
Food services	0.80***	4.40	1610	1.44***	6.94	1665	0.05	0.28	248
Other services	1.67***	9.31	1620	2.13***	11.32	1620	0.26	1.42	258

Notes: This table presents the cross-sectional mean for the gap between individual aggregate expectations and category specific expectations. t statistics represented by t-stat. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.8: Replication Study - Distribution

	$\text{abs}(\pi^{PF} - \pi^{\text{mean}})$	$\text{abs}(\pi^{PF} - \pi^{\text{median}})$	$\text{abs}(\pi^{PF} - \pi^{\text{mode}})$	N
Aggregate expectations	5.66	5.74	8.44	1479
Category expectations				
Motor vehicles	5.59	5.71	6.88	255
Recreational goods	6.24	6.19	6.91	261
Other durable goods	4.36	4.55	6.23	257
Food and beverages	6.24	6.30	7.98	272
Gasoline	5.37	5.17	5.95	272
Other nondurable goods	5.06	4.99	6.51	272
Housing and utilities	5.60	5.98	7.18	266
Health care	4.89	4.78	5.44	276
Transportation services	6.16	6.29	7.17	269
Food services	4.66	4.47	6.25	272
Other services	4.52	4.83	7.04	273

Notes: This table presents the cross-sectional mean for the absolute gap between point forecasts and distribution moments, for a replication survey conducted between February 14 and April 7, 2024.

C 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 ascertain consistency.

C.1 Summary Statistics

Table C.1: Summary Statistics - Low- and High-Inflation Environment

	Mean		Std. Dev. (Disagreement)		Time Series Volatility	
	Low	High	Low	High	Low	High
Inflation environment						
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						
<i>Plausibly rational aggregation</i>						
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
<i>Behavioral aggregation</i>						
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.

C.1.1 Socio-Demographics - Gender

Table C.2: Summary Statistics by Gender in the Low- vs. High-Inflation Environment

Inflation environment	Male				Female			
	Mean		Disagreement		Mean		Disagreement	
	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								
<i>Plausibly rational aggregation</i>								
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
<i>Behavioral aggregation</i>								
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.

C.1.2 Socio-Demographics - Grocery Shopper

Table C.3: Summary Statistics by Grocery Shopping in the Low- vs. High-Inflation Environment

Inflation environment	Grocery Shopper				Not Grocery Shopper			
	Mean		Disagreement		Mean		Disagreement	
	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								
<i>Plausibly rational aggregation</i>								
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
<i>Behavioral aggregation</i>								
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.

C.1.3 Socio-Demographics - Education

Table C.4: Summary Statistics by Education in the Low- vs. High-Inflation Environment

Inflation environment	Low Education				High Education			
	Mean		Disagreement		Mean		Disagreement	
	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								
<i>Plausibly rational aggregation</i>								
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
<i>Behavioral aggregation</i>								
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.

C.1.4 Socio-Demographics - Income

Table C.5: Summary Statistics by Income in the Low- vs. High-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												
<i>Plausibly rational aggregation</i>												
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
<i>Behavioral aggregation</i>												
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.

C.1.5 Socio-Demographics - Age

Table C.6: Summary Statistics by Age (mean) in the Low- vs. High-Inflation Environment

Inflation environment	Below 35		35 to 44		45 to 54		Above 55	
	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								
<i>Plausibly rational aggregation</i>								
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
<i>Behavioral aggregation</i>								
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 C.7: Summary Statistics by Age (disagreement) in the Low- vs. High-Inflation Environment

Inflation environment	Below 35		35 to 44		45 to 54		Above 55	
	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								
<i>Plausibly rational aggregation</i>								
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
<i>Behavioral aggregation</i>								
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.

C.2 Aggregate vs. Aggregated Inflation Expectations

C.2.1 Low-Inflation Environment

Table C.8: Aggregate vs. Aggregated Inflation Expectations - Before November 2021

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Expenditure	0.448*** (14.53)								-0.0146 (-0.12)
Importance		0.547*** (15.52)							-0.413** (-2.71)
PCE			0.551*** (15.06)						-0.218 (-1.49)
Equal				0.606*** (16.61)					1.026*** (5.19)
Core Inflation					0.402*** (13.65)				0.0367 (0.38)
Non-core Inflation						0.321*** (12.45)			0.0291 (0.54)
Max							0.281*** (16.54)		0.180*** (5.75)
Second Max								0.327*** (13.26)	-0.0677 (-1.44)
Constant	6.301*** (24.83)	5.861*** (22.47)	6.177*** (24.47)	5.774*** (22.64)	6.705*** (27.67)	6.875*** (27.25)	4.872*** (17.62)	6.164*** (22.75)	4.654*** (16.84)
N	20742	20742	20742	20742	20742	20742	20742	20742	20742
r2	0.0384	0.0448	0.0433	0.0501	0.0337	0.0291	0.0425	0.0345	0.0584
aic	180688.8	180549.9	180581.9	180434.5	180789.8	180888.3	180599.0	180771.5	180265.9

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

C.2.2 High-Inflation Environment

Table C.9: Aggregate vs. Aggregated Inflation Expectations - After November 2021

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Expenditure	0.561*** (32.16)								0.181* (2.07)
Importance		0.650*** (33.32)							-0.315** (-2.71)
PCE			0.661*** (32.14)						-0.335** (-2.70)
Equal				0.693*** (34.48)					1.088*** (6.56)
Core Inflation					0.531*** (28.77)				-0.0546 (-0.79)
Non;core Inflation						0.400*** (28.40)			-0.0676 (-1.88)
Max							0.319*** (29.20)		0.0959*** (4.36)
Second Max								0.439*** (29.52)	0.0557 (1.52)
Constant	8.699*** (45.62)	8.301*** (42.28)	8.517*** (43.16)	8.164*** (41.70)	9.161*** (47.90)	9.756*** (53.10)	7.763*** (37.39)	8.499*** (41.40)	7.349*** (36.12)
N	31293	31293	31293	31293	31293	31293	31293	31293	31293
r ²	0.0875	0.0948	0.0911	0.0983	0.0773	0.0682	0.0783	0.0819	0.105
aic	272075.5	271825.0	271952.2	271705.0	272425.9	272732.2	272389.9	272266.6	271489.5

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

C.3 The Aggregation Gap

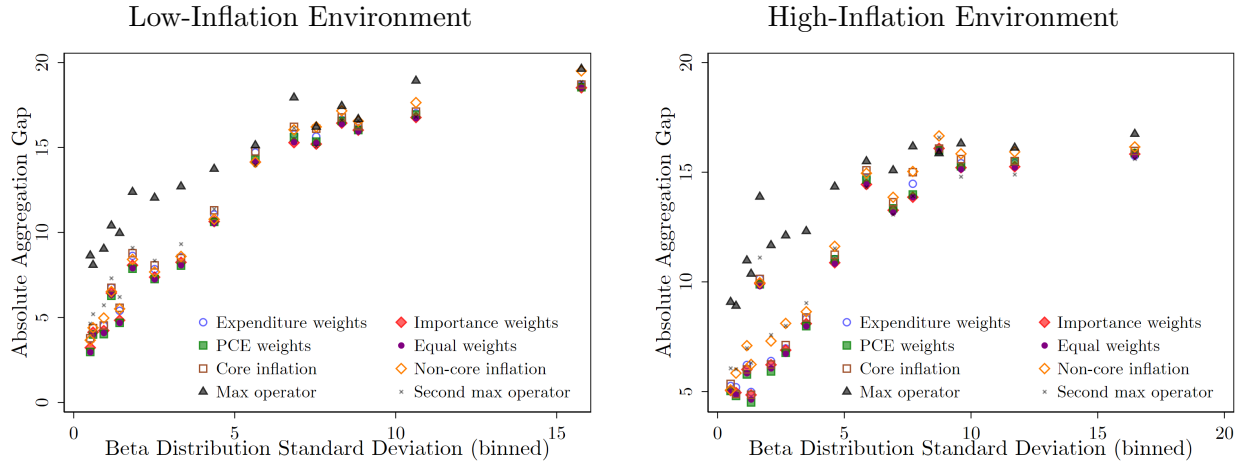
Table C.10: Summary Statistics

Inflation environment	Mean Aggregation Gap Λ_i		Mean Absolute Aggregation Gap $ \Lambda_i $	
	Low	High	Low	High
<i>Plausibly rational aggregation</i>				
Expenditure	0.74***	1.57***	5.57***	5.75***
Importance	0.91***	1.81***	5.33***	5.57***
PCE	1.32***	2.01***	5.22***	5.38***
<i>Behavioral aggregation</i>				
Equal	1.17***	1.94***	5.16***	5.52***
Core inflation	0.93***	1.79***	5.63***	5.74***
Non-core inflation	0.15*	1.15***	5.69***	6.38***
Max	-4.27***	-3.63***	9.20***	9.03***
Second max	-0.79***	-0.18***	6.52***	6.51***

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

C.3.1 The Absolute Aggregation Gap

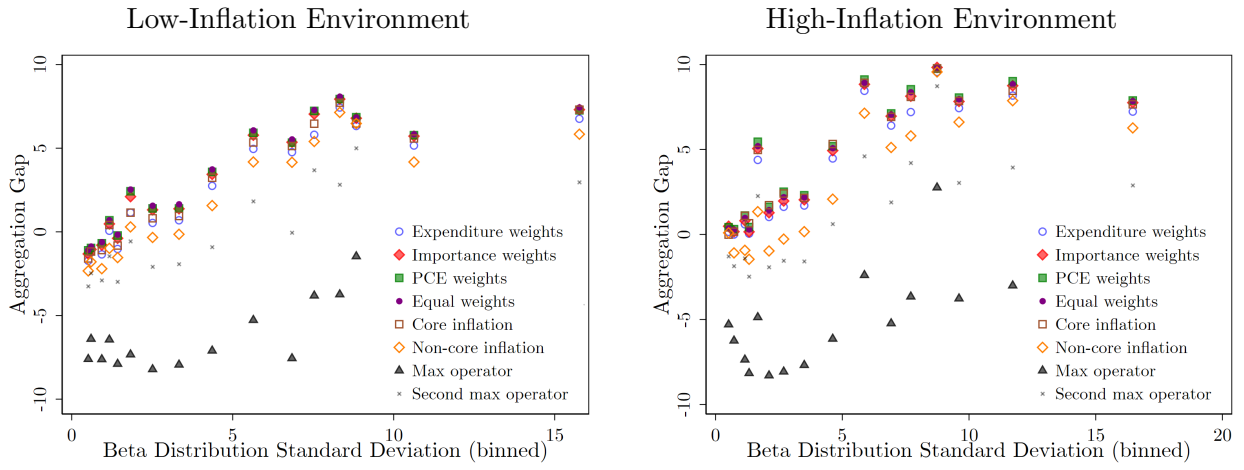
Figure C.1: The Absolute Aggregation Gap and Aggregate Uncertainty



Notes: The panels display the correlation between the absolute aggregation gap $|\Lambda_i|$ and the subjective uncertainty over aggregate inflation expectations obtained via a beta distribution over a probabilistic question; variable on horizontal axis is binned. The left panel displays the relationship in the low-inflation environment, the right panel in the high-inflation environment.

C.3.2 The Directed Aggregation Gap

Figure C.2: The Aggregation Gap and Aggregate Uncertainty



Notes: The panels display the correlation between the aggregation gap Λ_i and the subjective uncertainty over aggregate inflation expectations obtained via a beta distribution over a probabilistic question; the variable on horizontal axis is binned. The left panel displays the relationship in the low-inflation environment, the right panel in the high-inflation environment.

C.4 Spending Plans

Table C.11: One-Year-Ahead Spending Plans

	$\hat{\sigma} = 1 - \hat{\gamma}_1$	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 the second column, based on robust standard errors; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; the regression is adjusted with survey weights and Huber-robust weights to ensure that the sample is representative and robust to outliers, respectively. 59

Table C.12: 1 One-Year-Ahead Services Spending Plans

	$\hat{\sigma} = 1 - \hat{\gamma}_1$	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 the second column, based on robust standard errors; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; the regression is adjusted with survey weights and Huber-robust weights to ensure that the sample is representative and robust to outliers, respectively.

D Additional Proofs

D.1 Second-Order Approximation to the Price Index

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

$$1 = \int_0^1 \left(\frac{P(i)}{P} \right)^{1-\epsilon} di \quad (9)$$

$$= \int_0^1 e^{(1-\epsilon)(p(i)-p)} di \quad (10)$$

$$\approx 1 + (1-\epsilon) \int_0^1 (p(i) - p) di + \frac{(1-\epsilon)^2}{2} \int_0^1 (p(i) - p)^2 di \quad (11)$$

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

As a result,

$$p_t \approx \bar{p}_t + \frac{1-\epsilon}{2} \int_0^1 (p_t(i) - p_t)^2 di \quad (12)$$

$$= \bar{p}_t + \frac{1-\epsilon}{2} \text{var}(p_t(i)) \quad (13)$$

where \bar{p}_t denotes the average of log prices.

D.2 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 parameters in 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, we 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 then shows how probable model 1 is to minimize the information loss, relative to model 2.

E Model Proofs

This section contains the proofs for the model section.

E.1 Aggregation Gap

$$\Lambda = p_H * \pi_H \frac{\delta}{\Delta} - p_H \pi_H \quad (14)$$

$$= p_H \pi_H \left(\frac{\delta}{\Delta} - 1 \right) \quad (15)$$

$$= p_H \pi_H \left(\frac{\delta}{\delta p_H + 1 - p_H} - 1 \right) > 0 \quad (16)$$

which is positive if $\Delta < \delta$ which holds true by assumption of $\delta > 1$ because $\Delta = \delta p_H + 1 - p_H < \delta$ iff $\delta(p_H - 1) > p_H - 1$. \square

E.2 Variance of Aggregate Inflation Expectations

Assuming that category events are independent, the variance of aggregate inflation expectations is as follows:

$$var(\pi^{agg}) = var(\omega \mathbb{E}[\pi_1] + (1 - \omega)E[\pi_2]) = \omega^2 var(E[\pi_1]) + (1 - \omega)^2 var(E[\pi_2]) \quad (17)$$

$$= (\omega^2 + (1 - \omega)^2) var(E[\pi_k]) = (\omega^2 + (1 - \omega)^2) \tilde{p}_H (1 - \tilde{p}_H) \quad (18)$$

$$= (\omega^2 + (1 - \omega)^2) \left(\frac{\delta p_H}{\Delta} \right) \left(1 - \frac{\delta p_H}{\Delta} \right) \quad (19)$$

$$= (\omega^2 + (1 - \omega)^2) \left(\frac{\delta p_H}{\delta p_H + 1 - p_H} \right) \left(1 - \frac{\delta p_H}{\delta p_H + 1 - p_H} \right) \quad (20)$$

$$= (\omega^2 + (1 - \omega)^2) \frac{\delta p_H (1 - p_H)}{(\delta p_H + 1 - p_H)^2} \quad (21)$$

E.3 Positive Correlation Aggregate Inflation Expectations Uncertainty and Aggregation Gap

First, consider variation due to π_H . We have:

$$\frac{\partial var(\pi_k)}{\partial \pi_H} = \frac{\partial (p_H \cdot (1 - p_H) \cdot (\pi_H)^2)}{\partial \pi_H} = 2p_H \cdot (1 - p_H) \cdot (\pi_H) > 0 \quad (22)$$

and

$$\frac{\partial \Lambda}{\partial \pi_H} = \frac{\partial(p_H * \pi_H \left(\frac{\delta}{\Delta} - 1\right))}{\partial \pi_H} \quad (23)$$

$$= p_H \left(\frac{\delta}{\Delta} - 1\right) > 0. \quad (24)$$

Hence, any variation in π_H implies a positive correlation between $var(\pi_H)$ and Λ .

Second, variation due to p_H has the same implication, under a mild condition on p_H :

Note that the derivative of the variance with respect to p_H can be shown to equal the following expression:

$$V'(p_H) = (\omega^2 + (1 - \omega^2)) \frac{\delta(\delta p_H + 1 - p_H) - 2\delta p_H(\delta p_H + 1 - p_H) - 2\delta p_H(\delta - 1)(1 - p_H)}{(\delta p_H + 1 - p_H)^3}$$

And we have $V'(p_H) > 0$ iff $p_H \leq \frac{1}{1+\delta}$:

$$V'(p_H) = \delta(\delta p_H + 1 - p_H) - 2\delta p_H(\delta p_H + 1 - p_H) - 2\delta p_H(\delta - 1)(1 - p_H) \quad (25)$$

$$= \delta^2 p_H + \delta - \delta p_H - 2\delta^2 p_H^2 - 2\delta p_H + 2\delta p_H^2 - 2\delta p_H(\delta - \delta p_H - 1 + p_H) \quad (26)$$

$$= \delta^2 p_H + \delta - \delta p_H - 2\delta^2 p_H^2 - 2\delta p_H + 2\delta p_H^2 - 2\delta^2 p_H + 2\delta^2 p_H^2 + 2\delta p_H - 2\delta p_H^2 \quad (27)$$

$$= 0p_H^2 + (\delta^2 - \delta - 2\delta - 2\delta^2 + 2\delta) + \delta \quad (28)$$

$$= -p_H \delta(\delta + 1) + \delta \quad (29)$$

$$= -p_H(\delta + 1) + 1 \quad (30)$$

$$> 0 \quad (31)$$

iff $p_H < \frac{1}{1+\delta}$.

At the same time, the derivative of the gap with respect to p_H is as follows below, based on the chain rule, noting Λ is of the form $\Lambda = fg$ where $f = p_H$ and $g = \left(\frac{(1-p_H)(\delta-1)}{\delta p_H + 1 - p_H}\right)$.

The derivative of Λ is given by

$$\frac{d\Lambda}{dH} = f'g + fg'$$

We have:

$$f' = 1$$

$$g' = \frac{(\delta p_H + 1 - p_H)(-\delta + 1) - (1 - p_H)(\delta - 1)(\delta - 1)}{(\delta p_H + 1 - p_H)^2}$$

Putting this all together gives

$$\frac{d\Lambda}{dp_H} = \left(\frac{(1-p_H)(\delta-1)}{\delta p_H + 1 - p_H} \right) + p_H \frac{(\delta p_H + 1 - p_H)(-\delta + 1) - (1-p_H)(\delta-1)(\delta-1)}{(\delta p_H + 1 - p_H)^2} \quad (32)$$

$$= (\delta-1) \left(\left(\frac{(1-p_H)}{\delta p_H + 1 - p_H} \right) + p_H \frac{(-\delta p_H - 1 + p_H) - (1-p_H)(\delta-1)}{(\delta p_H + 1 - p_H)^2} \right) \quad (33)$$

$$= (\delta-1) \left(\left(\frac{(1-p_H)}{\delta p_H + 1 - p_H} \right) + p_H \frac{(-\delta p_H - 1 + p_H) - (\delta-1 - \delta p_H + p_H)}{(\delta p_H + 1 - p_H)^2} \right) \quad (34)$$

$$= (\delta-1) \left(\left(\frac{(1-p_H)}{\delta p_H + 1 - p_H} \right) + p_H \frac{(-\delta p_H - 1 + p_H) - \delta + 1 + \delta p_H - p_H}{(\delta p_H + 1 - p_H)^2} \right) \quad (35)$$

$$= (\delta-1) \left(\left(\frac{(1-p_H)}{\delta p_H + 1 - p_H} \right) + p_H \frac{-\delta}{(\delta p_H + 1 - p_H)^2} \right) \quad (36)$$

$$= (\delta-1) \left(\frac{(1-p_H)(\delta p_H + 1 - p_H) - \delta p_H}{(\delta p_H + 1 - p_H)^2} \right) \quad (37)$$

$$= (\delta-1) \left(\frac{\delta p_H + 1 - p_H - \delta p_H^2 - p_H + p_H^2 - \delta p_H}{(\delta p_H + 1 - p_H)^2} \right) \quad (38)$$

$$= (\delta-1) \left(\frac{1 - 2p_H - \delta p_H^2 + p_H^2}{(\delta p_H + 1 - p_H)^2} \right) \quad (39)$$

Given $\delta > 1$ and p_H sufficiently small, this derivative will be positive as long as $p_H < \frac{1-\delta^{0.5}}{1-\delta}$.

Comparing the two conditions, the following holds:

$$\frac{1}{1+\delta} < \frac{1-\delta^{0.5}}{1-\delta} \quad (40)$$

$$\frac{1}{1+\delta} < \frac{1-\delta^{0.5}}{(1-\delta^{0.5})(1+\delta^{0.5})} \quad (41)$$

$$\frac{1}{1+\delta} < \frac{1}{1+\delta^{0.5}} \quad (42)$$

Hence, the covariance is increasing for all $p_H < \frac{1}{1+\delta}$.

E.4 CES Price Index

Assume the price index to be defined as:

$$P_t = \left[\sum \alpha_k P_{k,t}^{1-\epsilon} \right]^{\frac{1}{1-\epsilon}} \quad (43)$$

Where $P(k)$ is the price index of sector k and α_k represents a constant utility weight. It follows that the expenditure share on products from category k is equal to

$$\omega_{k,t} = \alpha_k \left[\frac{P_{k,t}}{P_t} \right]^{1-\epsilon} \quad (44)$$

such that $\sum \omega_{k,t} = 1$. If the relative price of a sector increases, the expenditure share increases, if $\epsilon < 1$. At the same time, the relative consumption of products from that sector increases if $\epsilon < 0$ (products are complements). Inflation is defined as the relative change in the price index

$$\pi_t = \frac{P_t}{P_{t-1}} - 1 = \frac{\left[\sum \alpha_k P_{k,t}^{1-\epsilon} \right]^{\frac{1}{1-\epsilon}}}{P_{t-1}} - 1 \quad (45)$$

$$= \left[\sum \alpha_k \left[\frac{1}{P_{t-1}} \right]^{1-\epsilon} P_{k,t}^{1-\epsilon} \right]^{\frac{1}{1-\epsilon}} - 1 \quad (46)$$

$$= \left[\sum \alpha_k \left[\frac{P_{k,t-1}}{P_{t-1}} \right]^{1-\epsilon} (1 + \pi_{k,t})^{1-\epsilon} \right]^{\frac{1}{1-\epsilon}} - 1 \quad (47)$$

$$= \left[\sum \omega_{k,t-1} (1 + \pi_{k,t})^{1-\epsilon} \right]^{\frac{1}{1-\epsilon}} - 1 \quad (48)$$

where we define $\omega_{k,t-1} = \alpha_i \left[\frac{P_{k,t-1}}{P_{t-1}} \right]^{1-\epsilon}$.²¹ The aggregated price index is equal to

$$\pi_t^{Agg} = \sum \alpha_i \left[\frac{P_{k,t-1}}{P_{t-1}} \right]^{1-\epsilon} \left(\frac{P_t(k)}{P_{k,t-1}} \right) - 1 \quad (49)$$

$$= \sum \alpha_i \left[\frac{P_{k,t-1}}{P_{t-1}} \right]^{1-\epsilon} (1 + \pi_{k,t}) - 1 \quad (50)$$

$$= \sum \omega_{k,t-1} \pi_{k,t} \quad (51)$$

Taking expectations, the aggregation gap is now equal to:

$$\Lambda = \mathbb{E}_t \pi_{t+1} - \mathbb{E}_t \pi_{t+1}^{Agg} = \mathbb{E}_t \left[\sum \omega_{k,t} (1 + \pi_{t+1}(k))^{1-\epsilon} \right]^{\frac{1}{1-\epsilon}} - \mathbb{E}_t \left[\sum \omega_{k,t} (1 + \pi_{t+1}(k)) \right] \quad (52)$$

Proposition 3 (Aggregation Gap). *The aggregation gap $\Lambda = E_t \pi_{t+1} - E_t \pi_{t+1}^{Agg}$ is*

$$\Lambda = \begin{cases} \leq 0, & \epsilon > 0 \\ 0, & \epsilon = 0 \\ \geq 0, & \epsilon < 0 \end{cases} \quad (53)$$

with $\epsilon \neq 1$. ■

Thus, for the CES price index model to generate a positive aggregation gap, consumers would have to assume that $\epsilon < 0$, that is, have a negative elasticity of substitution. This is equivalent to consumption categories being complements.

²¹It holds that $\lim_{\epsilon \rightarrow -\infty} \pi = \max(\pi_k)$, that is, for $\epsilon \rightarrow -\infty$, aggregate inflation expectations converge to the max operator. Similarly, $\lim_{\epsilon \rightarrow \infty} \pi = \min(\pi_k)$. For $\epsilon = 0$, the generalized mean is equal to the aggregated expectation.

F Survey Details and Questions

This section lists relevant survey questions used within the paper. 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 span the time from July 9, 2020, to August 9, 2022. Participants were asked for their macroeconomic expectations. While the survey also contains other blocks with various questions, these are not reported here, since they are asked after the questions on macroeconomic expectations and thus do not affect the answers.

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 age 18 or above were brought into 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., “ $sd - \$rt2$ ”).

F.1 Aggregate Expectations

To elicit respondents’ expectations about future aggregate inflation and income, we used 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”.*

The survey then asks the following question on aggregate inflation over a 12-month horizon:

Q1: Aggregate 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 individual's inflation expectation:

QDIST: Aggregate 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 proceed 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 Increase*
- O Decrease*

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

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.*

F.2 Category-Specific Inflation Expectations and Spending

To elicit participants' category-specific inflation expectations, as well as their nominal expenditure on each consumption category and the subjective importance of each category to overall consumption, we ask the following questions:

Q2: Category-Specific Inflation

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

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

Q3: Nominal Expenditure on Categories

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, hair-dressers) _____

Q4: Subjective Importance of Categories

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, hair-dressers) 0__|__100

F.3 Expected Changes in Consumption Spending

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

Q5: Total Spending

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

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

Q6: 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. . .

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

Q7: 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. . .

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

F.4 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, income, the highest educational level, and whether the respondent is the main grocery shopper in the household.