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EXPOSURE TO GROCERY PRICES AND INFLATION EXPECTATIONS

Abstract

We show that, when forming expectations about aggregate inflation, consumers rely on the prices of goods in their personal grocery bundles. Our analysis uses novel representative micro data that uniquely match individual expectations, detailed information about consumption bundles, and item-level prices. The data also reveal that the weights consumers assign to price changes depend on the frequency of purchase, rather than expenditure share, and that positive price changes loom larger than similar-sized negative price changes. Prices of goods offered in the same store but not purchased (any more) do not affect inflation expectations, nor do other dimensions such as the volatility of price changes. Our results provide empirical guidance for models of expectations formation with heterogeneous consumers.

JEL Classification: C90, D14, D84, E31, E52, G11

Keywords: Beliefs formation, Inflation expectations, Heterogeneous Agents, macroeconomics with micro data, household finance, behavioral finance

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Exposure to Grocery Prices and Inflation Expectations*

Francesco D'Acunto[†] Ulrike Malmendier[‡] Juan Ospina[§] and Michael Weber[¶]

April 17, 2020

Abstract

We show that, when forming expectations about aggregate inflation, consumers rely on the prices of goods in their personal grocery bundles. Our analysis uses novel representative micro data that uniquely match individual expectations, detailed information about consumption bundles, and item-level prices. The data also reveal that the weights consumers assign to price changes depend on the frequency of purchase, rather than expenditure share, and that positive price changes loom larger than similar-sized negative price changes. Prices of goods offered in the same store but not purchased (any more) do not affect inflation expectations, nor do other dimensions such as the volatility of price changes. Our results provide empirical guidance for models of expectations formation with heterogeneous consumers.

JEL classification: C90, D14, D84, E31, E52, E71, G11

Keywords: Beliefs formation, inflation expectations, heterogeneous agents, macroeconomics with micro data, household finance, behavioral finance.

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I Introduction

In his seminal islands model, Lucas (1975) posited that agents use the prices they directly observe in their daily lives to form expectations about aggregate inflation. As he discussed in Lucas (1975), "[T]he history of prices [. . .], observed by an individual is his source of information on the current state of the economy and of the market z in which he currently finds himself; equivalently, this history is his source of information on future price." Although Lucas did not aim to provide a literal description of reality, this assumption triggered a debate about its logical consistency and realism. Despite the relevance of this assumption for modern models of belief formation, such as models of rational inattention, the evidence to assess its plausibility is scant.

In this paper, we investigate the extent to which consumers rely on the grocery-price changes they experience in their consumption bundles to form expectations about aggregate inflation. Our data uniquely link individual expectations, consumption bundles, and item-level prices. The richness of these data allows us to investigate the characteristics of price changes that matter the most in the expectations-formation process. We find that the price changes of goods consumers purchase influence their expectations about aggregate inflation significantly. When we dig deeper to understand which features of price changes matter, we find that the weight consumers assign to grocery price changes depends on the frequency of purchase, rather than the expenditure share, and that positive price changes receive a larger weight than negative ones. The prices of goods in the same store that the consumer does not purchase (any more) do not affect inflation expectations, nor do other dimensions of price changes such as their volatility.

These results are a robust feature of the data and do not depend on details of the inflation calculation such as considering gross rather than net prices; using shopping trips or volume to compute the frequency weights; varying the time horizon or the granularity of the definition of goods; moving from Laspeyres to alternative types of statistical weights; excluding goods purchased at low frequencies; or using the maximum or median price changes to calculate household-level inflation.

Our results are important in that they provide empirical guidance on which features of price changes are relevant, or irrelevant, to the formation of macro expectations. As such, they help advance models featuring heterogeneous beliefs and rational inattention.

To analyze the role of household-specific price changes on beliefs, we construct a novel data set. We combine detailed information about the quantity and prices of the non-durable consumption baskets of more than 90,000 households in the *Kilts Nielsen Consumer Panel* (KNCP) with new survey data on expectations we elicited from all members of the Nielsen households in June 2015 and June 2016. These data uniquely allow us to construct household-level inflation measures and match them with the inflation expectations of each survey participant at the time they shopped for groceries. Because of this level of granularity, we can study in detail which price changes are most relevant to shape inflation expectations, while keeping constant a large range of observables as well as other personal and macroeconomic expectations.

We construct a variety of household-level inflation measures, which capture alternative features of personal grocery price changes. Our first measure, the *Household CPI*, mirrors the Consumer Price Index (CPI), but uses each household's non-durable consumption basket instead of the representative consumption basket. The Household CPI is a significant predictor of 12-month-ahead inflation expectations. For example, when we group households into eight equal-sized bins of Household CPI, the difference in expected inflation between households in the lowest and highest bin is 0.5 p.p. This difference is economically sizable given a realized inflation rate of around 1% during the same period. The results hold conditioning on a rich set of demographics including age, income, gender, marital status, household size, education, employment status, and risk tolerance. Within-individual analyses across the two survey waves also confirm the results. Thus, time-invariant individual characteristics, such as cognitive abilities or financial sophistication, cannot explain our findings.

Given this evidence on the influence of personally experienced price changes, we then ask whether consumers weigh price changes based on expenditure shares, as the CPI assumes, or if instead the frequency with which consumers are exposed to price changes of different goods (see Angeletos and Lian (2016)). Our second measure, the *Frequency CPI*, uses the frequency of purchases to weigh shopping price changes. The positive association between the Frequency CPI and inflation expectations is 20-40% larger than the association of the Household CPI. In a horse race, the coefficient of the Household CPI shrinks to zero and loses statistical significance, whereas the statistical and economic significance of the Frequency CPI barely changes. Using the number of trips in which households purchase a good or considering only goods households purchase in high volumes to compute alternative versions of the Frequency CPI does not change the results.

We also consider a large array of additional features of price changes that might affect their role in consumers' belief formation, including their sign, volatility, horizon, and technical details of the inflation weighting. The one aspect that robustly matters is that positive price changes influence expectations more than negative ones. This result is consistent with Cavallo et al. (2017), who argue that households pay more attention to price increases.

As a final step, we assess the economic magnitude of our findings: To what extent does heterogeneity in experienced inflation rates explain observed heterogeneity in inflation expectations? Answering this question is not straightforward since the R^2 obtained in the baseline analysis is estimated on survey data, which tends to suffer from noise and measurement error, also due to rounding and heaping (Heitjan and Rubin (1990), Jappelli and Pistaferri (2010)). We start from a set of simulations that confirm the role of these known features of survey data in our setting. We then develop a more informative benchmark following the approach of Card and Lemieux (2001) to average out reporting noise in individual-level survey data. Specifically, we average the micro data within geography-based cells and then re-estimate the model on the less granular samples. The resulting R^2 increases monotonically with the size of the geographic areas, which is consistent with substantial amounts of noise being present in the micro data. With the maximum feasible noise averaged out, we obtain an R^2 of up to 28% without any controls and 79% with controls, indicating that heterogeneity in price exposure goes a long way toward explaining heterogeneity in inflation expectations after accounting for survey-induced noise.

Related Literature. Our analysis builds on prior work that demonstrates the large heterogeneity across households, both in terms of inflation in their consumption bundles (Kaplan and Schulhofer-Wohl (2017)) and in terms of inflation expectations (Bachmann et al. (2015)). Our household-level evidence suggests that consumers interpret price changes in their bundles as signals about aggregate price changes. We also build on Cavallo et al. (2017), who study the formation of inflation expectations in high- and low-inflation countries, based on recording one grocery bundle for a cohort of grocery shoppers. Our data record household-level shopping bundles for several years and multiple shopping trips, which allows creating several measures of realized inflation at the household level and to investigate which features do or do not matter in the formation of household-level expectations. We also observe both the realized and expected inflation within consumers over time, which allows us to abstract from time-invariant individual characteristics. We also build on Kuchler and Zafar (2019), who show individuals extrapolate from local house-price changes they observe in their counties to expectations about US-wide real estate inflation.

Finally, we relate to recent work on the determinants of cross-sectional variation in inflation expectations: Malmendier and Nagel (2015) show that cohorts form inflation expectations based on their personal lifetime aggregate inflation experiences. Other work on heterogeneity in beliefs formation include D'Acunto et al. (2019a,b,c), who show cognitive abilities are strongly correlated with forecast accuracy, uncertainty about future inflation, and responses to measures of fiscal and monetary policy. Coibion, Gorodnichenko, and Weber (2018) and D'Acunto, Hoang, and Weber (2019) show policy communication impacts inflation expectations differently across demographic groups.

II Data on Expectations and Consumption

Our data combine the *Chicago Booth Expectations and Attitudes Survey* (CBEAS), which we fielded in two waves in 2015 and 2016, and the *Kilts-Nielsen Consumer Panel* (KNCP). The KNCP is a panel of about 40,000-60,000 households from 2004-2018. Households report demographic characteristics as well as the prices, quantities, and shopping outlets of their consumption bundles. To avoid measurement and reporting errors, panelists use a Nielsen-provided optical scanners similar to those grocery stores use to read barcodes. The sample spans through 52 major consumer markets and nine census divisions. It records purchases of 1.5 million unique products, which include groceries, drugs, small appliances, and electronics. Nielsen estimates the KNCP covers about 25% of US households' consumption.

The CBEAS is a 44-question customized survey, which we designed in March 2015 and fielded in two waves (June 2015 and June 2016). The final sample includes 92,511 households. In the first wave, 49,383 respondents from 39,809 unique households completed the survey (43% response rate). The second wave had 43,036 unique respondents from 36,758 unique households. Of those, 15,104 only participated in wave 1, 7,269 participated only in wave 2, and 18,373 participated in both waves.[1] The survey builds on the Michigan Survey of Consumers, the New York Fed Survey of Consumer Expectations, as well as the pioneering work of de Bruin et al. (2011), Armantier et al. (2013), and Cavallo, Cruces, and Perez-Truglia (2017). We first elicit demographic

[1]The average response time was 14 minutes and 49 seconds in the first wave and 18 minutes and 35 seconds in the second wave, which includes a few more questions.

information the KNCP does not provide: college major, employment status, occupation, income expectations, rent, mortgage, and medical expenses. We also ask for the primary shopper of the household. We then elicit perceived inflation (over the previous 12 months) and expected inflation (over the next 12 months), in terms of both point estimates and the full probability distribution.[2]

Summary Statistics. The working sample consists of 59,126 individuals for whom we observe complete data from both the KNCP and survey responses. To limit the role of outliers, we winsorize all continuous variables at the 1%–99% level.

As shown in Table 1, the average age is 61, and, as in Kaplan and Schulhofer-Wohl (2017), women outnumber men. Five percent of respondents are unemployed and almost three quarters own a house. The average household size is 2.2. Survey respondents are more educated and wealthier than the average US individual: Almost half of the respondents hold a college degree. Survey participants expect, on average, stable income over the following 12 months, with a median income bracket of USD 45,000-60,000. In terms of racial and ethnic composition, 85% of the sample is white, 8.5% black, and 3.1% Asian.

Participants expect, on average, one-year-ahead inflation of 4.67%. Figure 1.A plots the distribution of 12-month-ahead expected inflation rates. Consistent with other surveys (e. g., Binder (2017)), we see substantial mass between 0%-5% and bunching at rounded multiples of 5%. The cross-sectional dispersion is substantial, ranging from -20% to +45%. Overall, our expectations data are similar to those in the MSC and SCE.

Appendix-Table A.1 reports summary statistics for these variables separately for respondents who participate only in the first wave, only in the second wave, and in both waves. No substantial differences in observables exist across these groups, which suggests that observable characteristics barely explain attrition.

III Household CPI and Frequency CPI

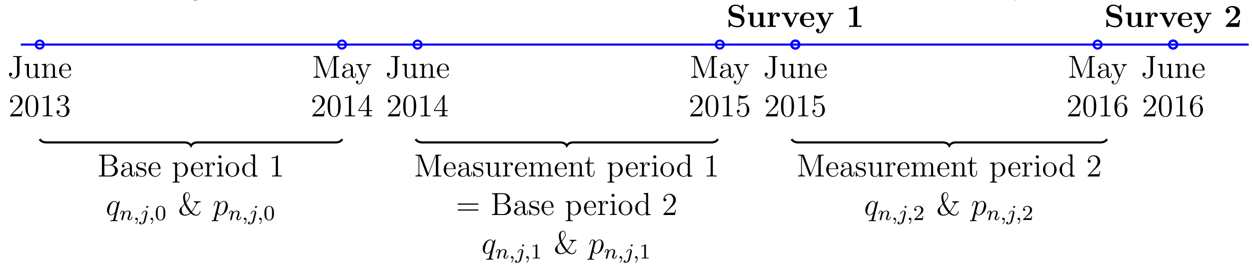
A. Defining Household-level Inflation

We define household-level inflation by mimicking the CPI:

$$Household\ CPI_{j,t} = \frac{\sum_{n=1}^{N} \Delta p_{n,j,t} \times \omega_{n,j}}{\sum_{n=1}^{N} \omega_{i,j}}, \tag{1}$$

[2]We randomized between two sets of questions: The Michigan Survey of Consumers (MSC)-inspired question asks about the prices of things on which respondents spend money. The New York Fed Survey of Consumer Expectations (SCE)'s question asks specifically about inflation.

Figure 2: **Timeline of Inflation Measurement and Surveys**



where $\Delta p_{n,j,t}$ is the log price change of good n bought by household j at time t, and $\omega_{n,j} = p_{n,j,0} \times q_{n,j,0}$ is the weight of good n in the inflation rate for household j, with $q_{n,j,0}$ being the amount of good n household j purchased in the base period. We use June 2013 to May 2014 as the base period for the first survey wave, and calculate price changes until the month before we fielded the first survey, i. e., June 2014 to May 2015. The timing varies accordingly for the second wave, fielded in June 2016 (see Figure 2).

Defining expenditure shares and price changes at the household level poses a set of conceptual and empirical challenges that do not arise in a representative-bundle setting. One such issues is seasonality in spending. We follow Kaplan and Schulhofer-Wohl (2017) and calculate volume-weighted average prices during both the base year, $p_{n,j,0}$, and the year over which we measure inflation, $p_{n,j,1}$. Another issue is that households might stop purchasing specific products over time. In this case, we impute entries based on the price of the good at the finest geographic partition available (county, state of residence, country).[3] All results are virtually identical if we do not impute any prices.

B. Household CPI and Inflation Expectations

Our baseline analysis estimates the following model by ordinary least squares:

$$\mathbb{E}\,\pi_{i,t\to t+1} = \alpha + \beta \times \pi_{i,t-1\to t} + X_i'\gamma + \mathbb{E}_i'\gamma + \eta_w + \eta_q + \eta_k + \eta_i + \eta_I + \epsilon_i, \qquad (2)$$

where $\mathbb{E}\,\pi_{i,t\to t+1}$ is the inflation rate individual i expects for the next 12 months, measured in percentage points; $\pi_{i,t-1\to t}$ is the Household CPI; X_i is a vector of individual characteristics (age, age squared, sex, employment status, home-ownership status, marital status, household size, college dummy, race dummies, risk tolerance), and $\mathbb{E}_i$ is a vector of expectations about household income, the aggregate economic outlook, and the personal financial outlook for the following 12 months. The survey-wave fixed effects η_w allow for systematic differences in (expected and realized) inflation between 6/2015 and 6/2016.

[3] If we still cannot find the price, we assume no price change. The last two steps almost never arise.

The inflation-question fixed effects η_q allow for systematic differences in expected inflation when asked about inflation versus changes in prices. County fixed effects η_k absorb unobserved time-invariant differences across counties. Individual fixed effects η_i are included in the most restrictive specifications, and absorb unobserved time-invariant differences across individuals. The income fixed-effects η_I consist of the 16 income dummies from Nielsen. We cluster standard errors at the household level to allow for arbitrary correlation in residuals across respondents within household, all of whom experience the same household-level inflation.

Columns (1)-(3) of Table 2 report the estimation results. We find a significantly positive relation between expected inflation and Household CPI. A one-standard-deviation increase in Household CPI is associated with a 0.17 p.p. increase in expected inflation, about 4% of the average expected inflation in the sample. The size of the association barely changes when we partial out a rich set of demographics, other individual expectations, and county fixed effects. The within-individual association in column (3) is slightly higher, which suggests that unobserved differences across consumers are unlikely to explain our findings. These results support the assumption in Lucas (1975) which, to the best of our knowledge, had not been formally tested with individual data.

C. The Role of Purchase Frequency: Frequency CPI

The Household CPI assumes that consumers weigh price changes by expenditure shares. Recent research in macroeconomics, though, proposes that price changes agents observe more often might be perceived as more precise signals (e.g., Angeletos and Lian (2016)) and/or might be easier to recall. We thus test if frequently-purchased goods have a larger impact on expectations. We define a Frequency CPI using the frequency of purchase in the base period as the weight in the household's consumption basket, $\omega_{i,j} = f_{i,j,0\to 1}$, where $f_{i,j,0\to 1}$ is the total quantity household i purchases of good j throughout the 12-month base period.

The distributional properties of the Frequency and Household CPI differ. Figure 1.B sorts survey respondents into eight bins, separately for each measure, and reports average expected inflation for each bin. The resulting range in expected inflation is 0.5 p.p. for the Household CPI, but 40% larger, 0.7 p.p., for the Frequency CPI. This value is sizable as it corresponds to about 47% of realized inflation in the US during the period we consider.

Columns (4)-(6) of Table 2 confirm the association from the raw data. Replicating specifications of columns (1)-(3) using the Frequency instead of the Household CPI, we estimate the association with inflation expectations to be 20%–50% larger. When we include both measures, in columns (7)-(9), the coefficient on the Household CPI shrinks towards 0 and is no longer significant. The point estimate on the Frequency CPI, instead, barely changes relative to columns (4)-(6), and remains statistically significant in all cases.

D. Robustness

These results are a robust feature of the data.[4] They are very similar when using changes in gross rather than net prices (Appendix-Tables A.2), or when using the share of shopping trips in which an item is purchased and overweighing goods sold at higher volumes (Appendix-Tables A.3). Neither of the alternative frequency definitions explain the cross-section of inflation expectations beyond the Frequency CPI (col. 3 and 6).

We also explore the role of price changes over shorter horizons. In Appendix-Table A.4, columns (1)-(3), we include Alternative CPIs that calculate household-level inflation over the prior 1, 6, or 12 months. These specifications also address concerns about reverse causality from consumers' perceptions and expectations to what to buy—consumers expecting worse times (and low inflation) buying goods with smaller price increases. Under such a mechanism, we would expect the price changes of the recently purchased goods to drive our results. Empirically, however, these price changes do not explain the cross-sectional variation of expectations conditional on the Frequency CPI.

Another aspect of the Frequency CPI that we explore is the use of average prices in the base and measurement period to construct price changes. Although the average summarizes information about all price changes consumers observe, values such as the maximum or median might be more memorable and hence matter more in the expectations formation process. Columns (4)-(5) of Appendix Table A.4 show that neither the changes in maximum or median prices explain expectations beyond the Frequency CPI.

A third aspect we consider is the level of granularity. The Frequency CPI defines price changes at the UPC level—the finest possible category of goods consumers observe. What if consumers think about price changes in broader categories, such as group, department, or module? Appendix-Table A.5 shows these broader categories, or using the prices at the stores instead of the ones scanned by households, do not add explanatory power.

Finally, we consider alternative weighting schemes. Columns (2)-(5) of Appendix-Table A.6 show that indices using Fisher, Paasche, or other weights do not add explanatory power to the baseline Frequency CPI, which follows the Laspeyres index construction.

[4]We thank Greg Kaplan and four referees for suggesting several of the variations we study below.

IV Which Price Changes Matter Most?

Our results so far reveal that the price changes to which consumers are exposed more frequently help explain their inflation expectations. We now ask whether there are particular types of goods or types of price changes that matter most, possibly because they capture consumers' attention and make price changes easier to recall.

Positive Price Changes. Positive price changes represent a loss for shoppers, and might influence expectations more than negative ones. In Table 3.A, column (1), we substitute the Frequency CPI from the baseline specification with two CPIs that use only positive or only negative price changes. We find that the experiences of positive inflation significantly influence expectations, whereas the experienced deflation does not matter.

A similar insight emerges when we modify the Frequency CPI to overweigh positive price changes by a factor of 2 and a factor of 4 (column 2). The CPI that overweighs positive changes by a larger factor drives the explanatory power of experienced inflation. We also distinguish the higher explanatory power of positive price changes from a possible role of 'frequent price changes.' In column (3), we compute the Frequency CPI separately for goods whose prices displayed above or below the median price volatility in households' baskets. Neither has explanatory power.

Overall, consumers appear to put more weight on positive than negative price changes they experience, a feature that should be incorporated in models of expectations formation, while volatility does not emerge as a significant factor.

Price Changes of Goods Not Purchased. Our data also allow us to consider price changes of goods that a consumer does not purchase but that are offered in the same store at the same time. Testing for the influence of such goods, though, requires a consideration set that avoids a mechanical non-result: If we used all goods in the shopping outlet, a non-result would be unsurprising as consumers would not even have noticed many of them. To avoid this confound, we consider only goods that households have bought in the past. Shoppers are likely aware of their prices and, in fact, might not have purchased them because of a large, salient price increase. Nevertheless, we find that an Alternative CPI based on the price changes of goods households no longer purchase does add not any additional information about inflation expectations beyond the Frequency CPI (Table 3.B, column (1)).

We also consider restricting, rather than expanding, the set of goods a household may take into account when forming beliefs about inflation. In column (2), we include a measure that restricts the CPI calculation to goods bought at least twice in the base period, and in column (3), to goods bought at least once in the measurement period. Neither alternative CPI has explanatory power relative to the default Frequency CPI.

V Survey Noise and Measures of Fit

As the final step, we assess how large the influence of personal exposure is: To what extent does heterogeneity in experienced inflation explain heterogeneity in inflation expectations? Using survey data complicates answering this question. Estimations using survey data tend to have a low R^2 even when the estimated model is correct because of noise in individually reported values and the tendency of respondents to round to integers or multiples of 5 (see, e. g., Heitjan and Rubin (1990), Jappelli and Pistaferri (2010)).

We proceed in two steps. First, we ask the following questions: If our proposed model were true in the underlying data generating process, implying an R^2 of 1, how much noise would be needed to obtain an R^2 akin to that in our baseline estimation? Table A.7 reports the corresponding simulations. We assume the estimating equation of column (5) in Table 2 as the true association between inflation expectations and the Frequency CPI. In Panel A, we allow for 70% of individuals rounding to multiples of 5, as is the case in our data. We vary the amount of zero-mean normally-distributed noise from 0 (column 1) to 10 (columns 2-11) at increments of 1. Adding noise reduces the measured fit from 82% to 5%. Results in Panel B, without any rounding, are similar. In Panel C, we proxy for an empirically plausible level of noise setting the standard deviation equal to the one of the estimated residuals of the specification we assume to be true (7.8%) and vary the degree of rounding. Across all columns, the R^2 is similar to our baseline estimation. Panel D shows that rounding without any noise reduces the R^2 only partially. All simulations are consistent with the R^2 in our baseline estimation reflecting survey noise, and the implied amount of noise is empirically plausible.

In a second step, we develop an appropriate measure of explanatory power. We follow Card and Lemieux (2001) and re-estimate our model after averaging the micro data within less granular partitions. The within-partition averages preserve relevant information from the original data but wash out noise due to rounding and outliers. The implication of individual-level survey noise is that the R^2 should increase monotonically as the partitions become larger.

A natural choice for the partitions are geographic areas, which allow us to consider various levels of granularity all fully included within each other. In Table 4, we collapse the individual-level data within geographic cells whose size increases moving to the right: ZIP code, county, 3-digits FIPS code, state, and census region. The three-digit FIPS code is assigned to counties in alphabetical order within each state, and the same codes are used across all 50 states. Thus, this partition pools together geographic areas in different states that typically do not share any borders. It allows us to verify that the averaging of noise, rather than common geographic shocks, explains the increase in R^2 as we reduce the number of partitions.

Table 4 shows that, when moving from the finest to the broadest geographic partition, the R^2 increases monotonically, consistent with substantial amounts of noise in the micro data. With the maximum noise averaged out, we obtain an R^2 of up to 66% without any controls and 69% with controls. Hence, heterogeneity in price exposure goes a long way toward explaining heterogeneity in inflation expectations after accounting for survey noise.

VI Conclusions

We document that household-level grocery-price changes significantly affect inflation expectations. We use unique, representative US data that link individual expectations to items purchased, frequency and outlet of purchase, and paid prices. These rich data also reveal which features of experienced price changes matter in the formation of inflation expectations—the frequency of purchase and the positive sign of price changes—, and inform advances in heterogeneous-beliefs models. Our findings motivate more research on the cognitive process agents use when forming expectations that drive economic decision making.

Future work might aim to understand how price changes in the non-grocery part of households' bundles interfere with grocery price changes. Another fruitful avenue for research is understanding how the inflationary environment in which consumers form expectations interacts with the role of personally experienced prices changes. For instance, is it optimal for consumers to focus on personal shopping experiences when forming expectations in a stable inflation environment, but to shift the focus on aggregate inflation in volatile times, as Frache and Lluberas (2018) suggest using firms' inflation expectations?

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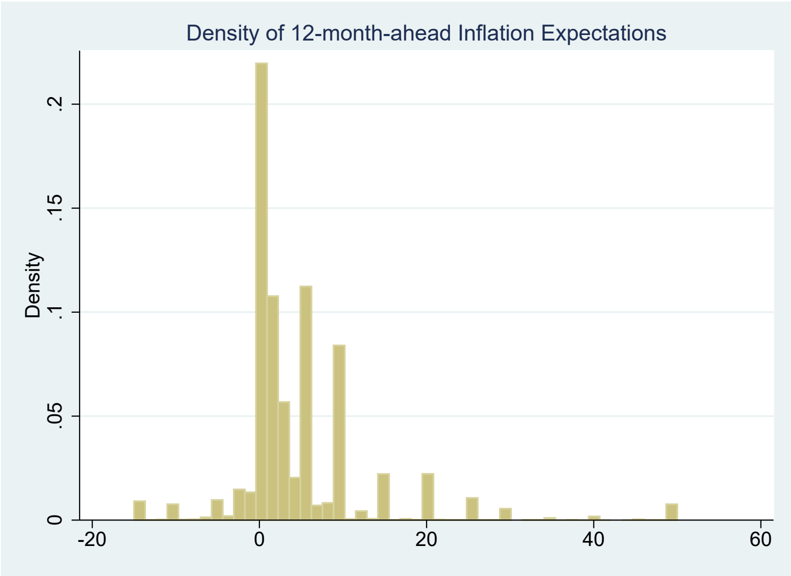
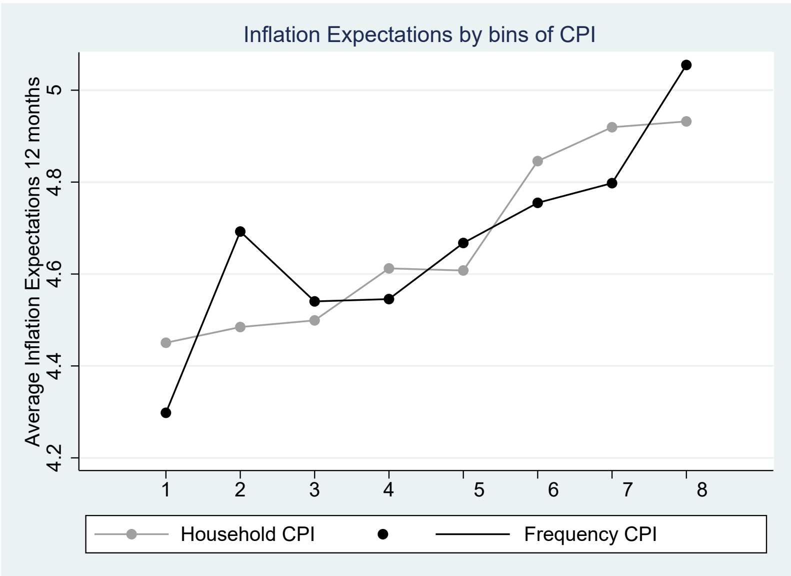
Figure 1: **Grocery Shopping and Inflation Expectations: Raw Data**

Panel A. Inflation Expectations



Panel B. Grocery Shopping and Inflation Expectations



Notes. Panel A plots the distribution of inflation expectations, and Panel B the averages of inflation expectations across households in eight equal-sized bins by experienced inflation. Inflation expectations are from the customized *Chicago Booth Attitudes and Expectations survey* fielded in 6/2015 and 6/2016. We use the micro data from the *Kilts-Nielsen Consumer Panel* to create different measures of experienced inflation. We use the 12 months before June of the survey wave as the measurement period, and the 12 months before that period as the base period. Household CPI uses the Nielsen expenditure shares in the base periods as weights, and Frequency CPI uses the frequencies of purchase in Nielsen in the base period as weights.

Table 1: **Summary Statistics**

Notes. This table reports summary statistics of the main independent and dependent variables for our running sample. Expected Inflation and Perceived Inflation are reported numerical expectations and perceptions of inflation rates for a 12-month period, and are bounded between -100 and +100 percentage points. Household CPI and Frequency CPI are the measures of household-level grocery inflation based on scanner data from the *Kilts-Nielsen Consumer Panel.* Both measures are computed over a horizon of 12 months before the respondent took part in the *Chicago Booth Expectations and Attitudes Survey.* Income Outlook, Economic Outlook, and Financial Outlook are qualitative respondent expectations on the soundness of income growth, personal financial conditions, and overall economic outlook of the country for the following 12 months, and are bounded between 1 (very bad) and 5 (very good).

	Observations	Mean	St. dev.	Min	25th	Median	75th	Max
Age	59,118	61.4	12.9	21	54	63	70	102
Male	59,126	0.36	0.48	0	0	0	1	1
Unemployed	59,126	0.05	0.22	0	0	0	0	1
Home Owner	59,126	0.74	0.44	0	0	1	1	1
Household Size	56,227	2.19	1.11	1	1	2	3	9
College	59,126	0.48	0.50	0	0	0	1	1
Income Outlook [1-3]	59,126	2.18	0.90	1	1	3	3	3
Economic Outlook [1-5]	59,126	2.69	1.04	1	2	3	4	5
Financial Outlook [1-5]	59,126	3.00	0.88	1	2	3	4	5
Expected Inflation	59,126	4.67	8.20	-15	0	2	6	50
Perceived Inflation	59,126	4.44	8.27	-20	0	2	5	45
Household CPI	59,126	0.81	7.14	-17.5	-3.17	0.23	4.02	27.16
Frequency CPI	59,126	1.61	5.85	-11.71	-1.91	0.83	4.21	23.08

Table 2: **Grocery Shopping and Inflation Expectations**

Notes. This table reports OLS estimates of regressing individuals' inflation expectations on the inflation rates in their household consumption bundles. Inflation expectations are from the customized *Chicago Booth Attitudes and Expectations Survey*, fielded in 6/2015 and 6/2016. The inflation question is randomized to ask about changes in prices (as in the Michigan Survey of Consumers) or about inflation (as in the New York Fed Survey). Measures of experienced inflation are constructed from the *Kilts-Nielsen Consumer Panel*. We use the 12 months before the June of each survey wave to measure price changes, and the 12 months before that period as the base period. The Household CPI uses the Nielsen expenditure shares in the base periods as weights; the Frequency CPI uses the frequencies of purchase (overall quantity) in the base period as weights; both CPIs use volume-weighted net prices (gross prices net of discounts). Demographic controls include age, square of age, sex, employment status, 16 income dummies, home ownership, marital status, household size, college dummy, four race dummies, and reported risk tolerance. Expectation controls include household income expectations, aggregate economic outlook, and personal financial outlook. All columns include survey-wave and inflation-question fixed effects, and we add county and individual fixed effects stepwise as indicated. Standard errors are clustered at the household level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Household CPI	0.171***	0.174***	0.192***				0.046	0.014	0.070
	(4.50)	(4.59)	(2.82)				(0.77)	(0.24)	(0.78)
Frequency CPI				0.199***	0.221***	0.304***	0.164***	0.211***	0.243**
				(5.19)	(5.83)	(3.40)	(2.73)	(3.56)	(2.04)
Observations	59,126	56,220	56,220	59,126	56,220	56,220	59,126	56,220	56,220
Adj R^2	0.028	0.090	0.245	0.028	0.091	0.245	0.028	0.091	0.245
Demographic controls		X	X		X	X		X	X
Expectation controls		X	X		X	X		X	X
County FE		X	X		X	X		X	X
Individual FE			X			X			X

t-statistics in parentheses

$^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$

Table 3: **Which Price Changes Matter?**

Notes. This table reports OLS estimates of regressing individuals' inflation expectations on the inflation rates in their household consumption bundles. Inflation expectations are from the customized *Chicago Booth Attitudes and Expectations Survey*, fielded in 6/2015 and 6/2016. The inflation question is randomized to ask about changes in prices (as in the Michigan Survey of Consumers) or about inflation (as in the New York Fed Survey). Measures of experienced inflation are constructed from the *Kilts-Nielsen Consumer Panel*. We use the 12 months before the June of each survey wave to measure price changes, and the 12 months before that period as the base period. The Frequency CPI employs the frequencies of purchase (overall quantity) in the base period as weights, and uses volume-weighted net prices (gross prices net of discounts). In Panel A, the main independent variables are, in column (1), separate indices for positive and negative price changes; in column (2), two measures that weigh positive price changes by a factor of 4 and 2, respectively; and in column (3), two separate Frequency CPIs based on the volatility of price changes in the *Kilts-Nielsen Retail Panel*. In Panel B, we include both the Frequency CPI and an Alternative CPI. In column (1), the Alternative CPI uses goods the consumer did not buy in the measurement period (but bought in the base period). In column (2), the Alternative CPI includes only goods the consumer purchased at least twice in the base period; and in column (3), only goods the consumer purchased at least once in the measurement period. Demographic controls include age, square of age, sex, employment status, 16 income dummies, home ownership, marital status, household size, college dummy, four race dummies, and reported risk tolerance. Expectation controls include household income expectations, aggregate economic outlook, and personal financial outlook. All columns include survey-wave, inflation-question, and county fixed effects. Standard errors are clustered at the household level.

Panel A	Positive Price Changes and Volatility		
	Price Changes Pos/Neg	Overweigh Pos Price Changes Factor 2/4	Price High/Low
	(1)	(2)	(3)
Positive/Factor 4/High	0.211***	0.315**	0.025
	(4.63)	(2.04)	(0.87)
Negative/Factor 2/Low	−0.040	−0.078	−0.039
	(−0.84)	(−0.25)	(−0.51)
Observations	56,212	56,220	49,568
Adj R^2	0.042	0.0042	0.042
Demographic controls	X	X	X
Expectation controls	X	X	X
County FE	X	X	X

Panel B	Variation in Sample		
	$Q_{Base} > 0$, $Q_{Meas} = 0$	$Q_{Base} \geq 2$	$Q_{Meas} \geq 1$
	(1)	(2)	(3)
Frequency CPI	0.212***	0.218***	0.229***
	(5.47)	(4.51)	(5.59)
Alternative CPI	−0.046	0.024	−0.017
	(−1.25)	(0.52)	(−0.40)
Observations	51,957	56,191	56,195
Adj R^2	0.092	0.091	0.091
Demographic controls	X	X	X
Expectation controls	X	X	X
County FE	X	X	X

Table 4: **Goodness-of-Fit and Noisy Survey Data: Evidence from Geographic Aggregates**

Notes. This table reports the estimates of regressing inflation expectations averaged at the geographic level reported on top of each column and across survey waves on the average inflation rates experienced by households' residing in such geographies in their consumption bundles. Inflation expectations are from the customized *Chicago Booth Attitudes and Expectations Survey*, fielded in 6/2015 and 6/2016. The inflation question is randomized to ask about changes in prices (as in the Michigan Survey of Consumers) or about inflation (as in the New York Fed Survey). Measures of experienced inflation are constructed from the *Kilts-Nielsen Consumer Panel*. We use the 12 months before the June of each survey wave to measure price changes, and the 12 months before that period as the base period. The Frequency CPI employs the frequencies of purchase (overall quantity) in the base period as weights, and uses volume-weighted net prices (gross prices net of discounts). *Zip code*, *County*, *FIPS Code*, *State*, and *Census region* represent the geographic partitions within which we average all variables. The three-digit FIPS codes are assigned in alphabetical order based on the county name within each state. This partition thus pools together geographic areas that typically do not share any borders and belong to all 50 US states. For each partition, the number of observations represents the number of partitions for which we have observations in Nielsen. Demographic controls include average age, square of age, share of men, share of employed, share of respondents across 16 income dummies, share of home owners, share of married respondents, average household size, share of college educated respondents, share of respondents across four races, and average reported risk tolerance. Expectation controls include household average income expectations, aggregate economic outlook, and personal financial outlook. All columns include survey-wave and inflation-question fixed effects. Standard errors are clustered at the household level. Huber-White standard errors are reported in parentheses.

	Zip code		County		3-digit FIPS code		State		Census region	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Frequency CPI	0.209***	0.198***	0.322***	0.313***	0.493***	0.337*	0.162*	0.193***	0.296**	*# Variables >*
	(4.15)	(3.94)	(2.85)	(2.75)	(2.75)	(1.70)	(1.66)	(1.96)	(1.98)	*Observations*
Observations	21,177	21,176	4,452	4,452	472	472	98	98	18	18
Adj R^2	**0.028**	**0.042**	**0.021**	**0.047**	**0.058**	**0.158**	**0.331**	**0.690**	**0.656**	**n.a.**
Demographic controls		X		X		X		X		X
Expectation controls		X		X		X		X		X

Online Appendix:

Exposure to Grocery Prices and Inflation Expectations

Francesco D'Acunto, Ulrike Malmendier, Juan Ospina, and Michael Weber

Not for Publication

Table A.1: **Summary Statistics by Participation Across Waves**

Notes. This table reports summary statistics of the main independent and dependent variables for our running sample and, separately, for respondents of only wave 1, only wave 2, and both waves. Expected Inflation and Perceived Inflation are reported numerical expectations and perceptions of inflation rates for a 12-month period, and are bounded between -100 and +100 percentage points. Household CPI and Frequency CPI are the measures of household-level grocery inflation based on scanner data from the *Kilts-Nielsen Consumer Panel*. Both measures are computed over a horizon of 12 months before the respondent took part in the *Chicago Booth Expectations and Attitudes Survey*. Income Outlook, Economic Outlook, and Financial Outlook are qualitative respondent expectations on the soundness of income growth, personal financial conditions, and overall economic outlook of the country for the following 12 months, and are bounded between 1 (very bad) and 5 (very good).

	Full Sample			Only Wave 1			Wave 1 & 2			Only Wave 2		
	Obs.	Mean	St. dev.	Obs.	Mean	St. dev.	Obs.	Mean	St. dev.	Obs.	Mean	St. dev.
Age	59,118	61.4	12.9	15,104	61.0	13.93	36,746	62.2	12.12	7,268	58.2	7.27
Male	59,126	0.36	0.48	15,111	0.37	0.48	36,746	0.34	0.48	7,269	0.39	0.49
Unemployed	59,126	0.05	0.22	15,111	0.05	0.22	36,746	0.05	0.21	7,269	0.05	0.22
Home Owner	59,126	0.74	0.44	15,111	0.74	0.44	36,746	0.75	0.43	7,269	0.72	0.45
Household Size	56,227	2.19	1.11	13,470	2.33	1.17	35,754	2.10	1.06	7,003	2.42	1.21
College	59,126	0.48	0.50	15,111	0.45	0.50	36,746	0.49	0.50	7,269	0.49	0.50
Income Outlook [1-3]	59,126	2.18	0.90	15,111	2.18	0.91	36,746	2.18	0.90	7,269	2.17	0.91
Economic Outlook [1-5]	59,126	2.69	1.04	15,111	2.76	1.06	36,746	2.68	1.03	7,269	2.62	0.91
Financial Outlook [1-5]	59,126	3.00	0.88	15,111	3.03	0.89	36,746	2.98	0.88	7,269	3.04	0.92
Expected Inflation	59,126	4.67	8.20	15,111	4.99	8.57	36,746	4.59	8.10	7,269	4.40	7.89
Perceived Inflation	59,126	4.44	8.27	15,111	4.92	8.75	36,746	4.34	8.16	7,269	3.96	7.74
Household CPI	59,126	0.81	7.14	15,111	1.18	6.90	36,746	0.75	7.20	7,269	0.39	7.26
Frequency CPI	59,126	1.61	5.85	15,111	1.79	5.80	36,746	1.63	5.86	7,269	1.12	5.83

Table A.2: **Grocery Shopping and Inflation Expectations: Gross Prices**

Notes. This table reports OLS estimates of regressing individuals' inflation expectations on the inflation rates in their household consumption bundles. Inflation expectations are from the customized *Chicago Booth Attitudes and Expectations Survey*, fielded in 6/2015 and 6/2016. The inflation question is randomized to ask about changes in prices (as in the Michigan Survey of Consumers) or about inflation (as in the New York Fed Survey). Measures of experienced inflation are constructed from the *Kilts-Nielsen Consumer Panel*. We use the 12 months before the June of each survey wave to measure price changes, and the 12 months before that period as the base period. The Household CPI uses the Nielsen expenditure shares in the base periods as weights; the Frequency CPI uses the frequencies of purchase (overall quantity) in the base period as weights; both CPIs use volume-weighted gross prices. Demographic controls include age, square of age, sex, employment status, 16 income dummies, home ownership, marital status, household size, college dummy, four race dummies, and reported risk tolerance. Expectation controls include household income expectations, aggregate economic outlook, and personal financial outlook. All columns include survey-wave and inflation-question fixed effects, and we add county and individual fixed effects stepwise as indicated. Standard errors are clustered at the household level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Household CPI	0.146^{***}	0.129^{***}	0.170^{***}				0.01	-0.02	0.07
	(3.80)	(3.38)	(2.79)				(0.14)	(-0.43)	(0.83)
Frequency CPI				0.196^{***}	0.197^{***}	0.232^{***}	0.191^{***}	0.214^{***}	0.176^{*}
				(4.98)	(4.99)	(3.20)	(3.31)	(3.76)	(1.79)
Observations	59,126	56,220	56,220	59,126	56,220	56,220	59,126	56,220	56,220
Adj R^2	0.028	0.090	0.245	0.028	0.091	0.245	0.028	0.091	0.245
Demographic controls		X	X		X	X		X	X
Expectation controls		X	X		X	X		X	X
County FE		X	X		X	X		X	X
Individual FE			X			X			X

t-statistics in parentheses

$^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$

Table A.3: **Alternative Frequency Measures**

Notes. This table reports OLS estimates of regressing individuals' inflation expectations on the inflation rates in their household consumption bundles. Inflation expectations are from the customized *Chicago Booth Attitudes and Expectations Survey*, fielded in 6/2015 and 6/2016. The inflation question is randomized to ask about changes in prices (as in the Michigan Survey of Consumers) or about inflation (as in the New York Fed Survey). Measures of experienced inflation are constructed from the *Kilts-Nielsen Consumer Panel*. We use the 12 months before the June of each survey wave to measure price changes, and the 12 months before that period as the base period. The Household CPI uses the Nielsen expenditure shares in the base periods as weights; the Frequency CPI uses the frequencies of purchase (overall quantity) in the base period; the Trip CPI uses the number of shopping trips in which a good was purchased in the base period; and the Volume CPI uses only the price changes of goods above the median by purchased volume at the household level. All CPIs use volume-weighted net prices (gross prices net of discounts). Demographic controls include age, square of age, sex, employment status, 16 income dummies, home ownership, marital status, household size, college dummy, four race dummies, and reported risk tolerance. Expectation controls include household income expectations, aggregate economic outlook, and personal financial outlook. All columns include survey-wave, inflation-question, and county fixed effects. Standard errors are clustered at the household level.

	Trip CPI			Volume CPI		
	(1)	(2)	(3)	(4)	(5)	(6)
Alternative CPI	0.172***	0.186***	0.075	0.175***	0.105**	0.048
	(4.24)	(3.30)	(1.29)	(4.42)	(2.08)	(0.05)
Household CPI		−0.021			0.113**	
		(−0.38)			(0.05)	
Frequency CPI			0.164***			0.193***
			(2.89)			(0.005)
Observations	56,220	56,220	56,220	56,212	56,212	56,212
Adj R^2	0.09	0.09	0.09	0.09	0.09	0.09
Demographic controls	X	X	X	X	X	X
Expectation controls	X	X	X	X	X	X
County FE	X	X	X	X	X	X

t-statistics in parentheses
$^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$

Table A.4: **Alternative Definitions of Inflation Expectations: Horizon and Prices**

Notes. This table reports OLS estimates of regressing individuals' inflation expectations on the inflation rates in their household consumption bundles. Inflation expectations are from the customized *Chicago Booth Attitudes and Expectations Survey*, fielded in 6/2015 and 6/2016. The inflation question is randomized to ask about changes in prices (as in the Michigan Survey of Consumers) or about inflation (as in the New York Fed Survey). Measures of experienced inflation are constructed from the *Kilts-Nielsen Consumer Panel.* We use the 12 months before the June of each survey wave to measure price changes, and the 12 months before that period as the base period. We include both the Frequency CPI and an Alternative CPI as independent variables. The Frequency CPI employs the frequencies of purchase (overall quantity) in the base period as weights. The Alternative CPIs in columns (1) to (3) conditions on goods the household purchased one month before the survey and vary the horizon over which the price changes are calculated: from April to May in column (1), from November to May in column (2), and from June to May in column (3). The Alternative CPI in column (4) uses the maximum price in both observation and measurement period to calculate price changes, and column (5) uses the median price change rather than volume-weighted prices. All CPIs use volume-weighted net prices (gross prices net of discounts). Demographic controls include age, square of age, sex, employment status, 16 income dummies, home ownership, marital status, household size, college dummy, four race dummies, and reported risk tolerance. Expectation controls include household income expectations, aggregate economic outlook, and personal financial outlook. All columns include survey-wave, inflation-question, and county fixed effects. Standard errors are clustered at the household level.

	Horizon 1	Horizon 6	Horizon 12	Max Change	Median Change
	(1)	(2)	(3)	(4)	(5)
Frequency CPI	0.207***	0.205***	0.212***	0.218***	0.224***
	(5.30)	(5.05)	(5.24)	(5.73)	(5.56)
Alternative CPI	−0.070*	−0.048	−0.032	−0.053	0.008
	(−1.82)	(−1.26)	(−0.86)	(−1.40)	(0.20)
Observations	53,331	53,128	54,064	56,220	56,220
Adj R^2	0.093	0.092	0.092	0.091	0.091
Demographic controls	X	X	X	X	X
Expectation controls	X	X	X	X	X
County FE	X	X	X	X	X

t-statistics in parentheses

$^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$

Table A.5: **Alternative Definitions of Inflation Expectations: Aggregation**

Notes. This table reports OLS estimates of regressing individuals' inflation expectations on the inflation rates in their household consumption bundles. Inflation expectations are from the customized *Chicago Booth Attitudes and Expectations Survey*, fielded in 6/2015 and 6/2016. The inflation question is randomized to ask about changes in prices (as in the Michigan Survey of Consumers) or about inflation (as in the New York Fed Survey). Measures of experienced inflation are constructed from the *Kilts-Nielsen Consumer Panel.* We use the 12 months before the June of each survey wave to measure price changes, and the 12 months before that period as the base period. We include both the Frequency CPI and an Alternative CPI as independent variables. The Frequency CPI employs the frequencies of purchase (overall quantity) in the base period as weights. The Alternative CPIs aggregates UPCs to the group level in column (1), to the department level in column (2), and to the module level in column (3). In column (4), we use prices from the retail panel instead of individual-level prices to calculate price changes. All CPIs use volume-weighted net prices (gross prices net of discounts). Demographic controls include age, square of age, sex, employment status, 16 income dummies, home ownership, marital status, household size, college dummy, four race dummies, and reported risk tolerance. Expectation controls include household income expectations, aggregate economic outlook, and personal financial outlook. All columns include survey-wave, inflation-question, and county fixed effects. Standard errors are clustered at the household level.

	Group	Department	Module	Store Prices
	(1)	(2)	(3)	(4)
Frequency CPI	0.208***	0.204***	0.209***	0.209***
	(5.38)	(5.28)	(5.40)	(5.40)
Alternative CPI	−0.043	0.013	−0.012	−0.042
	(−1.10)	(0.34)	(−0.32)	(−1.12)
Observations	52,048	52,048	52,048	52,048
Adj R^2	0.091	0.091	0.091	0.091
Demographic controls	X	X	X	X
Expectation controls	X	X	X	X
County FE	X	X	X	X

t-statistics in parentheses

${}^{*}p < 0.10, {}^{**}p < 0.05, {}^{***}p < 0.01$

Table A.6: **Alternative Definitions of Inflation Expectations: Weights**

Notes. This table reports OLS estimates of regressing individuals' inflation expectations on the inflation rates in their household consumption bundles. Inflation expectations are from the customized *Chicago Booth Attitudes and Expectations Survey*, fielded in 6/2015 and 6/2016. The inflation question is randomized to ask about changes in prices (as in the Michigan Survey of Consumers) or about inflation (as in the New York Fed Survey). Measures of experienced inflation are constructed from the *Kilts-Nielsen Consumer Panel.* We use the 12 months before the June of each survey wave to measure price changes, and the 12 months before that period as the base period. We include both Frequency CPI and, in columns (2) to (5), an Alternative CPI as independent variables, which are based on volume-weighted net prices (gross prices net of discounts). The Frequency CPI employs the frequencies of purchase (overall quantity) in the base period to construct Laspeyres weights. The Alternative CPIs use Paasche weights in column (2) and Fisher weights in column (3). In column (4), we construct weights across both the base and observation period; and in column (5), we use absolute price changes as weights. Demographic controls include age, square of age, sex, employment status, 16 income dummies, home ownership, marital status, household size, college dummy, four race dummies, and reported risk tolerance. Expectation controls include household income expectations, aggregate economic outlook, and personal financial outlook. All columns include survey-wave, inflation-question, and county fixed effects. Standard errors are clustered at the household level.

		Paasche	Fisher	Total	Absolute
	(1)	(2)	(3)	(4)	(5)
Frequency CPI	0.221***	0.218***	0.183***	0.186***	0.199***
	(5.83)	(5.63)	(3.93)	(3.65)	(4.42)
Alternative CPI		0.015	0.067	0.050	0.038
		(0.38)	(1.41)	(1.05)	(0.84)
Observations	56,220	56,220	56,219	56,195	56,220
Adj R^2	0.091	0.091	0.091	0.091	0.091
Demographic controls	X	X	X	X	X
Expectation controls	X	X	X	X	X
County FE	X	X	X	X	X

t-statistics in parentheses

$^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$

Table A.7: **Simulated R^2 with Variations in Noise and Rounding**

Notes. This table reports the estimates of regressing individuals' inflation expectations on the inflation rates experienced in their household consumption bundles in simulated data. We assume column (5) of Table 2 as the true underlying model. In Panel A, we add mean-zero, normally distributed noise, varying the standard deviation across columns, and round a random subset of 70% of observations to the closest multiple of 5, which approximately corresponds to the empirical fraction of rounders after adding the noise. Panel B repeats the same exercise but without rounding. Panel C varies the fraction of rounders but keeps the amount of noise constant, namely, equal to the error term standard deviation of the specification of column (5) of Table 2. Panel D repeats the same exercise as in Panel C but without adding any noise to the data. Standard errors are clustered at the household level.

	Panel A: Variation in Noise and Empirical Rounding										
	0	1	2	3	4	5	6	7	8	9	10
Frequency CPI	0.229***	0.219***	0.212***	0.208***	0.210***	0.247***	0.194***	0.224***	0.228***	0.251***	0.253***
	(42.47)	(32.55)	(21.01)	(15.03)	(11.49)	(11.26)	(7.40)	(7.44)	(6.61)	(6.31)	(5.80)
Adj R^2	0.818	0.712	0.522	0.362	0.254	0.183	0.132	0.109	0.086	0.066	0.054
	Panel B: Variation in Noise, No Rounding										
	0	1	2	3	4	5	6	7	8	9	10
Frequency CPI	0.221***	0.228***	0.232***	0.225***	0.224***	0.201***	0.260***	0.197***	0.199***	0.243***	0.267***
		(53.50)	(26.74)	(17.67)	(13.02)	(9.21)	(10.14)	(6.49)	(5.85)	(6.30)	(6.30)
Adj R^2	1.000	0.857	0.598	0.400	0.271	0.188	0.143	0.110	0.088	0.069	0.055
	Panel C: Variation in Rounding, Empirical Noise										
	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
Frequency CPI	0.297***	0.298***	0.297***	0.302***	0.302***	0.304***	0.306***	0.305***	0.305***	0.299***	0.303***
	(8.77)	(8.79)	(8.72)	(8.88)	(8.85)	(8.91)	(8.93)	(8.88)	(8.87)	(8.68)	(8.80)
Adj R^2	0.090	0.090	0.089	0.089	0.089	0.089	0.088	0.088	0.088	0.088	0.088
	Panel D: Variation in Rounding, No Noise										
	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
Frequency CPI	0.221***	0.222***	0.225***	0.226***	0.225***	0.225***	0.232***	0.236***	0.230***	0.234***	0.235***
		(110.62)	(78.01)	(63.96)	(55.70)	(49.86)	(46.73)	(43.82)	(40.19)	(38.28)	(36.27)
Adj R^2	1.000	0.967	0.937	0.909	0.883	0.859	0.836	0.816	0.799	0.781	0.764

t-statistics in parentheses
$^{*}p < 0.10, ^{**} p < 0.05, ^{***} p < 0.01$