Exposure to Grocery Prices and Inflation Expectations*

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

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Abstract

We show that consumers rely on the prices changes of goods in their personal grocery bundles when forming expectations about aggregate inflation. 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.

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†Carroll School of Management, Boston College. e-Mail: dacuntof@bc.edu

‡Department of Economics and Haas School of Business, University of California at Berkeley, CEPR and NBER. e-Mail: ulrike@berkeley.edu.

§Banco de la Republica de Colombia. e-Mail: juan.jose.ospina@gmail.com.

¶Booth School of Business, University of Chicago and NBER. e-Mail: michael.weber@chicagobooth.edu.

I Introduction

In his seminal islands model, Lucas (1972, 1973) 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. To what extent are consumers relying on prices they personally observe to form expectations about aggregate inflation, rather than simply looking up money supply (or, nowadays, the inflation rate on the internet)? 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. Assessing the empirical plausibility of this assumption is especially important in times of low interest rates and inflation (Summers (2018)), in which the ability to manage households' inflation expectations is key for the effectiveness monetary and fiscal policies (Feldstein (2002); Yellen (2016); Lagarde (2020)).

In this paper, we bring the Lucas assumption to the data and investigate the extent to which consumers rely on the grocery-price changes they observe in their consumption bundles to form expectations about aggregate inflation. Our data uniquely link expectations, consumption bundles, and item-level prices at the consumer level. 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 significantly influence their expectations about aggregate inflation. The weights consumers assign to different price changes in their grocery consumption bundle depends on the frequency of purchase, rather than the expenditure share, and positive price changes receive a larger weight than negative ones. The prices of goods in the same store that consumers do 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 prices rather than net prices (after discounts and coupons); using shopping trips or number of goods purchased to compute the frequency weights; varying the time horizon or the granularity of the definition of

goods; moving from Laspeyres to alternative ways of defining the consumption bundle; excluding goods purchased at low frequencies; using the maximum or median price changes or excluding temporary sales when calculating household level inflation measures.

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

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 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 individual-level characteristics 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 a 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.

Building on the finding that personal price changes impact beliefs about aggregate inflation, we then ask whether consumers weigh price changes based on expenditure shares, as the CPI assumes, or instead based on their frequency of exposure. The latter would be consistent with consumers perceiving the price signals from frequently purchased goods as

more precise (Angeletos and Lian (2016)) or easier to recall (Georganas et al. (2014)). We construct a second measure, the *Frequency CPI*, which uses the frequency of purchases to weigh price changes. The positive association between the Frequency CPI and inflation expectations is 20-40% larger than the association of the Household CPI. When we include both measures, 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. The estimation results are also robust to computing alternative versions of the Frequency CPI based on the number of trips in which households purchase a good or considering only goods households purchase in high volumes.

We also consider a large array of specific features of price changes that prior research has suggested as potential determinants of consumers' belief formation, including their sign, volatility, horizon, and technical details of the inflation weighting. The one aspect that robustly matters is the sign of price changes: positive price changes influence expectations more than negative ones. This differential effect of positive over negative price changes is robust to using gross prices (instead of prices net of discounts) and to excluding temporary price cuts such as weekly sales in retail scanner data. In other words, the asymmetric overweighing of positive price changes does not appear to reflect differential persistence in the price changes. Instead, the result is consistent with Cavallo et al. (2017), who argue that households pay more attention to price increases than price decreases.

Because we investigate many dimensions of price changes, one might be concerned about the role of multiple testing and searching across different measures for our results. We show that the frequency of purchase and the higher relevance of positive price changes compared to negative ones remain significant dimensions for the expectations formation process of individuals after adjusting p-values for multiple testing.

We also assess the explanatory power of past observed price changes on individuals' inflation expectations in more detail. The R^2 estimated in the purely cross-sectional part of our baseline regressions amounts to less than 10%. Since the Nielsen panel captures about 20-25% of respondents' overall consumption, and households naturally differ in the content, prices, and frequency of their remaining consumption, we might view an R^2 of 25% as a natural upper bound. This is in fact the degree of explanatory power we find when we exploit within-individual variation and thus keep constant the unobserved part of the consumption bundle. Hence, our findings leave room for other, complementary

determinants of expectations formation such as house-price experiences (Kuchler and Zafar, 2019), social interactions (Bailey et al., 2018), lifetime experiences (Malmendier and Nagel, 2011), and heterogeneous reactions to measures of economic policy (D'Acunto, Hoang, and Weber, 2020).

At the same time, it is likely that the R^2 from the baseline analysis under-estimates the true explanatory power of personal exposure to price changes for expectations since it is estimated on survey data. Survey data tend to suffer from noise and measurement error, also due to rounding (Binder (2017); D'Acunto et al. (2019c)) and heaping (Heitjan and Rubin (1990), Jappelli and Pistaferri (2010)). In fact, simulations (in the Online Appendix) reveal that plausible amounts of noise in the micro data would generate the R^2 from our baseline specifications even if personal inflation exposure fully explained inflation expectations.

To assess the extent to which noise in survey expectations might partially obscure the true explanatory power of personal exposure for inflation expectations, we follow the approach of Card and Lemieux (2001) and re-estimate our baseline model on increasingly coarser samples that result from averaging the micro data within economically meaningful partitions. This methodology aims to preserve economically relevant variation in inflation expectations and consumption baskets while reducing the role of rounding and heaping in lowering the R^2.

The first dimension we consider is households' spatial distribution, because households in the same geographic location tend to face common variation in price changes and in their economic expectations (Stroebel and Vavra (2019)). We find that the R^2 of our regressions increases monotonically with the size of the geographic areas, increasing up to 66% without any demographic controls when averaging over the largest feasible cells, which correspond to US Census regions.

As a second dimension, we consider consumers' cohorts or, equivalently (given the cross-sectional nature of our data), consumer age. In using this dimension, we follow Malmendier and Nagel (2011) and Aguiar and Hurst (2005), who show that cohort-level experiences and consumers' age are relevant in determining spending behavior and expectations. We further subsample by education because previous research documents its influence on consumption choices and inflation expectations (D'Acunto et al. (2019c); Das et al. (2020)). The R^2 of our resulting regressions increases monotonically with the size of the cohort-by-education groups, and increases to 25% for the largest partitions for

which we still have enough observations to meaningfully estimate our regressions.

These results are consistent with substantial amounts of noise being present in the micro data and indicate that heterogeneity in price exposure goes a long way toward explaining heterogeneity in inflation expectations after accounting for survey-induced noise. At the same time, we acknowledge that it is not possible to conclusively distinguish between noise and other sources of unmeasured heterogeneity. We cannot precisely estimate the extent to which the low R^2 are due to noise versus other individual-level unobserved determinants, which the Card-Lemieux approach might also average out. Further research in macroeconomics, microeconomics, marketing, and social and cognitive psychology is needed to investigate additional micro-level determinants of inflation expectations, especially in times when the effectiveness of monetary and fiscal policies hinges on their ability to shape households' inflation expectations (D'Acunto et al. (2019b)).

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 of price changes and consumption goods 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 further 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), Coibion et al. (2020) and D'Acunto, Hoang, and Weber (2020) 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 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 scanner 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.[1]

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.[2] The survey builds on the Michigan Survey of Consumers (MSC), the New York Fed Survey of Consumer Expectations (SCE), 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 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),

[1]For stores where Nielsen has point of sales (POS) information, Nielsen uses the average price for the UPC during the week of purchase to minimize the data-entry burden for panelists. For stores without POS information, households report item-level gross and net prices (minus discounts or coupons).

[2]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.

in terms of both point estimates and the full probability distribution.[3]

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

In this section, we study the association between household-level inflation and inflation expectations.

A. Defining Household-level Inflation

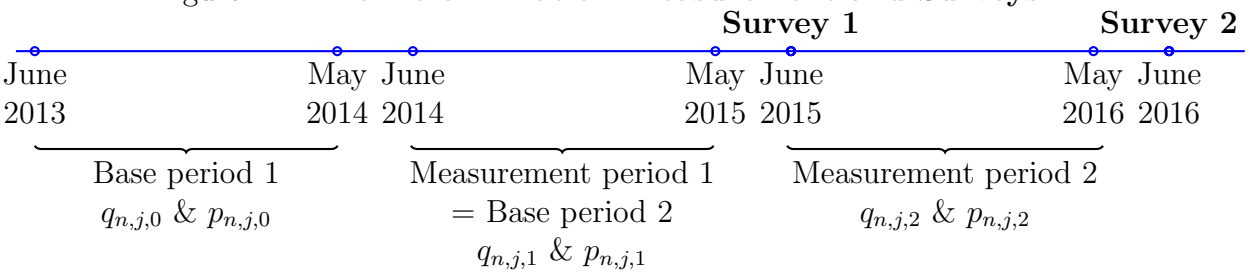
We define household-level inflation by mimicking the CPI:

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

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 $q_{n,j,0}$

[3]We randomized between two sets of questions: The MSC-inspired question asks about the prices of things on which respondents spend money. The New York Fed SCE's question asks specifically about inflation.

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



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 necessarily 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).[4] 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.

[4] 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, $\omega_{i,j} = f_{i,j,0\to1}$, where $f_{i,j,0\to1}$ 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.[5] They are very similar when using changes in gross rather than net prices (minus discounts) to compute inflation (Appendix-Table A.2), or when using the share of shopping trips in which an item is purchased and overweighing goods sold at higher volumes (Appendix-Table 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-

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

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.

IV Which Price Changes Matter Most?

Our results so far reveal that the price changes consumers are exposed to most frequently help explain their inflation expectations. We now ask whether there are particular types of goods or types of price changes that matter most. We test several hypotheses that emerge from prior work, especially Cavallo et al. (2017), in particular on the sign of the price changes and the set of consumption items consumers focus on. We also show that our results remain statistically significant after we account for multiple testing.

Positive Price Changes. Cavallo et al. (2017) argue that consumers pay more attention to price increases than price decreases. In Table 3, column (1), we substitute the Frequency CPI from the baseline specification with two CPIs that use only positive or only negative price changes, *Positive Price-Changes F-CPI* and *Negative Price-Changes F-CPI*, respectively. We find positive observed price changes significantly influence expectations, whereas negative past observed prices changes do not matter.

A similar insight emerges from the specification in column (2) where we modify the Frequency CPI to overweigh positive price changes by a factor of 2 and a factor of 4 (*Positive×2* and *Positive×4 F-CPI*). The CPI that overweighs positive changes by a larger factor drives the explanatory power of past observed 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 (*High-Volatility* and *Low-Volatility F-CPI*). Neither has explanatory power.

Lastly, we take some steps to ensure that our results are not confounded by a differential persistence of positive versus negative price changes. Price increases tend to be more permanent, whereas price cuts often reflect temporary sales that revert within days or weeks (Eichenbaum et al., 2011). The construction of our measures makes this explanation unlikely since we do not use trip-to-trip price changes. Rather, we calculate the log price change between the volume-weighted price in the base period and another volume-weighted average in the observation period for each individual good.

Two additional results help to differentiate sign from persistence directly. First, we can observe whether individuals purchased goods on discounts using coupons. As we

show in Appendix-Table A.2, results are virtually identical to those in Table 3 when we use gross rather than net prices (after discounts). Second, we follow Gorodnichenko and Weber (2016) and apply a V-shaped sales filter to the Nielsen weekly scanner data. That is, we compute alternative household-level CPIs when filtering temporary price changes. We exclude temporary sales if the price returns to the pre-sales price within one week, two weeks, or three weeks. In these cases, we use the regular prices to calculate realized inflation at the household level. The results, reported in columns (6)-(8) of Appendix-Table A.4 show that these alternative measures do not add any information about inflation expectations beyond the Frequency CPI.

Overall, the sign of price changes emerges as a significant factor: consumers appear to put more weight on positive than negative price changes they observe, a feature that should be incorporated in models of expectations formation. Volatility and persistence, instead, do not appear to play a significant role in our setting.

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. In column (1) of Table 4, we augment our baseline model by adding an alternative definition of the Frequency CPI, the *Imputation in Measurement Period CPI*. This measure uses the prices changes of all goods the household purchased in the base period, even though they stopped purchasing such goods in the measurement period. We find that this variable does not add any additional information about inflation expectations beyond the Frequency CPI.

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 Frequency CPI calculation to goods bought at least twice in the base period (*Recurring Purchases Base CPI*), and in column (3), to goods bought at least once in the measurement period (*Purchase in Measurement Period CPI*). Neither alternative CPI measure has explanatory power relative to the default Frequency CPI.

V Multiple Testing and Explanatory Power

One important concern which is typically underappreciated in economics research is the issue of multiple testing. By constructing several measures of realized inflation at the household level, we might find some being significant predictors of inflation expectations by pure chance. One common way to address the issue of specification searches or multiple testing in general is through adjustments to p-values such as Bonferroni, Holm, and Benjamini, Hochberg, and Yekutieli adjustments.

An important caveat to keep in mind in these adjustments is that none of the measures we tested were purely arbitrary but instead all our measures were motivated by theoretical reasons and findings in earlier literature, which, as Harvey et al. (2016) argue, reduces the concern that our results might be driven by chance.

To directly rule out this concern, we consider the Bonferroni adjustment, which is the most conservative one out of the standard p-value adjustments for multiple testing. It implies rejecting the null hypothesis of no association only if the p-value of a t-test for significance of an estimated coefficient is smaller than 0.05 divided by the number of measures tested throughout the analysis. In total, we tested 21 different measures of realized inflation at the household level. Hence, any estimate with a t-stat larger than about 3.01 would be significant at the 5% level after adjusting for multiple testing according to the Bonferroni adjustment.

The coefficients attached to our baseline measures—Frequency CPI and Household CPI—are highly statistically significant in across-individual specifications, and significant at the 10% level in within-individual specifications, even with the most stringent adjustment for multiple testing and ignoring the theoretical justification for testing these very measures. Crucially, the estimate on the positive price change CPI in Table 3, which is the most relevant dimension we uncover as related to inflation expectations, has a t-stat of almost 5 and hence is highly statistically significant even after applying the Bonferroni adjustment for multiple testing.

As a final step, we assess the explanatory power of households' personal exposure to grocery-price inflation for the observed heterogeneity in inflation expectations. In the purely cross-sectional part of our baseline regressions, the estimated R^2 amounts to less then 10%. Since the Nielsen panel captures about 20-25% of the overall consumption bundle for the average household, and since households naturally differ in their remaining consumption bundle, the prices they pay, and the frequency of purchase, we might view an

R^2 of 25% as a natural upper bound. This is in fact the degree of explanatory power we find when we exploit within-individual variation and thus keep constant the unobserved part of the consumption bundle. Hence, our findings on the role of exposure to grocery-price changes leave room for other, complementary determinants of expectations formation such as house-price experiences (Kuchler and Zafar, 2019), social interactions (Bailey et al., 2018), or lifetime experiences (Malmendier and Nagel, 2011).

At the same time, it is likely that our baseline R^2 significantly under-estimates the true explanatory power of personal exposure to price changes since it is estimated on survey data. Estimations using survey data tend to have a low R^2 even if the estimated model was correct because of noise in individually reported values and the tendency of respondents to round to integers or multiples of 5.[6]

In fact, we show with a simple simulation exercise (see section A.1 and Table A.7 in the Online Appendix) that, even if personal inflation exposure fully explained inflation expectations, implying an R^2 of 1, empirical estimations would generate an R^2 similar to that in our baseline specifications for plausible amounts of noise and rounding in the micro data. These simulation results do not mean that the lower R^2 in our baseline specifications is necessarily fully driven by noise and rounding in survey data, but they suggest that noise and rounding might indeed play a relevant role in the goodness of fit of our regressions.

To further assess the role of noise in our empirical data, we follow the approach of Card and Lemieux (2001). Their methodology relies on averaging the micro data within economically meaningful dimensions. The goal is to preserve economically relevant variation (here, in inflation expectations, consumption baskets, and good-level prices) while reducing the impact of rounding and heaping on R^2 by canceling out noisy values of opposite signs. The R^2 estimated on the coarser data would then provide for a more informative benchmark to assess the amount of cross-sectional variation in inflation expectations that is explained by household-level grocery price changes.

The first dimension we consider is households' geographic location. This analysis builds on Stroebel and Vavra (2019) who find that households in the same geographic location tend to face commonality in price changes and display comoving economic

[6]Heitjan and Rubin (1990) are among the first to study the implications of noise, rounding, and heaping in survey data; Jappelli and Pistaferri (2010) discuss these issues when studying consumption and income inequality using survey-based self-reported individual data from the Survey of Household Income and Wealth (SHIW).

expectations. Moreover, geographic splits provide aggregation of partitions with different levels of granularity that are fully contained within each other, which allows us to average out more and more noise as we move to coarser partitions, but still maintaining the same meaningful geographic-level variation within partitions.

In Table 5, we collapse the individual-level data within geographic cells whose size increases moving to the right: ZIP code, county, three-digit FIPS code, state, and census region. The three-digit FIPS code is assigned to counties within each state, and the same codes are used across all 50 states. Thus, this partition creates groups of counties that belong to different states. We find 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 65.6% without any controls.

As a second dimension, we consider consumers' cohorts or, equivalently (given the cross-sectional nature of our data), consumers' age. In using this dimension, we follow Malmendier and Nagel (2011) and Aguiar and Hurst (2005), who show that cohort-level experiences and consumers' age are relevant in determining spending behavior and expectations. We also note that, within a cohort/age group, observable dimensions such as education and cognitive abilities generate systematic differences in the composition of consumption bundles and in the formation of economic expectations (D'Acunto et al. (2019c); Das et al. (2020)). We therefore include aggregations of the data at the cohort-by-education level—within each cohort group, we aggregate the data separately for cohort members who hold a college degree and those without a college degree.

Columns (6)-(8) of Table 5 reveal that the R^2 of our regressions increases monotonically with the size of the cohort-by-education groups. It amounts to 24.7% for the largest partitions for which we still have enough observations to meaningfully estimate the empirical model. Note that this partition (column (8)) is based on 160 cohort-by-education observations, which is a similar number of observations as the state-level partition in column (4), and the size of the R^2 in these two partitions is similar.

Overall, as we aggregate across larger partitions, the R^2s of our regression models increase, which based on the approach in Card and Lemieux (2001) indicates that the low R^2 in regressions on the individual-level micro data might be driven by a substantial amount of noise, which then gets averaged out at the partition level. At the same time, it remains possible that unexplained individual heterogeneity that is orthogonal to both

geography and age and education will also be averaged out. Although the Card and Lemieux (2001) strategy cannot distinguish between noise and unexplained heterogeneity, the robustness of our findings across partitions points to the well-known role of survey noise as the key factor.

VI Conclusions

We document that household-level grocery-price changes significantly shape inflation expectations. We use unique, representative US data that link individual expectations to items purchased, frequency and outlet of purchase, and prices. These rich data also reveal which features of observed 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 results motivate additional work to further understand how consumers form aggregate expectations about inflation and other macroeconomic variables.

Future work should also 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 observed prices changes. For instance, is it optimal for consumers to focus on personal shopping exposure 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? The extent to which the increasing substitution of in-store shopping with online shopping affects the role of personal inflation on inflation expectations is also an interesting direction for future research.

References

Aguiar, M. and E. Hurst (2005). Consumption versus expenditure. *Journal of political Economy 113*(5), 919–948.

Angeletos, G.-M. and C. Lian (2016). Incomplete information in macroeconomics: Accommodating frictions in coordination. In *Handbook of macroeconomics*, Volume 2, pp. 1065–1240. Elsevier.

Armantier, O., W. Bruine de Bruin, S. Potter, G. Topa, W. van der Klaauw, and B. Zafar (2013). Measuring inflation expectations. *Annu. Rev. Econ. 5*(1), 273–301.

Bachmann, R., T. O. Berg, and E. R. Sims (2015). Inflation expectations and readiness to spend. *American Economic Journal: Economic Policy 7*(1), 1–35.

Bailey, M., R. Cao, T. Kuchler, and J. Stroebel (2018). The economic effects of social networks: Evidence from the housing market. *Journal of Political Economy 126*(6), 2224–2276.

Binder, C. C. (2017). Measuring uncertainty based on rounding: New method and application to inflation expectations. *Journal of Monetary Economics 90*, 1–12.

Card, D. and T. Lemieux (2001). Can falling supply explain the rising return to college for younger men? a cohort-based analysis. *The Quarterly Journal of Economics 116*(2), 705–746.

Cavallo, A., G. Cruces, and R. Perez-Truglia (2017). Inflation expectations, learning, and supermarket prices. *AEJ: Macroeconomics 9*(3), 1–35.

Coibion, O., D. Georgarakos, Y. Gorodnichenko, and M. Weber (2020). Forward guidance and household expectations. Technical report, National Bureau of Economic Research.

Coibion, O., Y. Gorodnichenko, and M. Weber (2018). Monetary policy communications and their effects on household inflation expectations. *Working Paper 120*(1), 116–159.

D'Acunto, F., D. Hoang, M. Paloviita, and M. Weber (2019a). Cognitive abilities and inflation expectations. *Working Paper*.

D'Acunto, F., D. Hoang, M. Paloviita, and M. Weber (2019b). Human frictions to the transmission of economic policy. Technical report, Working Paper.

D'Acunto, F., D. Hoang, M. Paloviita, and M. Weber (2019c). Iq, expectations, and choice. *Working Paper*.

D'Acunto, F., D. Hoang, and M. Weber (2020). Managing households' expectations with unconventional policies. *Working Paper*.

Das, S., C. M. Kuhnen, and S. Nagel (2020). Socioeconomic status and macroeconomic expectations. *The Review of Financial Studies 33*(1), 395–432.

de Bruin, W. B., W. Van der Klaauw, and G. Topa (2011). Expectations of inflation: The biasing effect of specific prices. *Journal of Economic Psychology 32*(5), 834–845.

Eichenbaum, M., N. Jaimovich, and S. Rebelo (2011). Reference prices, costs, and nominal rigidities. *American Economic Review 101*(1), 234–62.

Feldstein, M. (2002). The role for discretionary fiscal policy in a low interest rate environment. Technical report, National Bureau of Economic Research.

Frache, S. and R. Lluberas (2018). New information and inflation expectations.

Georganas, S., P. J. Healy, and N. Li (2014). Frequency bias in consumemers' perceptions

of inflation: An experimental study. *European Economic Review 67*, 144–158.

Gorodnichenko, Y. and M. Weber (2016). Are sticky prices costly? evidence from the stock market. *American Economic Review 106*(1), 165–99.

Harvey, C. R., Y. Liu, and H. Zhu (2016). ï¿½ and the cross-section of expected returns. *The Review of Financial Studies 29*(1), 5–68.

Heitjan, D. F. and D. B. Rubin (1990). Inference from coarse data via multiple imputation with application to age heaping. *Journal of the American Statistical Association 85*(410), 304–314.

Jappelli, T. and L. Pistaferri (2010). Does consumption inequality track income inequality in italy? *Review of Economic Dynamics 13*(1), 133–153.

Kaplan, G. and S. Schulhofer-Wohl (2017). Inflation at the household level. *Journal of Monetary Economics 91*, 19–38.

Kuchler, T. and B. Zafar (2019). Personal experiences and expectations about aggregate outcomes. *The Journal of Finance 74*(5), 2491–2542.

Lagarde, C. (2020). Ecb president press conference, june 4, 2020. Speech, European Central Bank.

Lucas, R. E. (1972). Expectations and the neutrality of money. *Journal of Economic Theory 4*(2), 103–124.

Lucas, R. E. (1973). Some international evidence on output-inflation tradeoffs. *The American Economic Review 63*(3), 326–334.

Lucas, R. E. (1975). An equilibrium model of the business cycle. *Journal of political economy 83*(6), 1113–1144.

Malmendier, U. and S. Nagel (2011). Depression babies: Do macroeconomic experiences affect risk-taking? *Quarterly Journal of Economics 126*, 373–416.

Malmendier, U. and S. Nagel (2015). Learning from inflation experiences. *Quarterly Journal of Economics 131*(1), 53–87.

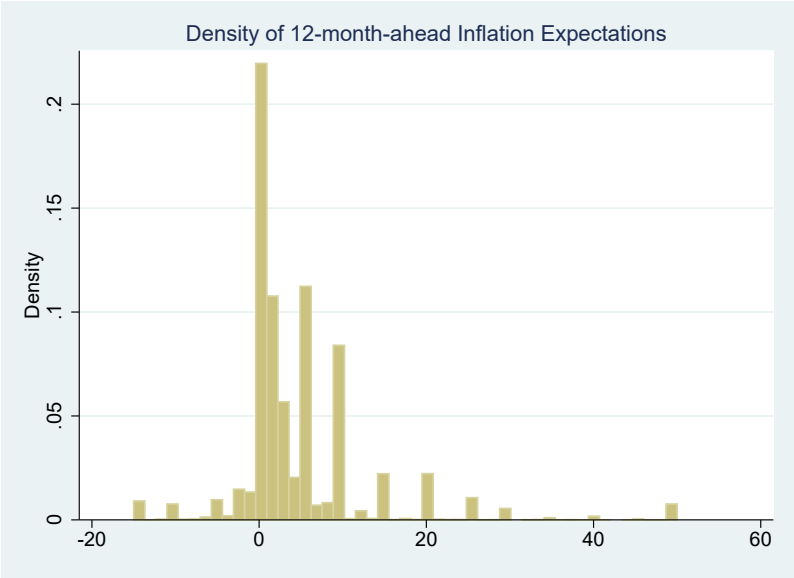
Stroebel, J. and J. Vavra (2019). House prices, local demand, and retail prices. *Journal of Political Economy 127*(3), 1391–1436.

Summers, L. (2018). The threat of secular stagnation has not gone away. *Available at http://larrysummers.com/2018/05/06/the-threat-of-secular-stagnation-has-not-gone-away/*.

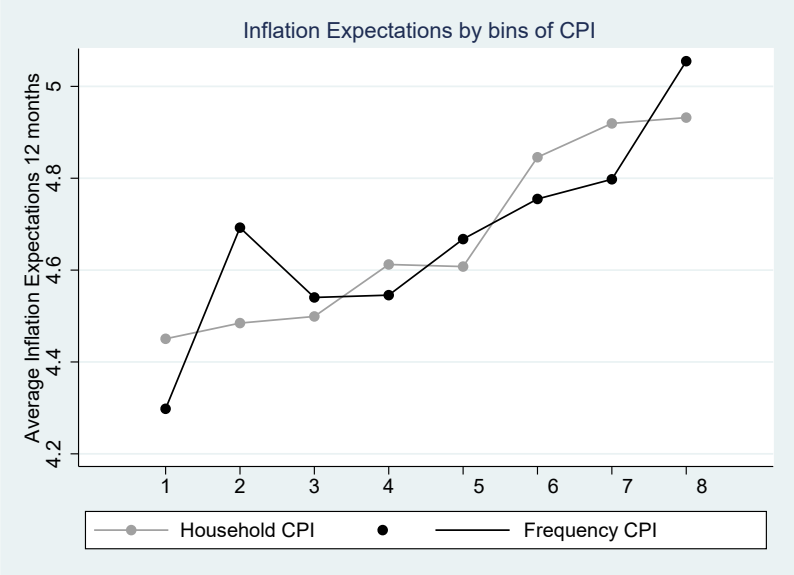
Yellen, J. L. (2016). Macroeconomic research after the crisis. Speech 915, Board of Governors of the Federal Reserve System (U.S.).

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. Demographic characteristics refer to respondents that took part in the *Chicago Booth Expectations and Attitudes Survey.* Income Outlook, Economic Outlook, and Financial Outlook are respondents' qualitative 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). 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.*

	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 Expectations and Attitudes 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: Sign and Volatility**

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 Expectations and Attitudes 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). 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*. 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.

	Positive Price Changes and Volatility		
	Sign of Price Change	Overweight Positive Price Changes	Volatility of Price Changes
	(1)	(2)	(3)
Positive Price-Changes F-CPI	0.211***		
	(4.63)		
Negative Price-Changes F-CPI	−0.040		
	(−0.84)		
Positive×4 F-CPI		0.315**	
		(2.04)	
Positive×2 F-CPI		−0.078	
		(−0.25)	
High-Volatility F-CPI			0.025
			(0.87)
Low-Volatility F-CPI			−0.039
			(−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

Table 4: **Which Price Changes Matter? Goods Not Purchased in Both Periods**

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 Expectations and Attitudes 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 each specification, we propose a horse race between the Frequency CPI and a version of the Frequency CPI measured using an alternative definition. The Imputation in Measurement Period CPI uses goods the consumer did not buy in the measurement period (but bought in the base period). The Recurring Purchases Base CPI includes only goods the consumer purchased at least twice in the base period; and the Purchase in Measurement Period CPI includes 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.

	Variation in Sample		
	Purchased Base Period not Measurement	Purchased Base at least twice	Purchased Meas. at least once
	(1)	(2)	(3)
Frequency CPI	0.212***	0.218***	0.229***
	(5.47)	(4.51)	(5.59)
Imputation in Measurement Period CPI	−0.046		
	(−1.25)		
Recurring Purchases Base CPI		0.024	
		(0.52)	
Purchase in Measurement Period CPI			−0.017
			(−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 5: **Goodness-of-Fit: Geographic and Cohort-by-Education Partitions**

Notes. This table reports the estimates of regressing inflation expectations averaged at the geographic and cohort-by-education levels reported on top of each column and across survey waves on the average inflation rates faced by households' who are part of such partitions. Inflation expectations are from the customized *Chicago Booth Expectations and Attitudes 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 variables. The three-digit FIPS codes are assigned in alphabetical order based on the county name within each state. This partition thus creates groups of counties that belong to different states. For the cohort-by-education partitions, *Birth Month*, *Birth − Quarter*, and *Birth Year* represent the cohort definitions by which we average variables. Within each cohort partition, we further average variables separately for respondents with and without college education, which produces two observations for each cohort. 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.

	Geographic Partitions					**Cohort-by-Education Partitions**		
	Zip Code	County	3-digit FIPS code	State	Census Region	Birth Month & College	Birth Quarter & College	Birth Year & College
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Frequency CPI	0.209***	0.322***	0.493***	0.162*	0.296**	0.194*	0.236*	0.409*
	(4.15)	(2.85)	(2.75)	(1.66)	(1.98)	(1.74)	(1.85)	(1.93)
Observations	21,177	4,452	472	98	18	1,753	617	160
Adj R^2	**0.028**	**0.021**	**0.058**	**0.331**	**0.656**	**0.029**	**0.032**	**0.247**

Online Appendix:

Exposure to Grocery Prices and Inflation Expectations

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

Not for Publication

A.1 Survey Noise and Simulation

In this section, we assess the role of survey 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)).

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. Panel A shows the R^2 from re-estimating column (5) of Table 2 (assumed to be the true model in the data generation) when 70% of respondents round to multiples of 5, as is the case in our data, and we add zero-mean normally-distributed noise, ranging from 0 to 10 (cf. columns 1-11). The noise reduces the measured fit from 82% to 5%. Results without any rounding (in Panel B) are similar.

In Panel C, we proxy for an empirically plausible level of noise by 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 noise reduces the R^2 only partially. All simulations indicate that an empirically plausible amount of survey noise suffices to generate the R^2 from our baseline estimation.

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 Expectations and Attitudes 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 Expectations and Attitudes 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 Household Inflation: 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 Expectations and Attitudes 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) condition 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 prices rather than volume-weighted prices. The Alternative CPIs in columns (6) to (8) follow Gorodnichenko and Weber (2016) and apply a V-shaped sales filter to the Nielsen weekly retail scanner data. We replace the temporary sales price with the regular price if the price returned to the pre-sales price after one week in column (6), two weeks in column (7), and after three weeks in column (6). 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 1 month	Horizon 6 months	Horizon 12 months	Max Change	Median Change	Temporary 1 week	Temporary 2 weeks	Temporary 3 weeks
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Frequency CPI	0.207***	0.205***	0.212***	0.218***	0.224***	0.184***	0.183***	0.183***
	(5.30)	(5.05)	(5.24)	(5.73)	(5.56)	(4.49)	(4.48)	(4.48)
Alternative CPI	−0.070*	−0.048	−0.032	−0.053	0.008	−0.033	−0.030	−0.029
	(−1.82)	(−1.26)	(−0.86)	(−1.40)	(0.20)	(−0.85)	(−0.77)	(−0.76)
Observations	53,331	53,128	54,064	56,220	56,220	51,821	51,821	51,821
Adj R^2	0.093	0.092	0.092	0.091	0.091	0.042	0.042	0.042
Demographic controls	X	X	X	X	X	X	X	X
Expectation controls	X	X	X	X	X	X	X	X
County FE	X	X	X	X	X	X	X	X

t-statistics in parentheses

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

Table A.5: **Alternative Definitions of Household Inflation: 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 Expectations and Attitudes 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 (store-level) 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 Household Inflation: 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 Expectations and Attitudes 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

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