Grocery Purchasing Behavior During Food Inflation Shocks of Households Based on Income, Family Structure, and Retirement Status

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ABSTRACT

This study examines household responses to food inflation surge under varying income levels, retirement status, and family structure. We find that low-income households change their grocery spending in response to food inflation shock. However, this observation is not prevalent across all types of households. While we find evidence of measurable change in grocery spending of families and retired households, we fail to find so for singles and couples-only households. Most interestingly, low-income households of single parents with children also do not show significant response to food inflation surge. The observed heterogeneity in grocery expenditure responses reflects budget and time constraints of different types of households.

1. Introduction

Until recently when the inflation rate exceeded 9% in June 2022, the US had experienced four decades of low inflation, limiting economists' capacity to study US households' spending behavior during inflation shocks. As Andreyeva et al. (2010) note price elasticity observed during normal times may not be informational of purchasing behavior choices during periods of economic shocks such as falling income in a recession or dramatic increases in energy or food prices. Nevo and Wong (2019) similarly motivate their study of implied substitution between time and goods expenditure in home production during the great recession. While international observations offer valuable policy insights, their applicability to U.S. households is limited due to distinct demographics, income distribution, and social factors. Thus, we analyze household spending patterns during the COVID-era inflation shock.

Using CES survey data, we analyze quarterly household spending from 2021 to 2023 across income levels. The data allows us to isolate grocery spending changes, even minor ones, due to food price fluctuations. Since 80% of U.S. grocery spending is on food (BLS, 2024), we use food price inflation as a proxy for grocery inflation. High-income households show no price sensitivity. Changes in their grocery spending are not explained by food inflation, but those of low-income households are. Their grocery expense increases by less than the food inflation rate, thereby suggesting that they make changes to their consumption behavior in response to price shock. However, not all types of low-income households demonstrate price sensitivity.

We analyze low-income households by retirement status and family structure. We find that grocery spending of families (excluding single-parent households) and retirees increases by less than food inflation. Change in that of singles, couples-only households, and single-parent families is not explained by the food inflation rate. This suggests that when faced with food price increases they continue to make similar purchases as before. We argue that the lack of price sensitivity of such households, though intriguing, is very understandable, given the choice set available to them.

U.S. households maximize utility from paid goods and leisure within income and time constraints, which vary by family structure and retirement status. Marginal utility from monetary and time resources differs across households. Despite financial constraints, single low-income parents maintain grocery spending, prioritizing time and attention for higher-value activities. Given work and child-rearing demands, they choose to preserve scarce personal time rather than invest effort in grocery cost-cutting. Similarly, couples

and individuals also forego grocery cost-saving efforts, as the utility gained from such efforts is lower than what they would derive from alternative uses of their time.

In a study cited over 1,600 times Andreyeva et al. (2010) conducted a systematic review of studies on price elasticity of demand for food and concluded that it is inelastic. They state, "Only a small number of studies (have) evaluated the effects of income level on demand elasticity." They note that two studies on specific food categories—milk (Bartlett, 1965) and fast food (Barnes & Gillingham, 1984)—find significantly higher price elasticity among low-income consumers, but three broader studies (Park et al., 1996; Huang & Lin, 2000; Raper et al., 2002) find no significant difference in elasticity across income groups.

Since then, a few other studies have explored this topic. Ni Mhurchu et al. (2013) found greater sensitivity to food prices among low-income households in New Zealand. Green et al. (2013) reviewed price elasticity across 162 countries, concluding that global food prices have a stronger impact on consumption in lower-income countries and poorer households within them. Codjia and Saghaian (2022) found conditional expenditure elasticities of income below one for all food types and Taylor (2022) used data from 2006–2019 to simulate household spending in 2021–22, finding that food inflation had the greatest impact on the lowest income quintile. While the literature suggests higher price elasticity among low-income populations, findings remain inconclusive.

Though consumer behavior during normal times is essential to policymaking, understanding of consumer response to economic shocks, at individual and macroeconomic level, is equally important. Scholdra et al., (2022) find that households buy fewer products and spend less in total after losing income but macroeconomic changes cause shifts in their shopping basket allocation wherein they spend more but on private label products during contractions. With higher unemployment households reallocate their expenses across retailers to mitigate inflation in effective prices (Coibion et al., 2015). Griffith et al. (2016) document methods used by households in UK to maintain quality and quantity of consumption during the great recession while Nevo and Wong (2019) do so for US households and McKenzie et al., (2011) do for Argentinian households during the crisis of 2001-2002.

In contrast with the above studies that focused on periods of income shock we study spending behavior during a period of price shock. In addition, unlike prior studies we document varying spending behavior across multiple dimensions based on income, retirement, and family structure. While not the primary aim of the study, our findings may also help reconcile some of the inconsistent results in prior research on low-income household grocery consumption during normal periods. For instance, higher price elasticity for milk among low-income households may reflect its relevance to families rather than singles, who we find to be more price-sensitive. Conversely, a study on convenience foods—more relevant to single-person households—might conclude that low-income consumers do not exhibit higher elasticity.

2. Theory and Hypothesis Development

2.1 Theoretical setup

We study spending behavior and time allocation choices of a household rather than an individual. A household maximizes its utility U subject to its income and time constraints.[1] A household's working age

[1] This is consistent with Becker (1965) theory of time allocation by households. Despite a lengthy career criticizing Becker's theory even Pollack (2003) recognizes the interdependent nature of family collective choices as they pertain to economic decision-making and leisure.

members have a fixed amount of time available C that they devote to income-generating activities or on leisure L measured in hours. Income M is used to acquire paid goods and services in one of three categories. 1) Relatively fixed expenses: These include costs of housing, childcare, taxes, transportation, health, education, childcare, alimony & child support, and retirement contributions. Households have limited flexibility in reducing these costs without significant lifestyle changes. 2) Discretionary expenses include spending on entertainment (streaming services, gym memberships, hobbies, restaurants, vacation, event tickets) pet care, apparel and personal care, and miscellaneous. Compared to fixed expenses, households have more ability to adjust these costs when facing income constraints. 3) Grocery spending. We collectively refer to fixed and discretionary expense as non-grocery expense x and grocery expense as y. The household pays P_x and P_y for x and y, respectively. Income M includes a non-labor component S and a labor component dependent on wage per hour w. Non-labor income may include social security payments, pension, child support, alimony, or any other welfare support. It also includes dividends, interest, capital gains, and all other income that is not a function of time spent working. Utility is increasing in x, y, and L but it increases with L at a decreasing rate. That is,

$$\frac{\partial U}{\partial M} > 0;\ \frac{\partial U}{\partial L} > 0\ ;\ \frac{\partial^2 U}{\partial L^2} < 0$$

The marginal utility of L approaches zero as L approaches C. That is, utility gained from additional free time is negligible if you are free most of the time.

$$\lim_{L \to C} \frac{\partial U}{\partial L} = 0 \tag{1}$$

Households may respond to grocery price (P_y) increase with one or more of the following: 1. Maintaining prior quantity and type of groceries, 2. Reducing quantity while making the same type of purchases, 3. Substituting with lower cost alternatives, 4. Altering shopping strategies (how, when, and where the purchases are made). In case 1, grocery spending $(P_y y)$ increases by the rate of inflation in (P_y). Those making no changes are either not financially-constrained or compensate by working more or reducing non-grocery expenses.[2] Households adapting to food inflation often experience psychological resistance to change and incur time costs in adjusting their shopping habits.

We define f as hours spent on cost-saving efforts and μ as savings in total spending per f, similar to shopping intensity and returns to shopping measures of Nevo and Wong (2019), respectively. A household maximizes its utility by its choice of L, x, y, and f with the following constraints.

$$M = S + w * (C - L - f) \tag{2}$$

$$P_x x + P_y y - \mu f \leq M \tag{3}$$

Cost-saving efforts, referred to as "shopping efforts" by Griffith et al. (2016), may include: 1) Purchasing from discount stores, local farmers' markets, and cooperatives; 2. Availing volume discounts; 3) Seeking and redeeming manufacturer coupons; 4) Shopping at multiple stores to secure better prices or promotions for specific products; 5) Choosing private-label or generic products over national brands; 6)

[2] Consumers may substitute grocery purchases with non-grocery alternatives, a factor considered in our empirical analysis. However, alternatives such as restaurant meals typically incur higher costs due to additional components, including service charges and business overhead.

Buying discounted items—such as those near expiry or random-weight products—potentially of lower (real or perceived) quality (Leibtag & Kaufman, 2003); 7) Opting for a less expensive product within a given product class; and, 8) Selecting a more affordable product class more frequently. Nevo and Wong (2019) examine the first five in the context of the 2008 Great Recession, providing both theoretical and empirical evidence, while Griffith et al. (2016) analyze the last four. These studies categorize such efforts as non-market work and assess them within the home production models of Benhabib et al. (1991) and Greenwood & Hercowitz (1991), showing that they lead to lower prices. Coibion et al. (2015) specifically highlight the shift to discount stores and reallocation of household expenditures across retailers as ways to reduce effective prices, while Kaplan & Menzio (2015) emphasize visits to multiple stores during shopping trips.

Leisure includes activities like watching television, playing sports, socializing with friends and family, reading, engaging in hobbies, and relaxing (Aguiar and Hurst, 2009). It captures the component of consumption not purchased in the market and is a function of time alone. Any associated monetary cost is accounted for in x. L decreases in f since cost saving efforts take away time from leisure.

For households making cost-saving effort at the expense of leisure time

$$\frac{\partial L}{\partial f} = -1 \; and \; \frac{\partial M}{\partial f} = 0$$

Such households engage in cost-saving efforts if utility from spending reduction outweighs that from leisure:

$$f > 0 \quad if \frac{\partial U}{\partial \mu} > \frac{\partial U}{\partial L} \tag{4}$$

assuming $\frac{\partial \mu}{\partial f} = 0$,[3] taking the derivative of equation (3) with respect to f yields:

$$\mu = \frac{\partial (P_x x + P_y y)}{\partial f} \tag{5}$$

Grocery spending is expected to decrease with hours spent on cost-saving efforts (f), but non-grocery expenses (x) may increase primarily due to increased transportation costs associated with driving to multiple stores or stores further away. In some cases, childcare costs may increase as the child stays a bit longer at the childcare facility while the parent engages in cost-saving efforts. The net effect μ is expected to be positive (i.e., $\mu > 0$) for economically relevant values of f.

$$\frac{\partial (P_y y)}{\partial f} < 0; \frac{\partial y}{\partial f} \leq 0; \frac{\partial P_y}{\partial f} \leq 0 \tag{6}$$

$$\frac{\partial x}{\partial f} \geq 0 \tag{7}$$

We define ϕ as the share of grocery spending relative to total expenditure. Given (5), (6) and (7), the effectiveness of cost-saving efforts (μ) increases as a household allocates a greater proportion of its budget to groceries:

[3] We recognize that cost-savings efforts exhibit diminishing returns. This simplifying assumption is not critical to our hypothesis development.

$$\frac{\partial \mu}{\partial \phi} \geq 0 \quad (8)$$

For households reducing work hours instead of leisure

$$\frac{\partial M}{\partial f} = -w$$

They engage in cost-savings if per-hour savings (μ) exceeds hourly wage (w).

$$f > 0 \quad if\ \mu > w \quad (9)$$

2.2 Hypotheses

For high-income households, income constraints may not be a factor, so food inflation may not significantly impact their grocery purchasing behavior. Even if they choose to respond, groceries typically make up a small portion of their total spending. As a result, it may be easier to offset a modest increase in grocery costs by reducing discretionary non-grocery spending—such as charitable donations—rather than investing time and effort in adjusting grocery consumption. For such households, the opportunity cost of effort and time is high. They earn more for their effort (That is, $w > \mu$) and gain higher utility from time spent on leisure (i.e, $\frac{\partial U}{\partial L} > \frac{\partial U}{\partial f}$), a point emphasized by Becker (1965) in his theory of allocation of time. Hence, high-income households are unlikely to allocate time or effort toward managing grocery spending at the cost of leisure or earnings. Even considering adjustments to grocery consumption requires attention and effort, which may be valued at a premium. Consequently, we hypothesize the following:

H1: Grocery spending of high-income households rises in line with their other spending without regard to food inflation rate

The calculus is different for those with income constraints. The ratio of grocery spending to total expenditure (ϕ) is higher among lower-income households. In 2021, low-income families allocated 30.6 percent of their income to food, compared to just 7.6 percent for higher-income households (Parum and Dharmasena, 2024). The monotonous relationship between income quintile and ϕ is also evident in our data (see Table 7). Such households may, in some conditions, find it necessary and feasible to alter their grocery spending habits when faced with inflation shock. Given equation (8), their higher ϕ implies higher μ. Given equation (4) the odds of engaging in cost-saving efforts ($f > 0$) increases with the efficiency of such efforts (μ). By definition, lower income households have lower w. Given equation (9) lower w also increase the odds of $f > 0$. That is, low-income households have higher odds of engaging in cost-saving efforts to mitigate the total cost of their groceries. We therefore hypothesize that:

H2: Grocery spending of low-income households likely rises at a rate lower than the food inflation rate

We further consider low-income households based on the following household characteristics:

Single parents with children (hereafter single-parents) face significant demands on their time, balancing income-generating activities alongside daily housework and childcare responsibilities (Bianchi, 2011). This raises their opportunity cost of time, leaving them with limited leisure. Consequenlty, their marginal utility of leisure is high. In Equation 4, this increases the threshold for f, thereby reducing the likelihood of single-parents allocating time to cost-saving efforts compared to other low-income households.

In addition, μ is likely smaller for them compared to other low-income households for two reasons. First, their ϕ is likely lower due to childcare costs' contribution to x (Ahn, 2012). Dual-parent families have an additional parent to rely on for childcare thereby reducing paid childcare, and other types of households (retired, single, and couples-only) do not have childcare needs. Single-parents also spend significantly more on food away from home compared to dual-parent ones, thereby decreasing ϕ (Ziol-Guest et al., 2006; Zoil-Guest, 2009). Restaurant meals impact ϕ by both increasing x while decreasing y.[4] Given equation 8, this implies lower μ. Second, given childcare constraints, μ is likely lower for single-parents also because of the negative contribution of changes in x due to f (equation 7). An additional hour of cost-saving effort by single-parents is more likely to increase childcare costs, hence x, than by any other household. Lower μ coupled with higher threshold for f implies lower odds of single-parents engaging in cost-saving effort to manage their grocery spending (equation 4). We thus hypothesize:

H3: Grocery spending of low-income single parent families is less likely to be sensitive to price changes.

Retired households are income-constrained due to the fixed nature of their retirement income which may adjust periodically for overall inflation but not for the more volatile food inflation. Moreover, groceries constitute a bigger portion of their total spending compared to other low-income households. Unlike other households they are less likely to have expenses such as child support, alimony, or student debt. Many have paid off their home mortgage and receive Medicare benefits. In addition, working households have some work-related expenses but retired individuals do not (Hurd and Rohwedder, 2013).

Despite having fewer household members—and therefore lower y—the ratio of grocery spending to total expenses remains high among low-income retired households.[5] Their higher ϕ increases μ (equation 8). Furthermore, they have low opportunity cost of time as they do not face competing demands from income-generating activities (Hurd and Rohwedder, 2013; Kaplan and Mezio, 2015). L approaches C for such households and the marginal utility of leisure is very low (equation 1). Given equation (4), this implies that they have very high odds of having ($f > 0$). In sum, low-income retired individuals may find it necessary to curtail grocery spending during periods of high food inflation, and lower time-constraints and higher expense share of groceries make it feasible for them to devote time to cost-reducing efforts. Consequently, we hypothesize as below:

H4: *Low-income retired households are more likely to be sensitive to food price shocks increasing their grocery spending at a rate lower than food inflation.*

Working couples or Individuals (WCI): Low income WCI are more likely to be wage-earners than salaried (Albelda and Carr, 2014). They are more likely to have an option of picking up an extra hour of work or overtime in response to financial pressures, such as food inflation shocks. Any efforts to reduce grocery costs would apply to relatively lower y of one person (or, two for working couples) thereby reducing their efficiency μ.

[4] Higher spending on food away from home leads to poorer health outcomes, which further has the potential to impact x by increasing healthcare costs (Zan and Fan, 2010). Single parents also exhibit poor mental and general health outcomes (Neises and Gruneberg, 2005; Westin and Westerling, 2006).

[5] Seonglim et al. (2014) studied older households in the US and documented that lowest income households in their data (with mean expenditure of $23,223) spent 43.3% on essentials, predominantly food, compared to others, who spent less than 25%.

Daniels and Glorieux (2015) show that WCI spend more on convenience food away from home (therefore, higher x) and lower on groceries (y). Also, low wage earners in low-income households are less likely to have employee-sponsored benefits (like health insurance) or have access to anti-poverty programs which are generally targeted towards families with children (Albelda and Carr, 2014). This further implies higher x. Lower y coupled with higher x implies lower ϕ for WCI compared to low-income families with children. Equation 4 thus suggests lower μ. Given that, though low, w is likely to be same for all low-income households, lower μ for WCI makes them relatively less likely to devote time to f at the expense of workhours (see equation 8).

Lower wages also require WCI to devote more time to work to make ends meet, thereby increasing the value they associate with their leisure time (Aguiar and Hurst, 2009). That is, $\partial U/\partial L$ is high. This coupled with lower μ also decreases the odds of such households devoting time to cost-saving efforts at the expense of leisure (equation 4). The above tradeoffs, consistent with leisure consumption models of Boppart and Ngai (2021) and survey findings of Aguiar and Hurst (2007; 2009), lead us to hypothesize:

H5a: Grocery spending of low-income couple-only families is less likely to be sensitive to price shocks.

H5b: Grocery spending of low-income single-person household is less likely to be sensitive to price shocks.

Dual-parent families with children (hereafter families): Groceries represent a substantial share of families' total spending. In 2022, families with an annual income below $30,000 spent an average of $5,200 on groceries, compared to less than $3,400 for others in the same income bracket. Due to economies of scale in cost-saving efforts, an increase in number of household members raises y, thereby increasing μ. The presence of a parent or older sibling providing childcare while another engages in cost-saving efforts reduces the negative impact of f on x further increasing μ (equations 5 and 7). Since working adults in these households work no more, on average, than comparable single-parents or WCI households (as discussed earlier in support of H3, H5a, and H5b), their marginal utility of leisure is not any higher. According to Equation 4, the higher μ for such households increases their odds of devoting time to cost-saving efforts. We therefore hypothesize:

H6: Families (excluding single parent families) are more likely to be sensitive to food price shocks, increasing their grocery spending at a rate lower than food inflation.

3. Data and Analysis

3.1 Data

We use the consumer expenditure survey (CES) interview dataset of the US Bureau of Labor Statistics (BLS) for interviews conducted between the first of January 2021 till the end of September 2023. This period coincides with the annualized quarterly rate of food inflation increasing from an average of 0% to a peak of 19.9% in April 2022 and decreasing back to 2.1%, resembling normal inflation of the pre-pandemic period.

The CES is a panel survey of U.S. households conducted every three months for up to four consecutive quarters. It captures recurring and large expenses, including housing, transportation, healthcare, and grocery spending. The BLS uses CES data to construct the CPI market basket, determining spending weights for expenditure categories to ensure the CPI reflects real-world consumer behavior and evolving

preferences. As a cornerstone of inflation measurement and economic policymaking, CES is uniquely suited for our study.

During our sample period, CES recorded 54,223 observations, including 21,501 first interviews. Since our analysis focuses on changes in grocery expenditure, respondents must have at least two consecutive quarterly observations, reducing the maximum number of usable observations to 32,722.[6] However, respondents missed an interview in 1,568 instances creating gaps of two quarters (1,326 observations) or three quarters (242 observations), ultimately resulting in 31,154 observations for our study.

3.1.1 BLS weights to adjust for known biases

The BLS conducts the CES using a stratified random sampling approach. Geographic areas, known as Primary Sampling Units (PSUs), are randomly selected, followed by a random selection of households within those areas. Each selected household initially represents itself and approximately 9,999 unselected households. The survey weight (FINLWT21) is then adjusted to account for non-response bias and to ensure alignment with the demographic and geographic distribution of households in the population. As a result, this weight varies across interviews, even for the same Consumer Unit (CU).

Additionally, because CES tracks spending at the household address level rather than by individual CUs, respondents who move out are dropped from the survey, while new occupants at the same address receive new unique IDs. Since renters are more likely to relocate than homeowners, this process leads to an overrepresentation of homeowners, who typically exhibit greater financial stability. In line with standard empirical research practices, we apply BLS-provided sample weights to ensure our estimates reflect the national population distribution.

3.1.2 Adjustment to income data

Some CUs report negative rental income, primarily due to depreciation expenses, which are tax-deductible but non-cash. In these cases (107 observations), we set rental income to zero and adjust income before tax accordingly to reflect a more accurate measure of disposable income. We similarly treat the 167 observations with negative self-employment income, likely attributable to tax-deductible business expenses rather than an actual financial loss. Prior to these corrections, three observations exhibited negative income before tax. Post adjustment, no observations remained with negative income, ensuring consistency in our dataset.

3.1.3 Recency bias

The value for quarterly expense for food at home in the CES is based on the following question:

Now I am going to ask about expenses for food, beverages and other items (you/your household) (have/has) purchased since the first of (reference month). What has been (you/your household) usual WEEKLY expense for grocery shopping?

Although the reference month marks the beginning of the three-month period preceding the interview, respondents may base their answers on recent purchases, potentially introducing recency bias. To account for this, we conduct our analysis using both three-month and one-month inflation data. Additionally, we

[6] For the 2,953 respondents who were in their second or subsequent interviews at the start of our sample period, we use data from their final interview to compute differences in observed values for relevant variables.

assess the robustness of our findings by incorporating the inflation measure for the interview month, addressing the possibility that, despite being asked about expenditures over the prior three months, respondents may report weekly spending based on their most recent grocery visit in the current month (i.e., the month of the interview). We find that these alternative measures do not improve the significance of the coefficient (results unreported), thereby suggesting that our results are not impacted by recency bias.

3.1.4 Geography- and category- specific CPI data

The BLS publishes various Consumer Price Index (CPI) series to measure inflation across different regions and population sizes. The CPI is categorized into two primary indices: CPI-U (All Urban Consumers) and CPI-W (Urban Wage Earners and Clerical Workers), reflecting spending patterns of different demographic groups. Additionally, the BLS provides regional breakdowns for the four Census regions—Northeast, Midwest, South, and West—as well as more granular subregional indices covering select metropolitan areas. The index is further disaggregated by expenditure categories, including overall CPI, food-specific inflation, housing, transportation, and other essential goods.

We utilize unadjusted monthly data from the CU series (i.e., all urban consumers). CES provides PSU information based on the survey respondent's location. In cases where PSU names align across CES and CPI datasets, direct mapping is applied. However, since the CES includes a broader range of PSU classifications than the CPI, discrepancies are addressed by logical matching—prioritizing the primary city PSU when naming differences arise. When no PSU match exists within the CES, we assign based first on population size and then regional classification.

For food inflation measurement, we employ the SAF11 series, which corresponds to inflation in food-at-home expenditures. The BLS periodically adjusts aggregation levels. Notably, beginning in 2018, BLS consolidated B/C and D class areas into a single classification labeled B/C. Throughout this study, we use the most granular data available for the geographical area and population size to ensure precision in our inflation measures. For some PSUs, where CPI is reported every two months instead of monthly, we impute the missing values.

3.2 Model and variables

$$\Delta Grocery\ Expense = f(food\ inflation, \Delta resource\ availability, tendency\ to\ spend, \Delta need, \Delta substitutions, initial\ state, seasonality, trend)$$

Since we employ difference-in-differences (DiD) estimation approach, our primary independent variables are change variables, which measure fluctuations in economic conditions rather than static determinants. We do not incorporate expectations of future inflation into our analysis, despite their potential influence on current purchases, particularly durable goods. This is because our dependent variable measures change in quarterly grocery spending, and households typically do not adjust their expenditure in anticipation of price increases three months ahead.

Our primary variables of interest pertain to food inflation. We measure *Food-Inf.* as the 3-month change in CPI for the "Food at home" series specific to the geographic area of the survey respondent. A separate binary measure *Hi-Inf.* takes unit value for interviews conducted between June 2021 and October 2022 when food inflation continuously exceeded 5%.

Control variables capturing changes in resources availability include measures for changes in household income (including supplemental income sources like Supplemental Nutrition Assistance Program (SNAP) payments) and non-food expenditures. Since available time is a critical household resource influencing the ability to prepare meals at home, we also measure changes in free time from work, reflecting adjustments in work schedules that impact food preparation and consumption patterns. Tendency to spend is a long-term trait and it directly impacts spending by its interaction with changes in resource availability. We measure it as the ratio of lagged values of total expense (annualized) to annual income.[7]

Changes in need for groceries are measured in terms of changes in the number of adults, kids, and infants in the household. Given that working members of the household and those at school have different grocery needs than the rest, we also measure changes in spending on school meals, meals as pay, and number of earners. Given that all models include change in income, change in number of earners captures the non-income impact.

We measure changes in spending on food away from home as a substitute for grocery spending. The initial state of the household is measured using lagged values of grocery spending, total spending, and spending on food away from home. We use month fixed effects to account for seasonality and a trend variable that increases by one each month of the sample period to account for long-term trend. Detailed variable information is provided in the Appendix (Table A1). Variables with *Δ* and *Lag* prefix represent the quarterly change and the lagged values, respectively.

All our regressions are weighted, report robust standard errors, and include month fixed effects.

3.3 Analysis

3.3.1. Inflation

Figure 1 presents the evolution of inflation during our sample period, comparing overall consumer price inflation with food-at-home inflation from January 2021 to mid-2023. While food prices are typically characterized by higher volatility, the data reveal that the annualized three-month food inflation rate exhibited a near-monotonic increase from 0% in early 2021 to a peak exceeding 15%, followed by a subsequent decline back to 0% by the second quarter of 2023. In contrast, overall inflation demonstrated greater variability, with noticeable fluctuations throughout the period, yet its peak rate remained lower than that of food inflation during the high-inflation phase. This divergence underscores the persistent and disproportionate impact of food price dynamics on essential consumption categories during this period.

Insert Figure 1 here

3.3.2 Descriptive Statistics

We present the descriptive statistics for key variables in Table 1. Since our analysis incorporates BLS weighting adjustments for nonresponse and underrepresentation of certain respondent groups, we report both unweighted and weighted means. As previously noted, CES data exhibits a slight overrepresentation of homeowners, who tend to have stronger financial standing. Consequently, applying weights results in

[7] The value of this variable is topcoded at 1 when yearly expense exceeds annual income. For low-income CUs, the value of this variable often exceeds one because the median income after tax exceeds income before tax by $580 and $305 for CUs in first- and second-income quintile, respectively, due to refundable credits.

a modest reduction in the weighted mean of the income variable. The mean value for quarterly change in grocery expenses is $22, aligning with increasing food prices during the period.

Insert Table 1 here

3.3.3 Correlation

Table 2 shows that our main variable of interest quarterly change in grocery expense *(Δ Groc)* has a very low correlation with income, expense, or their ratio. It also has a low correlation with change in such variables. The only variable with meaningful correlation (-0.45) is the lagged value of Groc In the same vein, the changes in *Tot-Exp*, *Income*, and *Food-Away* have correlations of -0.44, -0.23, and -0.43 with their respective lagged values.

Insert Table 2 here

3.3.4 Preliminary analysis

To begin, we estimate a weighted regression model to analyze quarterly changes in household grocery spending as a function of food inflation in its geographic area (Table 3). In addition to all control variables discussed earlier, we include binary measures of income quintiles with Q4 as the base excluded category Since our dependent variable is measured in dollars rather than percentages, coefficient estimates increase monotonically with income quintile.

We find a weakly significant positive coefficient, indicating that grocery expenses increase with rising food prices. However, the inclusion of *Hi_inf* in Model 2 causes the coefficient of *Food-Inf* to lose significance, suggesting households' grocery spending responsiveness to price increases may be limited to periods of inflation shock. This insignificance persists in Model 3, where we introduce measures for food expenditures away from home. We find a significant positive coefficient for *Δ Food-Away*, suggesting that households did not substitute restaurant meals for home-cooked meals during the sample period. Instead, expenditure on both categories increased in tandem. Additionally, our analysis does not yield a significant coefficient for *Δ Free-Time*, implying that the decision to cook at home for most households is primarily driven by lifestyle preferences rather than time constraints.

In 2023, the BLS revised its questionnaire and data organization structure. Beginning in April 2023, alcohol expenditures were included in the food away from home category. As a result, incorporating the Δ Food Away variable in Model 3 reduces the sample size from 30,924 to 25,409. However, given the consistency in the sign and significance of coefficient estimates across Models 2 and 3, along with the strong significance of food away expenditure variables, all models hereafter include these variables despite the reduced sample size.

Insert Table 3 here

In Model 4, incorporating interaction terms for food inflation and income quintiles yields weakly significant coefficients for some interactions but not others. These preliminary results present a mixed picture, suggesting that households may be more likely to adjust grocery spending during high inflation periods. However, changes in grocery expenditures appear to be driven by food price increases only in select income quintiles.

We next estimate a fixed effects model to control for unobserved variables at the CU level (Table 4). The sample is restricted to households participating in all four interviews. While not explicitly reported, the models in Table 4 include all control variables, including month fixed effects. In Model 1, we find insignificant coefficient estimates for both *Food-Inf* and *Hi-Inf*. However, incorporating interaction terms for income quintile and *Food-Inf* in Model 2 results in highly significant coefficient for *Food-Inf.* Despite having controlled for household-specific characteristics through 7,152 binary variables, the significant coefficient estimates in Model 2 suggest that food inflation affects different income groups differently. We therefore estimate models separately for income-based subsamples next.[8]

Insert Table 4 here

Models estimated using income-based subsamples (Table 5) provide a clearer picture of how food inflation influences household grocery spending. Models 1 and 2 present coefficient estimates for Q1, the lowest-income households. Households in Q1 are excluded if their expenditures exceed the median for the full sample, likely because they are relying on accumulated wealth. For this subsample, the coefficient estimate for food inflation is highly significant. This group is also the only subsample for which we find significant negative coefficients for *Δ Meal-as-Pay* and *Δ Num-Earners* (unreported), suggesting that receiving meals at work reduces home grocery needs, and economic hardship drives additional household members into the workforce.

For those in the Q2 (models 3 and 4), grocery expenditure increases with food inflation, but primarily during periods of high inflation. The results for higher income strata of the society show that there is no significant impact of food inflation on grocery spending. Their grocery spending increases in line with changes in their income and spending on other expenses regardless of grocery specific food inflation rate. While these results align with our theoretical expectations, we refrain from making definitive claims until extended empirical testing substantiates these preliminary observations.

Insert Table 5 here

3.3.5 Survivorship bias

During the sample period, a total of 15,263 unique CUs participated in their first interview. Of these, only 9,555 CUs completed all four interviews, representing 62.6% of the initial respondents. Approximately 14.5% of respondents dropped out after their first interview and are excluded from the final sample due to the difference-in-differences (DiD) methodology employed in this study. If these early-dropout respondents differ systematically from those completing multiple interviews, our findings may be subject to selection bias.

To assess potential biases, we study CU characteristics based on number of interviews completed (results unreported). We find CUs completing all four interviews have higher mean annual income ($93,025 vs. $90,108) and quarterly spending ($17,540 vs. $17,129), with the differences being statistically significant at 5% level. Both the pooled and the Welch's t-test reveal that CUs with multiple interviews have higher average age and education for the oldest and the most educated member, respectively. Respondents with multiple interviews are more likely to be retired (27% vs. 21%), married (50% vs. 46%), white (81% vs. 77%),

[8] In Tables 3 and 4, Quintile 4 serves as the base comparison category. We find significant coefficients for Quintiles 1, 2, and 5, whereas the coefficient estimate for Quintile 3 is relatively small and insignificant. Therefore, for subsequent analyses, we group respondents from Quintiles 3 and 4 together.

and homeowners (65% vs. 58%). Those with only one interview are more likely to be Black (14% vs. 10%) and single mothers (4.5% vs. 3.4%).

3.3.6 Analysis of change in grocery spending

To adjust for survivorship bias, we refine BLS weights for each interview. We estimate the probability of a CU completing the second interview based on its first interview participation, then apply inverse probability weighting. This method extends to the third and fourth interviews, ensuring adjustments for sampling, response bias, and attrition effects.

Estimates from models adjusted for survivorship bias (Table 6) indicate that Q1 households adjust their grocery consumption habits during high inflation, leading to spending increases below food inflation rates. The coefficients in the models with interaction term suggest that for a 3% increase in *food-inf*, grocery spending rises by 0.74% for Q1 households, compared to 2.1% for Q2. These results suggest that those in the lowest quintile demonstrate higher grocery price sensitivity as we contend in H2.

For higher income subsamples we find a significant coefficient for *Food-Inf* in one model estimated for the subsample including Q3 and Q4 CUs with income roughly between $55,000 and $150,000. Even in this model, the coefficients indicate a roughly 1:1 increase in grocery expenditure with food inflation. The largely insignificant coefficients for higher-income quintiles suggest that these households do not modify grocery spending in response to price changes, supporting H1.

To further validate H1 and H2, we re-estimate models using CU-level fixed effects, which reduce sample size but control for unobserved household characteristics affecting grocery spending. The already strong model fit for Q1 (R^2 = 0.41 vs. 0.24 for Q2, Panel A) improves to 0.45 for Q1 in Panel B. The food inflation coefficient remains significant only for Q1, offering strong empirical support for H1 and H2.

Insert Table 6 here

Though we have documented differences in the sensitivity of grocery spending to food price shocks across household income quintiles, we note, as Smeeding (2006) does, that a single-person household may face fewer financial constraints at a given income level due to lower overall needs, whereas a multi-person household may experience greater financial pressure. Therefore, we next analyze the composition of different income quintile subsamples across various dimensions in Table 7.[9]

Insert Table 7 here

Low-income subsamples are heavily weighted toward singles and retirees[10] prompting further analysis along these dimensions. Table 8 presents survivorship bias-adjusted weighted regression estimates for single-person CUs in the first two income quintiles. Unlike earlier analyses, these quintiles reflect single-

[9] Quintiles are based on BLS assigned Income Rank. Fewer observations for Q1 are due to exclusion of households with low income but sufficient wealth to fund expenditure exceeding median total expenditure for the full sample.
[10] The CES data does not directly identify the retirement status of respondents. We determine this based on the CU's income composition. Some people work even when receiving social security income while others stop working well before the retirement age. We use composition of income (including social security, pension, rent, interest, royalties, supplemental income, welfare, alimony, and other income) and number of hours worked to define retirement status. Our results are robust to alternative definitions. Results presented in the paper are based on a definition that would lead to conservative estimates against our hypotheses.

person household income distribution, rather than the general population. As before, Q1 observations with total expenses exceeding the median for single CUs are removed, leading to a smaller Q1 subsample.

Results indicate that Q1 single consumers do not adjust grocery spending in response to rising food prices, as shown in Panel A and the fixed effects model in Panel B. However, the significant negative coefficient for Hi-Inf in Q2 suggests adjustments during periods of high inflation. We also estimate models for higher-income subsamples (unreported), but none of the variables of interest are significant.

For context, Table A2 in the Appendix presents descriptive statistics on single consumers across income quintiles. Key observations include Q2 single-person CUs' mean income placing most in Q1 for the general population and a disproportionately high share of retired individuals (79%) in Q2. Given these patterns, we estimate models separately for non-retired and retired single-person CUs, as shown in Panels C and D of Table 8.

Findings confirm that working single-person CUs do not adjust grocery spending, with comparable results in the fixed effects model (unreported). In contrast, retired single-person CUs in Q2 display significant negative coefficients for *Hi-Inf*, mirroring Panel A, with similar outcomes in fixed effects models (unreported). The significance in Q2 appears driven by retiree over-representation.

Overall, results show single-person CUs do not modify grocery spending in response to high inflation unless they are retired, supporting H4 and H5b. Panel E presents estimates for retired CUs across all household compositions, confirming a highly significant negative coefficient in Q1, while other income quintiles remain insignificant. Findings suggest that a 3% increase in *Food-Inf* leads to virtually no increase in grocery spending among retired CUs in Q1, as these households actively adjust consumption behavior.

Insert Table 8 here

We next analyze CUs with multiple members, categorizing married couples without children as couples, households with one parent and at least a child under 18 as single-parents, and all others—primarily married couples with children—as families. Grouping based solely on income without considering household composition risks misclassifying households as income-constrained by overlooking differences in household needs.

To adjust for this, we regress total expenditures of households earning below $150,000 on the number of adults, children, and infants, generating factor loads that adjust CU incomes for subsample classifications. This method ensures that families and single parents are categorized based on income constraints, rather than raw income alone, aligning with Smeeding's (2006) approach using equivalence scales. Table 9 presents estimates for families, couples, and single parents.

Insert Table 9 here

Families in the lowest quintile have a mean income approximately 3.5 times higher ($29,000+) than single consumers ($8,223) (Panels A and B, Table A2). Despite this disparity, Q1 families adjust their grocery spending in response to food inflation. Panel B's fixed effects model suggests that a 3% rise in *Food-Inf* leads to only a 0.8% increase in grocery spending for Q1 families, while Q2 households exhibit a 1:1 increase. No significant coefficients emerge for other quintiles (unreported).

To verify that Q1 family responses are not driven by retired households, we estimate the model on a non-retired family subsample (results unreported). Findings reveal a significant positive coefficient for food

inflation and a significant negative coefficient for *Hi-Inf,* indicating that non-retired low-income families actively adjust grocery spending, increasing expenditures at a rate significantly lower than food inflation, supporting H6.

For single parents and working couples (Panels C and D), we find no evidence of grocery spending adjustments, consistent with H3 and H5a, despite significantly lower mean incomes—$8,635 for single parents and $13,049 for working couples, compared to $29,000+ for families. Across these subsamples, findings remain insignificant for other income quintiles and fixed effects models (results unreported).

Overall, our analysis confirms that lower-income households adjust grocery spending in response to inflation, aligning with price elasticity literature. However, these adjustments are limited to families and retired households, with no evidence of behavioral shifts among couples, single-parents, or single consumers. To substantiate this, we re-estimate the model using Panel B's income-based sample, excluding families and retired CUs, reducing the sample size to 1,214 observations. As expected, all coefficients remain insignificant (Panel E, Table 9), with fixed effects models yielding similar results (unreported).

3.3.7 Limitations and Discussion

Our analysis is based on data from an abnormal period. To provide further context, we replicate the analysis using 2016–2019 data, representative of the pre-COVID steady inflation regime. We find no significant coefficient estimates for food inflation, even among low-income families or retired CUs. However, it remains unclear whether this reflects a genuine lack of sensitivity to food prices or limitations in detecting such effects within our framework.

Prior to COVID, annual food inflation averaged below 2%, implying a quarterly grocery expense increase of approximately $4 for the average household and less than $2 for those in Q1. Though it is noteworthy that we have isolated even $10 -$20 change per quarter as attributable to food inflation, a $2 - $4 change may be nearly undetectable given measurement error and survey data noise. Alternatively, the slow and steady inflation of pre-COVID decades likely did not prompt measurable behavioral changes, even in low-income household.

Inflation rates decline with household income in the U.S. (Jaravel, 2021). Chen et al. (2025) documents that lower-income households experienced disproportionately higher inflation, as prices for lower-quality goods—which poorer households consume at higher rates—rose more sharply. We do not adjust inflation rates for this inequality, meaning CPI data may underestimate the true inflation shock faced by Q1 households. This biases data against us finding for support our hypotheses. Furthermore, our main findings focus on household-level differences within the lower-income category, where all groups experienced the same inflation rate, even if CPI understates it.

Aguiar and Hurst (2005) emphasize that food expenditure does not equate to food consumption, noting that retired households utilize home production to increase food consumption per dollar spent. Kaplan and Menzio (2016) observe similar behavior among the unemployed. Since our analysis focuses on expenditures, we do not make assertions about changes in actual consumption. Our framework does not distinguish between spending reductions due to lower consumption and those driven by home production (i.e., cost-saving efforts securing lower prices), limiting our ability to quantify behavioral adjustments.

4. Conclusion

Our study provides empirical evidence that household grocery spending responses to food inflation vary significantly by income, family composition, and retirement status. Using BLS's Consumer Expenditure Survey data from 2021-2023, we track changes in quarterly grocery spending across U.S. households, isolating the impact of food price fluctuations while controlling for income, household composition, and other spending. This approach allows us to attribute even small adjustments—on the scale of a couple dollars per week—to localized food price changes. The panel data structure further enables control for unobserved household characteristics.

Unlike prior studies focusing on specific categories such as milk or fast food, we examine total grocery spending, an essential expenditure for all households. By shifting focus from item-specific cross-price and own-price elasticities to their combined effect on household grocery budgets, our study offers a broader understanding of consumer adjustments during inflationary shocks.

Empirical findings reveal that higher-income households exhibit no meaningful adjustments to grocery spending in response to food inflation, consistent with their ability to absorb cost increases without altering consumption patterns. In contrast, certain low-income households, specifically families and retirees, display grocery spending increases significantly below the food inflation rate, suggesting behavioral adaptations such as reduced consumption and/or strategic shopping practices. However, we find no evidence of grocery spending adjustments among single consumers, single-parent families, or couples-only households.

Beyond its empirical contributions, our study presents a theoretical model linking price responsiveness to time constraints and opportunity costs. These findings hold policy implications, guiding governmental efforts in designing targeted relief programs for inflation-sensitive households. Additionally, businesses can leverage insights on consumer adaptation strategies to refine pricing, inventory management, and promotional strategies during inflationary periods.

The post-COVID inflation shock presents a unique opportunity to study consumer behavior under price volatility, distinct from prior research focused on income shocks during the 2008 financial crisis. Given that U.S. inflation had remained slow and steady for over four decades, these findings contribute meaningfully to the literature on inflation-driven household spending responses.

Future research could explore longer-term consumer adjustments, particularly the evolving role of substitution effects between grocery categories and broader changes in household shopping patterns. Additionally, investigating regional heterogeneity and variations in retailer strategies could provide further insights into the mechanics of household adaptation during inflation shocks.

References:

Aguiar, M., & Hurst, E. (2007). Measuring trends in leisure: The allocation of time over five decades. *The quarterly journal of economics*, *122*(3), 969-1006.

Aguiar, M., & Hurst, E. (2009). A summary of trends in American time allocation: 1965–2005. *Social Indicators Research*, *93*, 57-64.

Ahn, H. (2012). Child care subsidy, child care costs, and employment of low-income single mothers. *Children and Youth Services Review*, *34*(2), 379-387.

Albelda, R., & Carr, M. (2014). Double trouble: US low-wage and low-income workers, 1979–2011. *Feminist Economics*, *20*(2), 1-28.

Andreyeva, T., Long, M. W., & Brownell, K. D. (2010). The impact of food prices on consumption: a systematic review of research on the price elasticity of demand for food. *American journal of public health*, *100*(2), 216-222.

Barnes, R., & Gillingham, R. (1984). Demographic effects in demand analysis: estimation of the quadratic expenditure system using microdata. *The Review of Economics and Statistics*, 591-601.

Bartlett, R. W. (1964). Fluid milk sales as related to demand elasticities. *Journal of Dairy Science*, *47*(12), 1314-1321.

Becker, G. S. (1965). A theory of the allocation of time. *The Economic Journal*, 75 (299), 493-517.

Benhabib, J., Rogerson, R., & Wright, R. (1991). Homework in macroeconomics: Household production and aggregate fluctuations. *Journal of Political economy*, *99*(6), 1166-1187.

Bianchi, S. M. (2011). Family change and time allocation in American families. *The ANNALS of the American Academy of Political and Social Science*, *638*(1), 21-44.

BLS, (2024) "Consumer Expenditure Surveys Public Use Microdata: Quarter 2 2023 - Quarter 1 2024 Interview Survey Data – PUMD Errata – FMLI Food at Home" September 25, 2025 https://www.bls.gov/cex/pumd/errata/errata-2023.htm, Accessed on October 25, 2024.

Boppart, T., & Ngai, L. R. (2021). Rising inequality and trends in leisure. *Journal of Economic Growth*, *26*(2), 153-185.

Chen, T., Levell, P., & O'Connell, M. (2025). *Measuring cost of living inequality during an inflation surge* (No. W25/21). Institute for Fiscal Studies.

Coibion, O., Gorodnichenko, Y., & Hong, G. H. (2015). The cyclicality of sales, regular and effective prices: Business cycle and policy implications. *American Economic Review*, *105*(3), 993-1029.

Codjia, C. O., & Saghaian, S. H. (2022). Determinants of food expenditure patterns: evidence from US consumers in the context of the COVID-19 price shocks. *Sustainability*, *14*(13), 8156.

Daniels, S., & Glorieux, I. (2015). Convenience, food and family lives. A socio-typological study of household food expenditures in 21st-century Belgium. *Appetite*, *94*, 54-61.

Green, R., Cornelsen, L., Dangour, A. D., Turner, R., Shankar, B., Mazzocchi, M., & Smith, R. D. (2013). The effect of rising food prices on food consumption: systematic review with meta-regression. *Bmj*, *346*.

Greenwood, J., & Hercowitz, Z. (1991). The allocation of capital and time over the business cycle. *Journal of political Economy*, *99*(6), 1188-1214.

Griffith, R., O'Connell, M., & Smith, K. (2016). Shopping around: how households adjusted food spending over the great recession. *Economica*, *83*(330), 247-280.

Huang KS, Lin B. Estimation of Food Demand and Nutrient Elasticities From Household Survey Data. Washington, DC: US Dept of Agriculture; 2000.

Hurd, M. D., & Rohwedder, S. (2013). Heterogeneity in spending change at retirement. *The journal of the economics of ageing*, *1*, 60-71.

Jaravel, X. (2021). Inflation inequality: Measurement, causes, and policy implications. *Annual Review of Economics*, *13*(1), 599-629.

Kaplan, G., & Menzio, G. (2015). The morphology of price dispersion. *International Economic Review*, *56*(4), 1165-1206.

Kaplan, G., & Menzio, G. (2016). Shopping externalities and self-fulfilling unemployment fluctuations. *Journal of Political Economy*, *124*(3), 771-825.

Leibtag, E. S., & Kaufman, P. R. (2003). Exploring food purchase behavior of low-income households: how do they economize? U.S. Department of Agriculture, Economic Research Service, AIB 747-07

McKenzie, D., Schargrodsky, E., & Cruces, G. (2011). Buying less but shopping more: The use of nonmarket labor during a crisis [with comment]. *Economia*, *11*(2), 1-43.

Neises, G., & Grüneberg, C. (2005). Socioeconomic situation and health outcomes of single parents. *Journal of public health*, *13*, 270-278.

Nevo, A., & Wong, A. (2019). The elasticity of substitution between time and market goods: Evidence from the Great Recession. *International Economic Review*, *60*(1), 25-51.

Ni Mhurchu, C., Eyles, H., Schilling, C., Yang, Q., Kaye-Blake, W., Genç, M., & Blakely, T. (2013). Food prices and consumer demand: differences across income levels and ethnic groups. *PloS one*, *8*(10), e75934.

Park, J. L., Holcomb, R. B., Raper, K. C., & Capps Jr, O. (1996). A demand systems analysis of food commodities by US households segmented by income. *American Journal of Agricultural Economics*, *78*(2), 290-300.

Parum, F., & Dharmasena, S. (2024). Food Price Inflation in the United States as a Complex Dynamic Economic System. *Journal of Agricultural & Food Industrial Organization*, *22*(2), 113-132.

Pollak, R. A. (2003). Gary Becker's contributions to family and household economics. *Review of Economics of the Household*, *1*, 111-141.

Raper, K. C., Wanzala, M. N., & Nayga Jr, R. M. (2002). Food expenditures and household demographic composition in the US: a demand systems approach. *Applied Economics*, *34*(8), 981-992.

Scholdra, T. P., Wichmann, J. R., Eisenbeiss, M., & Reinartz, W. J. (2022). Households under economic change: How micro-and macroeconomic conditions shape grocery shopping behavior. *Journal of Marketing*, *86*(4), 95-117.

Seonglim, L., Sohn, S. H., Rhee, E., & Lee, Y. G. (2014). Consumption patterns and economic status of older households in the United States. *Monthly Labor Review*, *137*, 1.

Smeeding, T. (2006). Poor people in rich nations: The United States in comparative perspective. *Journal of Economic Perspectives*, *20*(1), 69-90.

Taylor, L. D. (2022). Analysis of impacts of inflation on the distribution of household consumption expenditures. *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie*, *70*(3), 239-258.

Westin, M., & Westerling, R. (2006). Health and healthcare utilization among single mothers and single fathers in Sweden. *Scandinavian journal of public health*, *34*(2), 182-189.

Zan, H. U. A., & Fan, J. X. (2010). Cohort effects of household expenditures on food away from home. *Journal of Consumer Affairs*, *44*(1), 213-233.

Ziol-Guest, K. M. (2009). A single father's shopping bag: Purchasing decisions in single-father families. *Journal of Family Issues*, *30*(5), 605-622.

Ziol-Guest, K. M., DeLeire, T., & Kalil, A. (2006). The allocation of food expenditure in married-and single-parent families. *Journal of Consumer Affairs*, *40*(2), 347-371.

Figure 1: This figure shows the change in CPI over the 3-month period for all items and that for food consumed at home, including beverages. Both measures are annualized.

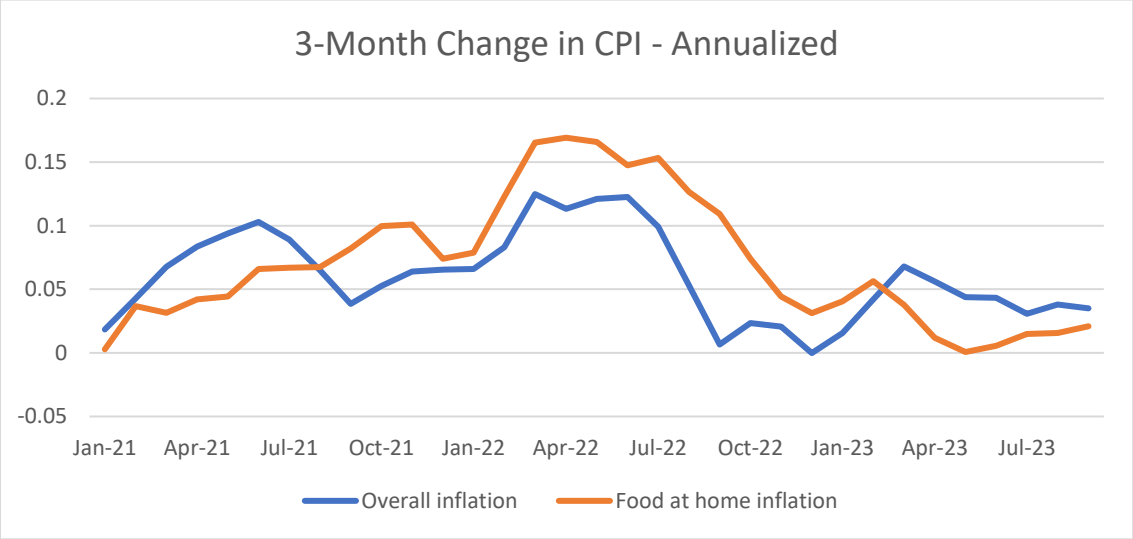


Table 1: Descriptives statistics

	N	Mean	Std Dev	Minimum	Median	Maximum	Weighted Mean
Weight	31,151	26,693	11,307	1,109	26,862	126,245	
Food-Inf. (%)	31,151	1.74	1.58	(6.33)	1.55	7.64	1.77
Income Rank	31,151	0.50	0.29	0.00	0.50	1.00	0.50
Income (annual)	31,151	93,222	92,990	-	64,728	1,195,061	92,745
Δ Food-Away	25,615	17	767	(18,200)	-	18,850	17
Δ Groc	30,959	22	1,248	(20,800)	-	32,500	17
Δ Income	31,151	767	43,286	(565,279)	-	805,000	771
Δ Salary	31,151	612	35,190	(553,319)	-	500,083	675
Δ Supp-Income	31,151	(2)	1,390	(44,222)	-	78,000	3
Δ School-Meals	31,151	1	42	(1,944)	-	1,500	0
Δ Meal-as-Pay	31,151	(0)	73	(4,875)	-	6,500	(0)
Δ Num-Kids	31,151	0	0	(4)	-	5	0
Δ Num-16+	31,151	0	0	(6)	-	5	0
Δ Num-Infants	31,151	0	0	(2)	-	2	0
Δ Number-Earners	31,151	0	0	(6)	-	6	0
Lag Groc (3-mo)	31,151	1,985	1,373	-	1,625	26,000	2,008
Lag Food-Away (3-mo)	28,409	658	864	-	390	19,500	668
Lag Tot-Exp (3-mo)	31,135	17,255	16,128	153	13,745	1,066,865	17,139
Lag Income	31,151	92,455	92,617	-	64,087	1,195,061	91,975
Free-Time (category)	31,151	0	0	(2)	-	2	0
Hi-Inf. (binary)	31,151	1	0	-	1	1	1

Table 2: Correlation coefficients (significant at ***1% level***; **5% level**)

		1	2	3	4	5	6	7	8	9	10	11
1	Δ Groc											
2	Lag Groc	***-0.45***										
3	Δ Non-Groc	***-0.02***	***0.02***									
4	Income	0.01	***0.34***	***0.02***								
5	Δ Income	***0.02***	-0.01	***0.09***	***0.24***							
6	Lag Income	0.00	***0.34***	***-0.02***	***0.89***	***-0.23***						
7	Income Rank	**0.01**	***0.36***	***0.02***	***0.83***	***0.15***	***0.76***					
8	Exp. Rank	***0.06***	***0.43***	***0.10***	***0.67***	***0.05***	***0.65***	***0.77***				
9	Lag Tot-Exp.	***-0.03***	***0.38***	***-0.44***	***0.57***	***-0.03***	***0.58***	***0.51***	***0.60***			
10	Lag Exp-to-Inc	***-0.05***	***-0.02***	***-0.11***	***-0.49***	***0.20***	***-0.59***	***-0.54***	***-0.22***	***-0.03***		
11	Δ Food-Away	***0.08***	***-0.03***	***0.09***	**0.01**	***0.04***	0.00	0.01	***0.05***	***-0.05***	***-0.04***	
12	Lag Food-Away	***-0.03***	***0.30***	***-0.02***	***0.37***	-0.01	***0.38***	***0.36***	***0.40***	***0.39***	***-0.07***	***-0.43***

Table 3: This table shows the coefficient estimate of weighted regression models to estimate the quarterly change in the grocery expense for a consumer unit. All models include month fixed effects. Robust standard errors are adjusted for clustering at the PSU level. ** significant at 1% level; * 5% level.

	Coeff	SE		Coeff	SE		Coeff	SE		Coeff	SE	
Intercept	740.10	40.36	**	727.79	42.55	**	664.70	35.49	**	614.41	44.16	**
Food-Inf	26.98	9.83	*	20.76	11.25		12.17	10.41		36.84	14.46	*
Hi-Inf				31.86	14.26	*	27.76	11.60	*	26.87	11.93	*
Q1	-516.63	31.95	**	-516.38	31.95	**	-453.39	34.03	**	-396.07	47.84	**
Q2	-294.97	32.86	**	-294.79	32.94	**	-259.62	36.79	**	-217.47	61.12	**
Q3	-138.43	26.09	**	-138.44	26.10	**	-124.91	23.94	**	-71.34	39.29	
Q5	219.22	26.04	**	218.96	26.09	**	197.10	34.06	**	295.83	54.69	**
Q1 * Food-inf										-27.39	11.38	*
Q2 * Food-inf										-20.18	17.27	
Q3 * Food-inf										-25.69	11.79	*
Q5 * Food-inf										-47.58	23.99	
Lag Groc	-0.51	0.01	**	-0.51	0.01	**	-0.51	0.02	**	-0.51	0.02	**
Lag Exp-to-Inc	222.30	37.80	**	221.99	37.80	**	196.20	39.49	**	196.68	39.47	**
Δ Income	0.00	0.00	*	0.00	0.00	*	0.00	0.00		0.00	0.00	
Δ Non-Groc	0.00	0.00	*	0.00	0.00	*	0.00	0.00		0.00	0.00	
Lag Tot-Exp	0.01	0.00	**	0.01	0.00	**	0.01	0.00	**	0.01	0.00	**
Δ Free-Time	47.99	26.36		48.38	26.38		40.82	22.48		40.58	22.43	
Δ Supp-Inc	0.00	0.00		0.00	0.00		0.00	0.00		0.00	0.00	
Δ School-Meal	0.12	0.16		0.12	0.16		0.12	0.14		0.12	0.14	
Δ Meal-as-Pay	0.09	0.07		0.09	0.07		0.03	0.05		0.03	0.05	
Δ Num-Kids	198.24	38.27	**	198.15	38.34	**	192.17	49.41	**	192.36	49.45	**
Δ Num-16+	159.40	34.64	**	159.16	34.64	**	193.28	42.45	**	192.42	42.47	**
Δ Num-Infant	-13.87	59.41		-13.54	59.37		-17.89	58.53		-19.10	59.07	
Δ Num-Earners	0.64	30.45		0.72	30.46		-32.19	28.28		-32.70	27.72	
Lag Food-Away							0.11	0.02	**	0.11	0.02	**
Δ Food-Away							0.18	0.03	**	0.18	0.03	**
Trend	5.27	0.81	**	5.84	0.95	**	6.95	1.19	**	6.89	1.18	**
N	30924			30924			25409			25409		
R-Square	0.250			0.254			0.251			0.251		

Table 4: This table shows the coefficient estimates for a weighted regression that include CU-level fixed effects. It includes all control variables and month fixed effects. The sample is restricted to CUs that participated in all four interviews. Standard errors are adjusted for clustering at the PSU level. ** significant at 1% level; * 5% level.

	Model 1			Model 2		
label	**Coeff**	**SE**		**Coeff**	**SE**	
Intercept	695.580	46.52	**	641.250	58.09	**
Food-Inf	15.240	12.91		41.911	14.91	**
Hi-Inf	31.800	18.76		31.516	19.68	
Q1	-464.210	58.21	**	-409.380	63.77	**
Q2	-257.350	53.82	**	-221.216	66.66	**
Q3	-119.530	34.45	**	-69.129	51.22	
Q5	177.930	29.95	**	307.080	60.30	**
Q1 * Food-inf				-25.952	13.08	
Q2 * Food-inf				-17.089	15.87	
Q3 * Food-inf				-24.018	11.04	*
Q5 * Food-inf				-61.994	24.49	*
N	17,625			17,625		
R-Square	0.260			0.257		

Table 5: The table below shows the coefficient estimates for a weighted regression model for income-based subsamples. All models include month fixed effects and control variables. A*B is the interaction of *Food-Inf* and *Hi-Inf*. Standard errors are adjusted for clustering at the PSU level. ** significant at 1% level; * 5% level.

	Quintile 1			Quintile 2			
	Coeff	SE		Coeff	SE		
Food-Inf (A)	23.60	8.16	**	18.91	21.26	35.53	18.71	-29.87	34.25	
Hi-Inf (B)	-37.84	31.44		-44.99	30.46	-7.10	39.65	-101.80	50.29	
A * B				5.55	19.68			75.68	28.97	*
N	4,164			4,164		5,035		5,035		
R-sq	0.398			0.398		0.249		0.250		
	Rank > 0.4 and rank <=0.8					Rank > 0.80				
Food-Inf (A)	23.07	11.48		5.29	21.20	-31.35	18.58	-47.31	34.77	
Hi-Inf (B)	26.09	25.89		-1.47	45.81	92.28	61.69	64.73	64.01	
A * B				21.39	26.04			20.46	36.70	
N	10,096			10,096		5,348		5,348		
R-sq	0.226			0.226		0.260		0.260		

Table 6: This table shows the estimates of weighted regression for income-based subsamples. BLS weights are further adjusted for survivorship bias. Month fixed effects are included in addition to all other control variables. Panel B includes CU-level fixed effects and is restricted to CUs participating in all four interviews. The standard errors are adjusted for clustering at PSU level. ** significant at 1% level; * 5% level.

Panel A

	Quintile 1						Quintile 2				
	Coeff	SE		Coeff	SE		Coeff	SE	Coeff	SE	
Food-Inf (A)	27.22	8.32	**	16.75	23.8		35.05	18.1	-24.82	31.1	
Hi-Inf (B)	-62.5	31.4		-78.62	28.1	**	-11.88	39	-99.76	43.8	*
A * B				12.43	21.3				69.73	24.3	**
N	4,164			4,164			5,035		5,035		
R-sq	0.409			0.409			0.242		0.243		
	Rank > 0.4 and rank <=0.8						Rank > 0.80				
Food-Inf (A)	23.58	10.2	*	4.99	21.1		-35.79	18.5	-74.34	39.9	
Hi-Inf (B)	13.75	25		-15.23	41.2		118.2	59.5	50.4	61.7	
A * B				22.47	24.7				50.13	43.7	
N	10,096			10,096			5,348		5,348		
R-sq	0.214			0.214			0.245		0.245		

Panel B

	Quintile 1						Quintile 2			
	Coeff	SE		Coeff	SE		Coeff	SE	Coeff	SE
Food-Inf (A)	39.54	13.23	**	66.14	19.50	**	43.11	22.24	29.45	31.23
Hi-Inf (B)	-51.40	31.27		-9.64	37.45		-1.29	56.53	-21.41	73.40
A * B				-31.82	18.96				15.78	26.43
N	2,808			2,808			3,484		3,484	
R-sq	0.4534			0.4536			0.2171		0.2171	
	Rank > 0.4 and rank <=0.8						Rank > 0.80			
Food-Inf (A)	25.98	12.86		-1.99	20.77		-35.52	22.28	-90.24	52.53
Hi-Inf (B)	19.11	35.25		34.58	25.78		63.02	58.16	-34.40	97.55
A * B				-26.91	59.58				71.17	63.20
N	7,039			7,039			3,785		3,785	
R-sq	0.1995			0.1996			2991		0.2996	

Table 7: Composition and characteristics of subsamples based on income quintile

	Q1		Q2		Q3		Q4		Q5	
Variable	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**
Income ('000)	14.45	15.71	36.79	36.18	60.69	62.40	103.43	104.40	231.28	198.01
TOTALEXP	5,923	5,588	11,390	9,603	14,601	13,149	19,627	18,032	32,629	28,248
Groc (GE)	1,206	975	1,665	1,300	1,956	1,690	2,244	1,950	2,782	2,600
Food away (FA)	216	65	449	325	598	416	774	650	1,190	845
GE + FA	1,382	1,196	2,031	1,755	2,452	2,210	2,883	2,600	3,765	3,250
Num-16+	1.28	1	1.66	2	1.89	2	2.19	2	2.43	2
Num-Kids	0.15	0	0.28	0	0.42	0	0.49	0	0.6	0
Num-Infant	0.02	0	0.03	0	0.04	0	0.05	0	0.06	0
(GE+FA)/Tot. Exp	25%	22%	20%	18%	18%	16%	16%	14%	13%	12%
Tot. Exp. / Inc.	92%	37%	32%	26%	42%	21%	38%	17%	55%	14%
Married	14%		39%		49%		63%		80%	
Widowed	24%		15%		9%		5%		2%	
Divorced	28%		20%		16%		11%		7%	
Separated	4%		3%		2%		1%		1%	
Never married	30%		24%		24%		19%		10%	
Homeowner	44%		61%		66%		76%		87%	
Salaried	28%		54%		71%		83%		91%	
Retired	**63%**		46%		25%		12%		6%	
Couples-only	8%		25%		26%		28%		29%	
Family	14%		27%		39%		52%		61%	
Single-Parents	6%		5%		5%		3%		1%	
Single-Person	**72%**		43%		31%		18%		8%	
Nobs	5,245		6,217		6,631		6,415		6,622	

Table 8: This table shows coefficients of survivorship bias-adjusted weighted regressions. Control variables & month fixed effects included. Variables A, B and A*B represent *Food-Inf, Hi-Inf*, and *Food-Inf * Hi-Inf*, respectively. Panels A to D limit sample to single-person CUs and define quintiles based on single-person CUs only. Panel B estimates CU fixed effects model. Panels C and D are limited to the non-retired and retired, respectively. Panel E is estimated for all retired CUs using CES income rank for quintile cutoffs. Standard errors (SE) are adjusted for clustering at the PSU level. ** significant at 1% level; * 5% level.

	Quintile 1						**Quintile 2**					
	Coeff	SE		Coeff	SE		Coeff	SE		Coeff	SE	
Panel A: Single CUs												
A	30.73	13.61	*	28.39	30.50		21.73	19.18		-1.71	35.46	
B	7.15	48.21		3.38	59.97		-123.99	42.13	**	-159.40	55.26	**
A*B				2.85	34.39					27.64	36.50	
N	1,451			1,451			1,652			1,652		
R-sq	0.350			0.350			0.303			0.304		
Panel B: Fixed Effects – Single CUs												
A	31.72	20.41		61.48	36.58		30.29	26.97		16.68	37.77	
B	12.91	52.51		61.48	76.88		-121.49	48.01	*	-140.56	79.88	
A*B				-36.06	42.61					15.70	41.58	
N	953			953			1,189			1,189		
R-sq	0.374			0.375			0.303			0.304		
Panel C: Non-retired – Single CUs												
A	38.99	30.66		29.52	62.33		29.69	27.73		52.90	58.85	
B	-43.59	94.43		-59.26	107.66		-95.47	81.41		-62.68	99.61	
A*B				11.68	59.25					-27.35	59.09	
N	547			547			353			353		
R-sq	0.365			0.365			0.423			0.424		
Panel D: Retired – Single CUs												
A	26.18	16.67		20.81	22.19		19.09	18.41		-20.79	32.45	
B	32.85	55.50		24.18	69.46		-126.88	36.66	**	-187.48	67.33	**
A*B				6.54	28.80					46.96	37.41	
N	904			904			1,299			1,299		
R-sq	0.368			0.368			0.277			0.278		
Panel E: Retired – All CUs												
A	33.37	12.26	*	43.33	19.21	*	46.71	36.01		-34.65	39.68	
B	-112.96	23.18	**	-98.42	34.69	**	-8.84	85.68		-135.83	131.07	
A*B				-11.56	20.72					97.44	51.85	
N	2,608			2,608			2,268			2,268		
R-sq	0.407			0.407			0.262			0.264		

Table 9: This table shows the coefficients of survivorship bias-adjusted weighted regression for subsamples based on income and family characteristics. Variables A, B and A*B represent *Food-Inf, Hi-Inf*, and *Food-Inf * Hi-Inf*, respectively. Panels A and B are restricted to families (excluding single parent and couples), Panel C is restricted to working couples, Panel D is restricted to single parent, and Panel E includes all CUs except families and retired CUs. All models include control variables and month fixed effects. Standard errors are adjusted for clustering at the PSU level. ** significant at 1% level; * 5% level.

	Quintile 1						**Quintile 2**					
	Coeff	SE		Coeff	SE		Coeff	SE		Coeff	SE	
Panel A: Families												
A	75.23	19.96	**	27.83	50.15		29.16	14.39		-23.19	45.27	
B	-224.46	62.71	**	-295.02	80.94	**	-47.03	50.55		-121.35	77.11	
A*B				55.53	47.98					59.66	48.53	
N	1,993			1,993			2,096			2,096		
R-sq	0.373			0.374			0.246			0.247		
Panel B: Fixed Effects Model – Families												
A	72.67	26.58	*	70.06	66.15		55.07	21.49	*	12.04	61.01	
B	-200.49	67.59	**	-204.28	89.88	*	-82.14	92.73		-145.20	136.53	
A*B				3.02	63.16					49.35	67.54	
N	1,281			1,281			1,417			1,417		
R-sq	0.411			0.411			0.248			0.248		
Panel C: Working Couples												
A	-50.17	115.10		-199.20	117.70		33.48	50.10		-66.38	92.68	
B	295.73	274.50		36.16	484.10		-81.59	138.00		-207.90	146.60	
A*B				187.36	206.60					110.65	90.21	
N	103			103			308			308		
R-sq	0.415			0.423			0.338			0.34		
Panel D: Single Parent												
A	11.44	83.33		74.58	129.87		-46.92	58.20		-141.64	123.75	
B	220.13	170.81		312.39	173.45		66.18	145.52		-94.23	158.81	
A*B				-69.80	83.34					118.12	128.20	
N	195			195			204			204		
R-sq	0.461			0.461			0.577			0.579		
Panel E: CUs excluding retired and families												
A	28.47	22.40		-0.53	43.60		13.06	16.50		-64.32	37.30	
B	-17.97	68.10		-68.78	77.60		82.15	58.60		-25.39	45.10	
A*B				36.58	46.40					88.54	36.20	*
N	1,214			1,214			1,752			1,752		
R-sq	0.325			0.325			0.379			0.379		

Appendix

Table A1: Variable definitions

Name	CE variable	Definition & comments
Tot-Exp	ETOTAPX4	Adjusted total outlays in the quarter, sum of outlays from all major expenditure categories. If food expense is twice the value for total expense, it is treated as erroneous, hence, missing.
Food-Away	JDINEOQV	Quarterly expenditure for dining out
Groc	JMKPURQV	Quarterly expenditure for grocery store purchases. Zero expense is treated as missing. Quarterly deviations in this expense from the prior quarter exceeding $3,000 when the value of this variable also exceeds total expense is treated as erroneous, hence missing.
Meal-as-Pay	JMLPAYQV	Quarterly value of meals received as part of pay (FMLPYYRX/4)
School-Meals	JSCHMLQV	Quarterly expenditure for meals at school (summed across member level)
Income Rank	INC_RNKM	Weighted cumulative percent ranking based on total current income, based on mean of imputation iterations
Exp. Rank	ERANKHM	Weighted cumulative percent expenditure outlay ranking of CU to total population. Value between 0 and 1.
Income	FINCBTXM	Total annual family income before taxes (Imputed or collected data). Adjusted to exclude negative rental income and negative self-employment income. <=$100 treated as zero.
Supp-Income	FSSIXM	Total amount received in supplemental security income checks combined, mean of imputation iterations
Salary	FSALARYM	Total amount of income received from salary or wages before deduction by family grouping, mean of imputation iterations
Num-16+		Number of people in the CU aged 16 or over. Calculated as AS_COMP1 + AS_COMP2
Num of kids		Number of people in the CU between 2 and 16 . Calculated as AS_COMP3 + AS_COMP4
Num-Infants	AS_COMP5	Number of people in the CU aged under 2.
Num-Earners	NO_EARNR	Number of people in the CU reported as income earners
Δ free-time		A categorical variable conceptually representing meaningful change in number of hours worked from the previous quarter. Value of -2 and -1 for single-parents or single-person CU represents an increase in weekly workhours by 40 or more, and between 20 and 40, respectively. Similarly positive values imply reduction in workhours. For families (couples) with one stay-home parent (spouse), change from non-working to working is coded -1 for part-time and -2 for full-time. Positive values imply the reverse. When both are working, a change for one of them working less than 15 hours to 35+ or from part-time to 60+ hours is coded as -1. When this happens for both parents, it is coded as -2. The same logic applies in reverse for positive values.
Exp-to-Inc		Calculated as a ratio of 4 times *Tot-Exp* to *Income*. Top-coded to 1 when expenses exceed income.

Food-inf	The percent change in the unadjusted CPI value for SAF11 series for the PSU of the CU for the three-month period ending right before the interview month. (%)
Hi-inf	A binary variable that takes unit value for interviews conducted between (inclusive) June 2021 and Oct 2022
Retired	Categorical variable that takes unit value if any of the following are true: Combination of investment income and retirement income accounts for at least 80% of the total income; For those with income below the median retirement income accounts for at least 50% of the income.

Table A2: This table presents the composition of households across income quintiles. The quintiles on the left represent families, excluding single-parent families and couples-only CUs, while those on the right correspond to single-person CUs. The income quintile cutoffs for each panel are determined based on the income distribution within the respective subsamples, rather than the overall household income distribution in the US.

	Families					Single Person CU				
Variable	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**
Income rank	0.23	0.5	0.67	0.81	0.93	0.06	0.15	0.26	0.43	0.71
Income '000	29.24	64.81	99.74	145.30	282.02	8.22	19.95	31.80	53.84	127.92
Tot. Exp. '000	10.50	15.07	19.03	24.96	37.75	4.83	7.24	9.52	11.79	18.77
Groc Exp	2,142	2,387	2,540	2,732	3,135	1,003	1,029	1,189	1,286	1,501
Food away	457	686	807	1,027	1,386	179	237	388	464	729
Groc / Total	26%	21%	18%	15%	13%	26%	20%	18%	16%	13%
Homeowner	51%	61%	74%	82%	89%	33%	56%	56%	57%	67%
Salaried	64%	85%	91%	94%	98%	21%	20%	48%	72%	80%
Retired	**31%**	10%	3%	2%	0.40%	**63%**	**79%**	51%	28%	15%
Aged 16+	2.55	2.7	2.74	2.68	2.58					
Kids	0.81	0.89	0.86	0.85	0.91					
Infants	0.08	0.1	0.1	0.11	0.11					
Earners	1.14	1.83	2.1	2.21	2.23					
N	2,393	2,475	2,476	2,475	2,475	1,773	2,033	2,039	2,053	2,007