Household Food Waste Patterns: Exploring Categorical Price and Expenditure Elasticities Using a Demand System Approach

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Abstract

In the United States, billions of pounds of food are wasted each year. Food waste can cause enormous economic losses and environmental damage. To reduce food waste, we need to understand how key drivers of household food demand including price and expenditures shape the amount of food that is wasted. This paper is the first to provide estimates of U.S. household food waste elasticities at a granular level (at-home vs. away-from-home, and by different food categories) and to explore heterogeneity across critical subsets of the population. By applying the Quadratic Almost Ideal Demand System (QU-AIDS) model, I find at-home food waste is expenditure inelastic and unitary price elastic, while away-from-home food waste is expenditure elastic and unitary price elastic. When assessing waste across eight categories of food, I find waste of fruits and vegetables to be expenditure elastic while the waste of potatoes, proteins, snacks, and beverages are expenditure inelastic. Most food categories feature unitary price elasticities, though the waste of meats and other proteins is highly price elastic. The QU-AIDS model was also used to explore the heterogeneity of elasticities by household characteristics, including whether households were enrolled in critical nutrition programs. The ability to assess the elasticity of household waste at a granular level and to assess household heterogeneity can provide insights into how nutrition policies may influence food waste creation and permit a more wholistic evaluation of such policies.

Key Words: Food waste, demand systems, price elasticity, expenditure elasticity
JEL codes: D12, Q18

Introduction

Food waste occurs in households when an edible food item goes unconsumed. In the United States, 30% to 40% of food is wasted (Buzby et al., 2014) with about half of the waste occurring at the household level (ReFED 2023). In 2010 the United States wasted 133 billion pounds of food at the retail and consumption level (1249 calories per capita per day), equivalent to more than $160 billion based on retail prices (Buzby et al., 2014). While a large portion of food is wasted, many people in the US still experience food insecurity issues (Coleman-Jensen et al., 2020; Gundersen, 2013). Food waste reduction at the household level is an essential step to reducing greenhouse gas emissions since 96 percent of households' food waste goes to landfills, combustion facilities, or down the drain to the sewer system (EPA 2023), which generates substantial amounts of methane. These factors motivated the United States to articulate a national goal to reduce food loss and waste by 50% (USDA 2015) and spurred two subsequent administrations to develop federal efforts to support this goal (EPA 2018, USDA 2023). Most people do not realize how much food they discard, e.g., Qi and Roe (2016) find that a majority of households feel guilty about food waste, but more than 80% of people do not think they waste more than other households. To better guide the reduction of household food waste, we need to understand how household waste creation is impacted by food prices through adjustments to the household budgeting process. The price and expenditure elasticities for household food waste are two foundational expressions of consumer behavior that can yield insights into food waste reduction efforts. Given that different types of food have differential environmental impacts and are subject to different treatment in Federal nutrition policies, the ability to estimate waste elasticities at a more granular level and to explore their heterogeneity across households is needed to forward relevant policy discussions.

The purpose of this paper is to estimate the household expenditure and price elasticities for food waste using recent US data. I explore these elasticities by using the Quadratic Almost Ideal Demand System (QU-AIDS) model (Banks et al., 1997; Lecocq and Robin, 2015). The QU-AIDS model estimated in this paper relates food prices and total expenditures on wasted food items to shares of the budget expended on wasted foods in distinct categories. The first categorization divides foods into those purchased for at-home preparation (FAH) versus those foods prepared away from home (FAFH) while the second categorization divides foods into eight functional categories (e.g., produce, proteins, beverages, etc.). Understanding waste elasticities by category is important as there are policies and programs that seek to limit the use of federal nutrition funds on certain types of foods (e.g., restricting the use of funds from the Supplemental Nutrition Assistance Program (SNAP) on foods intended for home preparation) and other policies seeking to subsidize the price of certain foods such as produce that are viewed to be healthy and nutritious (Mozzaffrian et al., 2022; Niebylski et al., 2015). Simply applying an overall elasticity result may lead to incorrect predictions of how such interventions will affect waste created in particular categories and, hence, limit the ability to evaluate intended policies. The models are estimated by using data from the 2012 National Household Food Acquisition and Purchase Survey (FoodAPS), which contains granular food price and quantity data at the household level, and the household-wide food waste estimates created by Yu and Jaenicke (2020) for each FoodAPS household. To create categorical food waste estimates necessary for the QU-AIDS system model, and which are not available from Yu and Jaenicke (2020), I develop categorical food waste share estimates from data collected by Li et al. (2023). Moreover, I exploit the translating approach of Pollack and Wales (1981) and model the intercepts of budget shares as a function of key demographics to explore the heterogeneity of the estimated elasticities across household characteristics.

A few previous studies calculated the elasticity of household food waste. Landry and Smith (2019) estimate price and expenditure elasticities for household at-home food waste by using the 1977-78 Nationwide Food Consumption Survey (NFCS). They calculate the elasticity for at-home food waste using a Working-Leser model by exploring the linear relationship between budget share of waste and food prices and expenditures. The linear relationship relies on the assumption that household meal production is constant returns to scale (Landry and Smith, 2019). In their paper, they do not estimate elasticity for away-from-home food waste or waste at the functional food category level, and are unable to assess how the results may have been impacted by more than four decades of changes in U.S. household food habits since their data was collected. Vargas-Lopez et al. (2022) calculate expenditure and price elasticity for Mexican household food waste at the functional category level. They employ the QU-AIDS model and calculate price and expenditure elasticities before and during the COVID period. However, Vargas-Lopez et al. (2022) rely upon a small, convenience sample of households who retrospectively self-report food expenditures and waste levels, and they rely upon regional governmental statistics for price information. The authors also lack data on food away from home. The approach in this paper builds upon the foundational modeling efforts of Yu and Jaenicke (2020) who create a novel approach to modeling household food waste as a production process in which household food waste is considered input inefficiency. They calculate the number of calories acquired from detailed food acquisition records and then subtract food consumption, which is estimated using a biological model of calorie needs calibrated using known characteristics of the household members (e.g., age, gender). While Yu and Jaenicke (2020) explore how individual characteristics relate to the overall level of food waste created by a household, they do not estimate waste elasticities, nor are they able to explore waste differences across food categories.

By using the QU-AIDS model, I find the household food waste expenditure elasticity for at-home food waste is 0.869, which is inelastic. The expenditure elasticity for away-from-home food waste is elastic at 1.362. The own-price elasticities for at-home and away-from-home food waste are not statistically different from unitary. Households with different characteristics have different waste elasticities including SNAP participants who have a higher price elasticity for away-from-home waste than nonparticipants. I also find differences in elasticities across food groups. Households have elastic expenditure for the waste of fruits and vegetables (FVs), and inelastic expenditure for the waste of potatoes and potato products, protein, snacks, and beverages (including milk). The waste of potatoes and potato products is price-inelastic, while the waste of meats and proteins is price elastic. The system estimation approach also yields a full set of cross-price elasticities, permitting me to check if different food categories are waste substitutes or complements. I find that at-home food waste and away-from-home food waste are neither substitutes nor complements, but several waste substitutes and complements are found at the category level. The results identify several household characteristics that are significant when estimating the model, but also reveal several critical null effects, including that households participating in SNAP have similar price and expenditure elasticities for FVs as other households.

This study contributes to the literature in several ways. It is the first to explore the elasticity for household food waste using more current US data. The paper not only explores the expenditure and price elasticities for at-home food waste, as Landry and Smith (2019) did, but also calculates the household expenditure and price elasticities for away-from-home food waste and food waste by functional categories. Moreover, I explore the heterogeneity of expenditure and price elasticities across household characteristics and by the scale of total waste created. This paper is also the first to estimate food waste elasticities at the food category level by leveraging granular data on category-level waste from US household food waste tracking data to allocate overall waste levels estimated from detailed food acquisition data. By leveraging the estimates to explore price elasticity for subgroups (e.g. SNAP participants vs. nonparticipants), it contributes to assessments of how different policies may impact food waste and, more generally, provide insights to policymakers to reduce food waste by making more appropriate policies for targeting households.

The rest of the paper is organized as follows. The first section below presents the data and summary statistics that anchor the analysis. Then section 2 presents the theoretical model used to generate specific hypotheses, and then the empirical models and econometric methods are detailed. Section 3 presents the empirical results, including results for two summarized categories (at-home and away-from-home) and eight function categories. This section also contains the heterogeneous results and a brief case study applying the elasticity estimates. The final section concludes and discusses the results.

Data

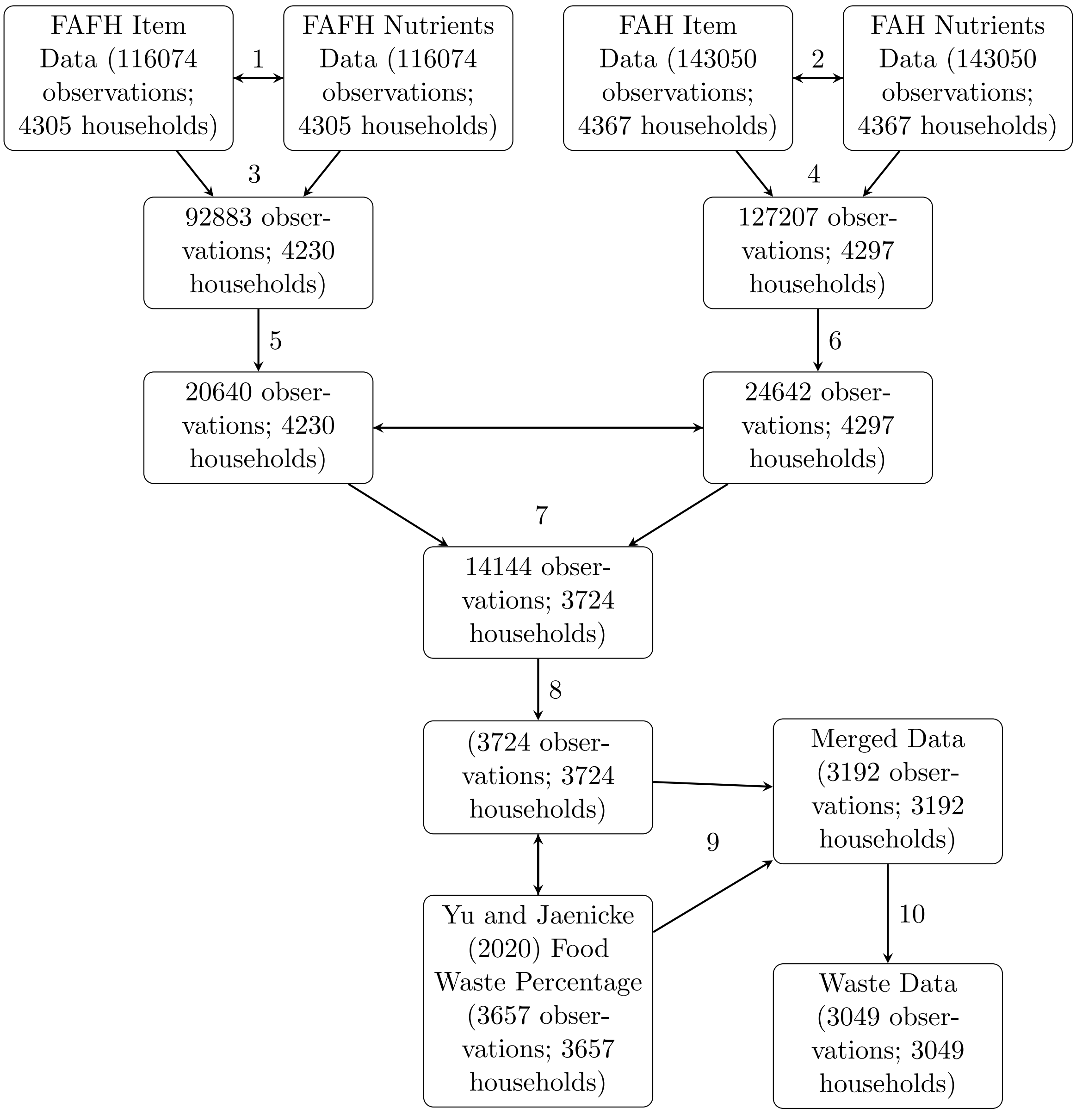
This paper relies upon two data sources. The first is the USDA's National Household Food Acquisition and Purchase Survey (FoodAPS) data. This data is nationally representative and includes detailed information about household characteristics, food purchases, and other forms of food acquisition. Although FoodAPS data does not have food waste information, Yu and Jaenicke (2020) use FoodAPS data to estimate the percentage of food waste at the individual household level by modeling household food consumption as a production process that transforms food contents into the energy needed to live given household members' ages, weights, and BMI. Food waste is estimated by subtracting predicted household caloric needs from total calories acquired. They find the average food waste percentage is 31.9%. By using their food waste percentage, I am able to exploit variations in food prices and expenditures to explore at-home and away-from-home waste elasticities.

The FoodAPS data was collected from 4826 households between April 2012 and January 2013. The data include 1) quantities and expenditures for at-home and away-from-home food purchases and acquisitions for the last seven days; 2) household eating occasions; 3) demographic characteristics, including individual characteristics such as gender, age, and BMI, and household characteristics such as household income; 4) household food purchasing patterns, such as whether the household shops with or without a grocery list.

To construct the sample, I used two FoodAPS modules - Food At Home (FAH) Item data and Food Away From Home (FAFH) Item data. Each data entry includes the total expenditure on the item and the weight of the item in grams. The sample creation process is shown in Figure 1. Observations are dropped if the item expenditure is missing. A few observations are dropped because the item is unable to be allocated to one of 8 food categories described below. Then total expenditures across each household are added across all FAH and FAFH items to provide categorical total expenditures. After merging the cleaned FAH Item data and FAFH Item data, I assemble the merged data for 3724 households.

The food waste percentage calculated by Yu and Jaenicke (2020) represents all household food waste, and they do not attempt to estimate the amount wasted in any subcategories (e.g., FAH vs. FAFH, or by food category). I then merged the cleaned and merged FAH and FAFH Item data and the food waste percentage data from Yu and Jaenicke (2020), and constructed the food waste amounts for two sets of categories. The first approach allocates wasted food for FAH and FAFH by assuming that the same fraction is wasted for FAH and FAFH. The second approach allocates food (regardless of FAH vs. FAFH) to eight distinct food type categories using a method detailed later. The merged data contains 3192 households. Then I dropped observations containing FAH and FAFH prices with values that are three standard deviations greater than the mean. Finally, the number of observations used to estimate the expenditure and price elasticities for FAH and FAFH food waste is 3049. Although some observations are dropped, the characteristics of the final sample are almost the same as the original dataset (Table 1).

Figure 1. Sample Selection Process



Notes:

1, 2, 7, 9: merge

3, 4: drop if food expenditure is missing, drop if food is not listed in Table A.1 column 2

5, 6: sum expenditure and amount by category and keep 1 observation for each category per household

8: reshape long to wide, keep 1 observation for each household

10: drop outliers that are three standard deviations greater than the mean

Table 1: Summary Statistics (FoodAPS Sample)

Variables	Mean/Proportion	SD	Min	Max	Observations
Household Size	3.17	1.67	1	14	3049
Household Size Change (<3 Months)	0.11	0.31	0	1	3048
Household Monthly Income	4127.11	3653.14	197	25650	3049
Age	45.52	16.01	16.50	85	3047
Hispanic or Latino	0.19	0.40	0	1	3048
Rural	0.29	0.45	0	1	3049
Gender:					3049
Female	76.09%				
Male	23.91%				
Region:					3049
Northeast	16.14%				
Midwest	25.22%				
South	37.29%				
West	21.35%				
Employment Status:					3047
Work at A Job	49.59%				
Not Working at A Job	39.22%				
With A Job but Not at Work	2.86%				
Look for Work	7.48%				
Worked, but Look for A Job	0.85%				
Education:					3045
10th Grade or Less	9.43%				
11th or 12th Grade, No Diploma	5.55%				
High School Diploma	28.21%				
Some College	34.12%				
Bachelor's Degree	15.76%				
Master's Degree or Above	6.93%				
Race:					3045
White	73.66%				
Black	11.76%				
American Indian	0.92%				
Asian or Pacific Islander	4.01%				
Other	7.59%				
Multiple Race	2.07%				
Marital Status:					3044
Married	48.62%				
Widowed	5.58%				
Divorced	17.25%				
Separated	4.57%				
Never Married	23.98%				
SNAP Participation:					3048
SNAP	30.31%				
Non-SNAP, Income<100%PT	5.58%				
Non-SNAP, 100%PT<Income<185%PT	17.42%				
Non-SNAP, Income>185%PT	46.69%				
WIC Eligibility:					3049
Yes	65.40%				
No	34.60%				

To allocate the wasted food to categories based on the type of food, I use household food waste survey data to estimate the percentage of a household's wasted food that originates from each category. The novel food waste tracking survey data, collected during six waves between February 2021 and November 2022, is built on a validated online survey (van Herpen et al., 2019), adapted for US households (Shu et al., 2021), and recently used to assess national trends in US household food waste (Li et al., 2023). The survey involves participants filling out an initial survey in which participants are informed that a follow-up survey will be distributed in around a week. After the initial survey, participants are directed to monitor the food wasted during the following seven days. Then survey participants are instructed to complete the follow-up survey in which food waste amounts are selected from a range, and then the final waste amounts are the midpoints of the selected range. Some previous studies find that the amount of wasted food reported by self-administered survey is less than directly measured amounts, but the survey method is very useful for tracking changes and variations in food waste levels (van Herpen et al., 2019). Furthermore, Roe et al. (2022), who compare results from food waste surveys to curbside audits of food waste from the same households, find that the fraction of total food waste attributable to key food categories (e.g., dairy and eggs, meat and fish) are nearly identical whether measured by survey or curbside audit despite the absolute levels being greater when measured via curbside audits (Roe et al., 2022).

The survey data has detailed information from 4367 households (see Table 2 for detailed summary statistics), and food waste for 24 food subcategories, including fresh vegetables, other vegetables (eg. canned vegetables), fresh fruits, other fruits, potatoes, potato products, pasta, rice, beans, meat, meat alternative, fish, sandwich components, bread, cereal, yogurt, cheese, eggs, soup, condiments, candy, salty snacks, non-alcohol beverages (including milk), and alcoholic beverages. Meat alternatives and sandwich components are excluded from the analysis because there are no equivalent food categories in FoodAPS data. Soup is also excluded because there are very few observations in the data. Finally, 21 food subcategories are combined into 8 main food categories based on the 1-digit, 2-digit, and 4-digit food category definitions in USDA FoodAPS data. Table A.1 shows how FoodAPS data is allocated to different food categories through alignment with the waste amounts reported from the Household Food Waste Tracking Survey. Less than 1% of food items that are not contained in Table A.1 Column 2 are dropped from FoodAPS data. Eight food categories include 1) vegetables and fruits, 2) potatoes and potato products, 3) grains, bread, and cereal, 4) protein foods (meats, fish, eggs), 5) dairy (except milk), 6) condiments, 7) snacks (candy and salty snacks), 8) beverages (alcoholic and non-alcohol beverages, including milk). The key data extracted from the household tracking survey is the fraction of total household waste attributable to each of these eight food categories. The waste of fruits and vegetables constitutes 46.33% of total food waste, followed by grains, which is 20.54% of total food waste. These figures are comparable to Hoover and Moreno (2017) who use curbside audits of waste from three US cities to estimate the fraction of edible wasted food in key categories. For example, Hoover and Moreno estimate produce to be 39% of waste versus the tracking survey's estimate of 46.33%. See Table 3 for summary statistics concerning the share of total food waste attributable to the 21 original and the eight consolidated food categories from the tracking survey. Yu and Jaenicke (2020) use the FoodAPS 1-digit food category which contains nine food categories, but their food categories are different from the tracking survey categories. Therefore, the categorical groupings are slightly changed to create consistency across the two data sources.

Table 2: Summary Statistics (Tracking Survey Data)[1]

Variables	Mean/Proportion	SD	Min	Max	Observations
Household Size	2.43	1.80	1	77	4367
Number of Child (Age 0-5)	0.14	0.45	0	4	4367
Number of Child (Age 6-17)	0.30	0.74	0	12	4367
Number of Child (Male, Age 18+)	0.92	0.81	0	28	4367
Number of Child (Female, Age 18+)	1.06	0.87	0	35	4367
Hispanic or Latino	0.07	0.26	0	1	4350
Gender:					4335
Female	56.93%				
Male	42.38%				
Race:					4364
White	77.46%				
Black	8.71%				
Asian	7.38%				
Other	6.46%				
Household Income:					4365
<50k	39.82%				
50-99k	34.50%				
>100k	25.68%				
Age:					4365
18-44	45.13%				
45-64	30.04%				
65 or Older	24.82%				
Employment Status:					4363
Full Time	44.63%				
Part Time	13.88%				
Retired	24.40%				
Student	3.00%				
Unable to Work	2.91%				
Unemployed	11.18%				
Region:					4365
Northeast	21.85%				
Midwest	23.30%				
South	30.69%				
West	24.15%				
Education:					4364
Bachelor	35.16%				
Below Bachelor	47.34%				
Above Bachelor	17.50%				

[1]Source: The U.S. Household Food Waste Tracking Survey, see Li et al. (2023)

Table 3: Fraction of Total Household Waste[1]

Food Category in Tracking Survey	Weight Share of Food Waste Attributable to subcategory	Combined Category	Waste Share[2]
Fresh Vegetables	27.13%	Fruits and Vegetables	46.33%
Non-fresh Vegetables	3.03%		
Fresh Fruits	15.40%		
Non-fresh Fruits	0.77%		
Potatoes	6.32%	Potatoes and Potato Products	8.15%
Potato Products	1.83%		
Pasta	3.79%	Grains	20.54%
Rice	3.64%		
Beans	1.86%		
Bread	9.67%		
Cereals	1.59%		
Meat	5.39%	Protein	8.44%
Fish	0.97%		
Eggs	2.08%		
Yogurt	3.15%	Dairy products (except milk)	5.00%
Cheese	1.86%		
Condiments	3.48%	Condiments	3.48%
Candy	0.63%	Snacks	1.36%
Salty Snacks	0.73%		
Non-alcoholic Beverages	5.97%	Beverages (including milk)	6.70%
Alcoholic Beverages	0.73%		
Total	100%	Total	100%

[1]Shares in column 2 are calculated based on the food waste tracking survey data, with 4367 observations.
[2]Share is calculated by adding up the shares in column 2 by combined categories

The food input prices, FAH and FAFH prices, are calculated by using food expenditures divided by the weight of food inputs. The original data is recorded in nominal dollars (2012-13) and grams, though prices are expressed in $\$/lb$ for visualization and summary purposes. The distribution of food prices is shown in Figure 2 and 3. As we can observe, food prices are mostly within the range of 0 to 3 dollars per pound. The summary statistics for food prices are shown in Table 4. The mean of the FAFH price is smaller than the mean of the FAH price, while the median FAFH price exceeds the median FAH price by 9.6% (see footnotes to Figures 2 and 3). Table 4 panel B shows the summary statistics for prices and expenditure across the eight categories. Protein and dairy products (without milk) have the top unit price among these categories, while beverages, which constitute the largest category by physical weight (62% of total weight), have the lowest mean unit price.

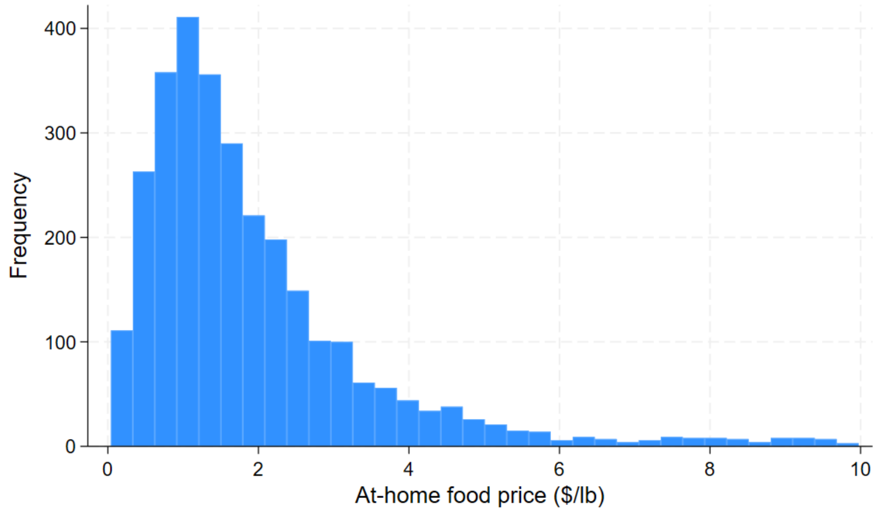


Figure 2. The Distribution of FAH Prices[1]

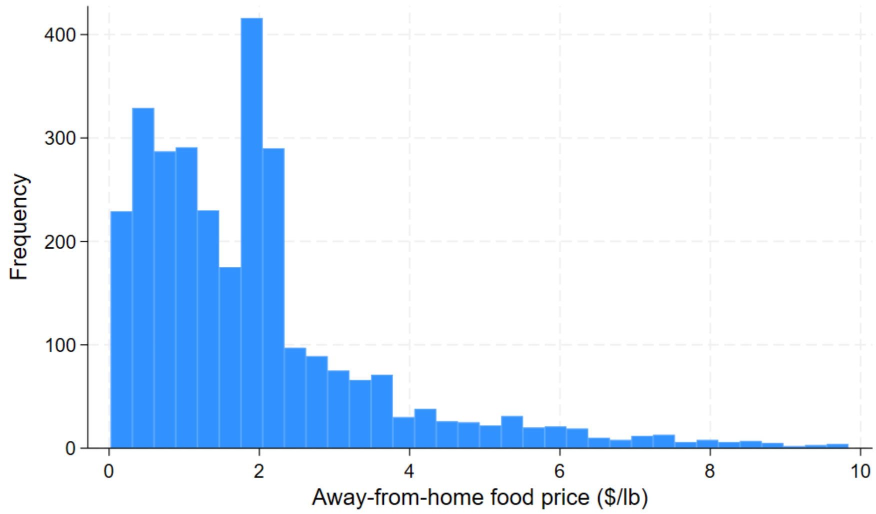


Figure 3. The Distribution of FAFH Prices[2]

[1]2961 observations with the median at 1.483 ($/lb); 88 observations (2.89% of total observations) are larger and not displayed to match the horizontal axis of FAFH prices.

[2]2961 observations with the median at 1.626 ($/lb)

Table 4: Summary Statistics for Categorical Price and Expenditure Variables

Variable	Mean	SD	Min	Max	Observations
Panel A					
FAH Price ($/lb)	2.271	2.809	0.039	31.173	3049
FAFH Price ($/lb)	1.978	1.772	0.021	11.647	3049
FAH Waste Expenditure Share	0.726	0.241	0	1	3049
FAFH Waste Expenditure Share	0.274	0.241	0	1	3049
Total Expenditure on Wasted Food ($)	26.77	28.02	0.080	327.9	3049
Panel B					
FV Price ($/lb)	2.813	2.516	0.036	35.641	3037
Potato Price ($/lb)	2.948	1.700	0.101	22.190	3037
Grain Price ($/lb)	2.723	1.431	0.079	11.722	3037
Protein Price ($/lb)	8.540	5.260	0.138	34.488	3037
Dairy Product Price ($/lb)	7.460	3.606	0.231	63.12	3037
Condiment Price ($/lb)	4.421	5.911	0.073	154.4	3037
Snack Price ($/lb)	5.143	4.468	0.104	61.329	3037
Milk & Beverage Price ($/lb)	0.695	0.508	0.001	3.677	3037
Total Expenditure on Wasted Food ($)	25.86	26.85	0.081	242.34	3037

Notes: Author calculations based upon the FoodAPS data sample.

Theory and Methods

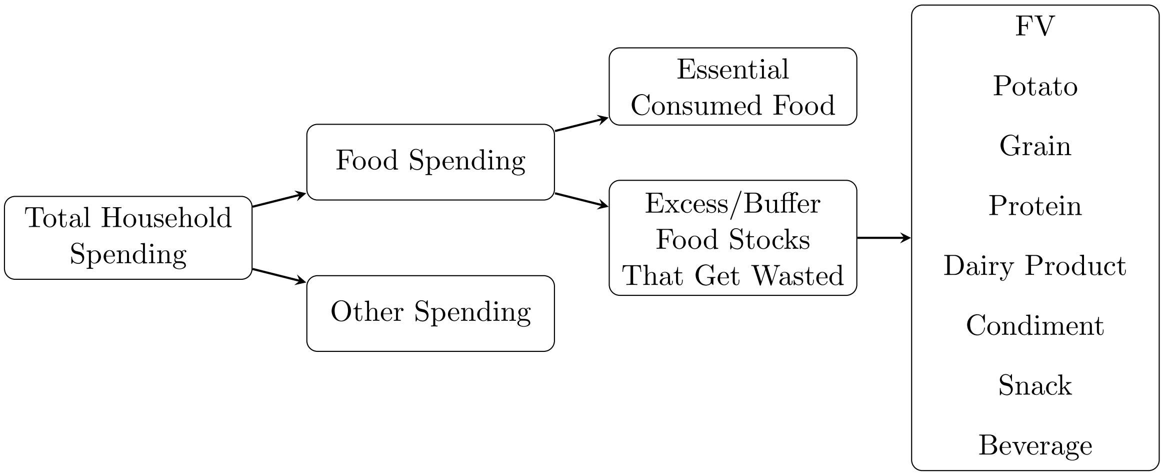
Previous studies developed frameworks to explore the economic drivers of household food waste largely in the context of the theory of household production (Hamilton and Richards, 2019; Katare et al., 2017; Lusk and Ellison, 2017) and found food prices, policies, and various household characteristics could affect food waste. Food waste has been postulated to be influenced by food policies designed to impact food prices, with the waste amount related to household price elasticity of demand for food (Hamilton and Richards, 2019). Households are assumed to maximize their utilities subject to budget constraints, and they derive utilities from the consumption of food (Lusk and Ellison, 2017). Katare et al. (2017) established a theoretical framework for household food waste to determine a social-optimal food waste tax, and they modeled food waste as an optimum of household decision-making. Their theoretical work also shows the importance of estimating the responsiveness of household food waste to government policies.

Several studies applied empirical models to explore drivers of food waste and the household responsiveness of food waste to food prices and expenditures (Yu and Jaenike, 2020; Landry and Smith, 2019; Smith and Landry, 2021; Vargas-Lopez et al., 2022). Among these empirical studies, household food waste is modeled to connect food price, total food expenditure, and the waste amount or share. These studies have shown the significant role of demographics in estimating food waste elasticities. However, the studies featuring U.S. data have been silent as to how these elasticities may differ across food categories, and none of the studies have explored how demographic characteristics might influence waste behaviors within different categories of food. Given the increasing interest in, e.g., subsidizing foods from particular food categories (produce) and forbidding the use of funds from programs such as SNAP on food acquired away from home, understanding the elasticity of waste created in particular categories of food becomes relevant to such policy discussions. Therefore, in this paper, I applied the QU-AIDS model with a set of demographics to assess the responsiveness of food waste to food price and household food expenditure, which can inform relevant government policies on food waste.

The Quadratic Almost Ideal Demand System (QU-AIDS) Model

The AIDS model, developed by Deaton and Muellbauer (1980), relates the share of expenditure on different categories of food to total food expenditures and prices and is commonly used to estimate expenditure and price elasticities (Zhao et al., 2023; Seale et al., 2003; Leifert and Lucinda, 2014). The AIDS model and its successors rely upon a maintained assumption of multistage budgeting across sets of weakly separable goods that provide utility to the consumers. To extend this approach in a setting involving waste, I implicitly assume that households allocate budget to buy exactly enough food to meet base nutritional demands and then additional funds to buy buffer stocks of food that have a high probability of being wasted. These wasted buffer stocks have value to the consuming household because they provide a 'cushion' during the household's production of meals during the given time period, where the cushion allows for the loss of palatability or safety of some fraction of the acquired food or the option to create meals for unexpected guests or occasions, i.e., to maintain the identity of a 'good provider' (Aschemann-Witzel et al., 2019). Figure 4 depicts this budgeting process for one of the possible waste categorization schemes.

Figure 4. Hypothesized Budgeting Process: 8 Categories Example



Banks et al. (1997) extended the model and added a quadratic logarithmic income term, and their model is known as the Quadratic Almost Ideal Demand System (QU-AIDS) model. The QU-AIDS model is based on the indirect utility function:

$$ln\,\phi = [(\frac{ln\,m - ln\,a(p)}{b\,(p)})^{-1} + \lambda(p)]^{-1} \tag{1a}$$

Where ϕ is the indirect utility function that relates p and m to consumer utility, p represents prices and m represents the total expenditure. $a(p)$ is a transcendental logarithm function and $b(p)$ is the Cobb-Douglas price aggregator. The functions $a(p)$, $b(p)$, and $\lambda(p)$ are shown below.

$$ln\,a(p) \;=\; \alpha_0 + \sum_{i=1}^{n} \alpha_i\,ln\,p_i + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \gamma_{ij}\,ln\,p_i\,ln\,p_j \tag{1b}$$

$$b(p) = exp\,(\sum_{i=1}^{n} \beta_i\,ln\,p_i) \tag{1c}$$

$$\lambda(p) = \sum_{i=1}^{n} \lambda_i \, ln \, p_i \tag{1d}$$

To estimate food waste, the elements in the AIDS model are adapted to represent the share of the household budget expended on wasted food that originates from each category. The share equation is derived by using Roy's identity to the indirect utility function:

$$w_i = \boldsymbol{\alpha} + \sum_{j=1}^{n} \gamma_{ij} \, ln(p_j) + \beta_i \, ln(\frac{m}{a(p)}) + \frac{\lambda_i}{b(p)}(\frac{ln \, m}{a(p)})^2 + u_i \tag{2}$$

$$\boldsymbol{\alpha} = \boldsymbol{As} \tag{3a}$$

$$\boldsymbol{A} = \boldsymbol{\alpha_i'} \tag{3b}$$

Where w_i is the share of a household's budget spent on wasted food that originates from category i, n represents the number of food waste categories, and u_i is an error term. The demographic variables enter into the demand system through vector α, which is modeled as linear combinations of a set of demographic variables. In eq(3a), α is expressed by a set of demographic variables s, including 18 demographic variables, $(s_1, ..., s_{18})$. The method allows the budget share, and hence the resulting price and expenditure elasticities, to depend on demographic variables, which is called the translating approach (Pollak and Wales, 1981; Lecocq and Robin, 2015). Demographic characteristics are included in the model because previous studies find that household factors could affect food waste (Yu and Jaenicke, 2020; Landry and Smith, 2019; Smith and Landry, 2020; Lusk and Ellison, 2017; Szabó-Bódi et al., 2018; Li et al., 2023). The parameters, α_i, γ_{ij}, β_i, and λ_i are target parameters to be estimated.

The QU-AIDS model has three restrictions due to the assumption of utility maximization. First, the adding-up restriction ensures that the shares across food categories sum to 1. Second, the homogeneity restriction ensures that the prices and total food expenditure change at the same rate. The third restriction is Slutsky symmetry. These three restrictions imply that the parameters should satisfy the following conditions, where z is (1, ..., 18).

$$\sum_{i=1}^{n} \alpha_{iz} = 1 \tag{4a}$$

$$\sum_{i=1}^{n} \beta_i = 0 \tag{4b}$$

$$\sum_{i=1}^{n} \lambda_i = 0 \tag{4c}$$

$$\sum_{i=1}^{n} \gamma_{ij} = 0 \tag{4d}$$

$$\sum_{j=1}^{n} \gamma_{ij} = 0 \tag{4e}$$

$$\gamma_{ij} = \gamma_{ji} \tag{4f}$$

Weak separability is also assumed in the demand system. The assumption implies that substitution between wasted foods within the system is unaffected by the consumption of goods outside the system (Sellen and Goddard, 1997). For example, if a consumer purchases more food than can be consumed before the food is no longer palatable, then the choice between which of the expiring foods to waste is unaffected by choices outside the system and is invariant to the amount of excess food acquired. This assumption may be more tenable when considering the system of eight types of food, but it is maintained for methodological consistency when analyzing waste for food at home versus away from home.

The QU-AIDS model is first applied to estimate expenditure and price elasticity for at-home and away-from-home food waste, then used to explore elasticities for food waste in eight food categories (Table 2 Column 3). When the categories are at-home and away-from-home waste, I assume that waste rates are identical in each category and equal to Yu and Jaenicke's (2020) overall household food waste rate. While I know of no detailed studies that directly verify that FAH and FAFH are wasted at identical rates, Qi and Roe (2017) find a waste rate of 8% among consumers participating in a dining experiment while Roe et al. (2022) find the ratio of avoidable food waste to the sum of avoidable food waste and food intake among consumers using a smartphone app to track wasted food both at home and away from home was also 8%.

However, previous literature firmly establishes that waste rates across the eight food categories considered here are not identical (Li et al. 2023), which necessitates a different approach for developing budget shares. For the eight categories, the waste rates rely on an external source of waste rates calculated using the food waste tracking survey data. The budget share of the food waste for category i is calculated by using eq(5a). The major elements used in the QU-AIDS model are the average price of each food category (p_i) and the budget share of a household's wasted food that originates from category i (w_i).

$$w_i = \frac{E_{fw,\,i}}{E_{fw,\,total}} = \frac{Q_{fw,\,i} * p_i}{Q_{fw,\,total} * p_{total}} \tag{5a}$$

$$p_{total} = \frac{E_{total}}{Q_{total}} \tag{5b}$$

$$w_i = \frac{Q_{fw,i} * p_i}{Q_{fw,\,total} * \frac{E_{total}}{Q_{total}}} = QS_{fw,\,i} * \frac{p_i}{\frac{E_{total}}{Q_{total}}} \tag{5c}$$

Where $E_{fw,\,i}$ is the expenditure on food from category i that is wasted, $E_{fw,\,total}$ is the amount spent on all food that is wasted. The expenditure on food waste is calculated by using food expenditure times food waste percentage. The expenditure on food waste for category i, $E_{fw,\,i}$, is calculated by using the gram weight of category i food waste ($Q_{fw,\,i}$) times the price of food category i (p_i). The total expenditure on food waste ($E_{fw,\,total}$) is calculated by using the gram weight of total food waste ($Q_{fw,\,total}$) times the average price of total food (p_{total}). Then plug Eq(5b) into Eq(5a), and get Eq(5c). In Eq(5c), $QS_{fw,\,i}$ represents the share of a household's wasted food expenditures that originates from category i.

The elements needed to calculate the budget share of the food waste for category i include Q_{total}, p_i, E_{total}, and $QS_{fw,\,i}$. The first three elements can be calculated using FoodAPS data associated with the food waste percentage method from Yu and Jaenicke (2020). However, FoodAPS data does not have enough information to calculate the share of waste amount originating from category i, $QS_{fw,\,i}$. To calculate $QS_{fw,\,i}$ for the case of eight categories, I use food waste tracking survey data that has the gram weight of food waste for each food category.

$$QS_{fw,i} = mean(\frac{\hat{Q}_{fw,i}}{\hat{Q}_{fw,total}}) \tag{5d}$$

Where $\hat{Q}_{fw,i}$ is the quantity of food waste for category i using food waste tracking survey data, and $\hat{Q}_{fw,total}$ is the total gram weight of food waste. Then I use Eq(5c) to calculate the $QS_{fw,i}$, and assume the share is the same across different households.

The function "aidsills" in Stata is used to estimate the expenditure and price elasticity of food waste, and is commonly used to estimate a system of demand functions with endogenous regressors (Lecocq and Robin, 2015). The function is based on the iterated linear least squares (ILLS) estimator developed by Blundell and Robin (1999), and allows us to estimate QU-AIDS model and check robustness with asymptotic Taylor approximation standard errors. The coefficients, α_i, γ_{ij}, β_i, and λ_i are estimated from the system of demand functions. Then the own-, cross-price (ϵ_{ij}), and expenditure elasticities (e_i) can be calculated by eq(6a) and eq(6b), respectively, where $\mu_i = \beta_i + \frac{2\lambda_i}{b(p)} \times log\frac{m}{a(p)}$, $\mu_{ij} = \gamma_{ij} - \mu_i(\alpha_j + \sum_{i=1}^{n} \gamma_{ji}\, logp_i) - \frac{\lambda_i \beta_j}{b(p)}(log\frac{m}{a(p)})^2$, and δ_{ij} is Kronecker delta (equals one if i = j, equals zero otherwise).

$$\epsilon_{ij} = -\delta_{ij} + \frac{\mu_{ij}}{w_i} \tag{6a}$$

$$e_i = 1 + \frac{\mu_i}{w_i} \tag{6b}$$

The above functions show that the elasticity measures are non-linear combinations of estimated parameters that will require additional effort to create confidence intervals and conduct testing (e.g., the asymptotic Taylor series approximation, bootstrapping method, etc.). I use the asymptotic Taylor series approximations of elasticity standard errors to get the confidence interval of the elasticity. Taylor series approximation, a series expansion of a function, is commonly used to derive standard errors for elasticities (Green et al., 2012). Confidence intervals of the sample estimates provided by the Taylor series approximation can be used to check whether the elasticity is unit elastic or not.

The consistency of the QU-AIDS model estimates may be challenged by at least two sources of endogeneity. First, the price in the model may be endogenous. The price is calculated by using expenditure divided by quantity, so people might purchase more food when food is cheaper. Previous studies find most at-home foods are normal goods, and the quantity purchased increases when the price decreases (Lee and Chern, 1992). Since the food waste percentage is estimated using a production function approach (Yu and Jaenicke, 2020), more food purchased will cause more food waste. The issue clearly applies to at-home food, while the case for endogeneity in away-from-home settings is not as strong. For example, lower prices on favorite products at a supermarket may spur consumers to purchase additional food in hopes of storing the food at home, as many consumers admit that they often waste items they purchase on sale in stores (Qi and Roe 2016). However, increased purchases and storage of sale-priced food in away-from-home settings, which are mainly sourced from restaurants and eaten on-site, is more difficult. I use instrumental variables for at-home and away-from-home food prices. The prices for eight food categories are not instrumented because of use of standard instruments resulted in infeasible estimates.

Second, the household's total food expenditure may also be endogenous for both systems (FAH and FAFH waste, and eight-category food waste). When households have higher food expenditures, they are likely to have more food waste. To deal with the endogeneity of price, I use two instrumental variables (IVs) for food price to estimate the expenditure and price elasticity for food waste. The first IV is the logged average FAH price experienced by FoodAPS respondents in other strata, where strata were built as part of the FoodAPS sampling procedure, and were created by using a combined race/ethnicity variable, household income, SNAP participation, household size, number of children, and age. There are 25 strata in our sample. Then, the logged average FAFH price in other strata is applied as an IV for the away-from-home food price. For example, the FAFH price for households in strata 1 is instrumented by the logged average FAFH price in the other 24 strata. Then, the logged value of the average household monthly income in other strata is used to instrument the total expenditure on food waste for both systems. The income could be a valid instrument due to the weak separability assumption that household short-run food input and consumption decisions are weakly separable from labor decisions determining income. These instrumental variables have shown good strength in the first-stage results (see Table A.2). The correlations between IVs and their instrumented variables are strong and statistically significant with F-statistics substantially larger than the conventional value of 10 (Stock and Yogo, 2005).

Heterogeneous Effects

Food waste might be impacted by household characteristics and other factors. Yu and Jaenicke (2020) show that some variations exist in the estimated level of food waste across various households. For example, households with high food security status waste more food than households with low food security status. Landry and Smith (2019) find food waste decreases with household size due to scale effects that larger households are more efficient in meal production. Smith and Landry (2021) find less waste attributable to households with older heads who identify as white and homemakers, have more formal education, and shop more frequently.

In this paper, factors that might impact household food waste have been included as intercepts into the QU-AIDS model. This paper expands the analysis of heterogeneous effects beyond looking for differences in the level of waste across groups to exploring differences in responsiveness of waste to changes in prices and expenditures for using subgroups. The sample has also been divided into two groups by different absolute food waste amounts. The high-waste group includes households that waste more than the median of food waste amount, and the other group includes households that waste less than the median. The reason to divide the sample in this way is to explore the robustness of the embedded assumption of invariance of waste to the scale of waste being created. Table 6 shows the difference between households with low waste amount and high waste amount. The average amount of food waste in the low food waste group is much lower than the amount of waste in the high food waste group. As a comparison, I also divide the sample into two groups by the median of food waste percentage. The waste difference in two groups split by waste percentage is not as large as the difference between groups divided by the median amount of food waste (Table A.3).

Table 6: Average Food Waste Amount in Different Groups (Absolute Low vs. High)

	Low Food Waste Group	High Food Waste Group
FAH Waste	2228.12	8744.03
FAFH Waste	1212.33	3000.31
Observations	1525	1524
FV Waste	261.73	1019.44
Potato Waste	52.42	167.27
Grain Waste	245.72	825.61
Protein Waste	297.60	832.68
Dairy Product Waste	12.39	65.30
Condiment Waste	84.70	424.91
Snack Waste	199.50	626.14
Milk & Beverage Waste	2133.44	7619.39
Observations	1518	1519

Notes: The whole sample has been separated into low-waste and high-waste groups at the median value of waste amount. All amounts in grams.

Results

The AIDS Model for FAH and FAFH Waste

The expenditure and price elasticity for at-home and away-from-home food waste from the QU-AIDS model are reported in Table 7. The table also contains the asymptotic Taylor approximation 95% confidence interval. The expenditure elasticity for at-home food waste is 0.869. Hence at-home food waste increases significantly with total expenditures on excess or buffer foods, but the quantity change in the waste is less than the change in the household's expenditure on excess food. To be more specific, when the expenditure increases by 10%, the at-home food waste will increase by 8.69%. The expenditure elasticity implies that at-home food waste is expenditure-inelastic since the upper bound of the 95% confidence interval is less than 1 (unit elasticity). The expenditure elasticity for away-from-home food waste is 1.362, which is statistically different from unit elasticity, and greater than the at-home expenditure elasticity, i.e., the 95% confidence interval lies above the 95% confidence interval for the at-home expenditure elasticity. A 10% increase in expenditure would result in a 13.62% increase in away-from-home food waste.

Table 7: Elasticities for Food Waste with 95% Asymptotic Taylor Approximation Confidence Intervals

	Expenditure	FAH Price	FAFH Price
At-Home Waste	0.869***	-1.000***	0.131
	(0.816, 0.922)	(-1.182, -0.818)	(-0.008, 0.270)
Away-from-Home Waste	1.362***	0.001	-1.362***
	(1.211, 1.513)	(-0.502, 0.504)	(-1.752, -0.972)
Demographics	Yes		
N	3043		
R^2	0.202		

Notes: *, **, *** represent values significantly different from 0 at 10%, 5%, and 1% level; values inside parenthesis are 95% asymptotic Taylor approximation confidence intervals.

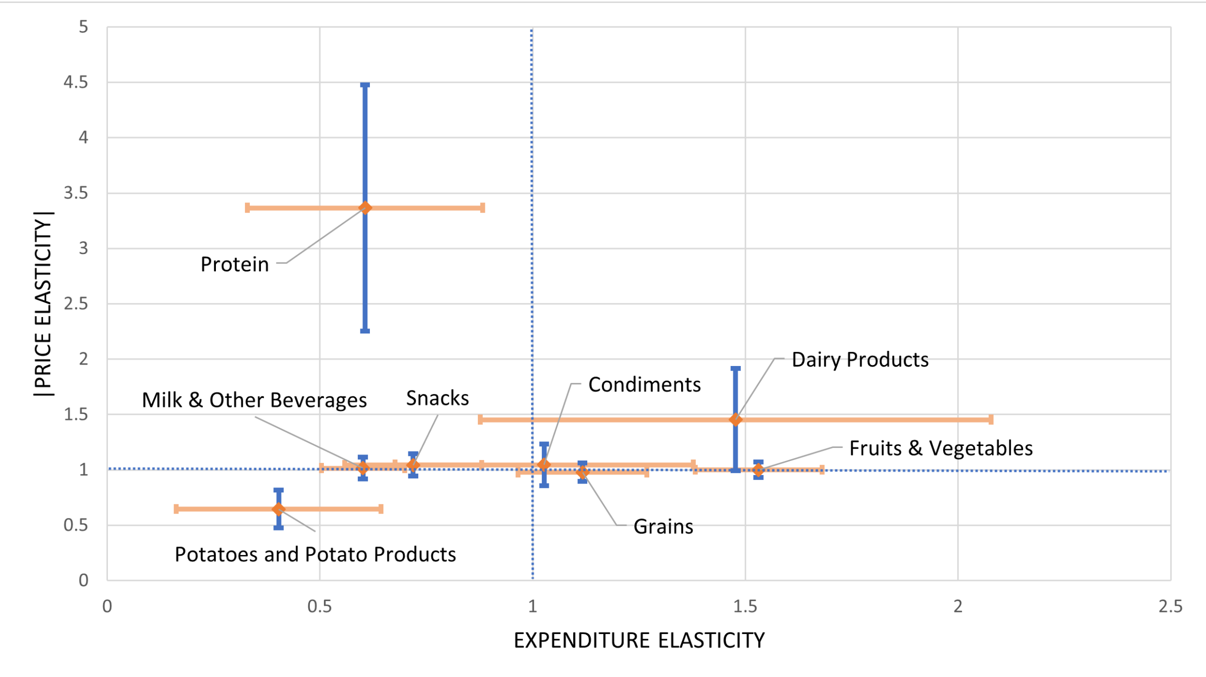
The price elasticity estimate for at-home food waste is exactly at -1, which implies that at-home food waste increases in a unitary fashion with decreases in the price of at-home foods. The price elasticity for away-from-home food waste is -1.362, and like the at-home category, is also not statistically different from unit elasticity at the 5% level (though the 90% confidence interval excludes -1). The finding of unit price elasticity implies that the quantity change in waste is inversely proportional to the change in price. In addition, the standard error of the away-from-home waste elasticities are larger than that for at-home elasticities. The relative lack of precision in elasticities for the away-from-home food waste may stem from data challenges in the away-from-home settings, particularly given some well-established challenges in assigning quantity values to FAFH within the FoodAPS data set (see Yu and Jaenicke 2020). Neither cross-price elasticity is statistically different from zero, which implies that the at-home (or away-from-home) food waste will stay unchanged if the FAFH (or FAH) prices increase.

Based on the results from the QU-AIDS model, both at-home and away-from-home food waste increases with food expenditure and decreases with within-category food prices. The results yield several implications. As households spend more on food intended as a buffer for food production, it is not surprising that they might have more food waste since they may not have the skill or time to ensure the buffer stock items are incorporated into meals. However, the percentage change of food waste in response to the change in food expenditure and price differs in different settings. The findings are not consistent with Landry and Smith (2019) who find households have elastic expenditure and price for at-home food waste using data from the 1970s. They find that for at-home food waste expenditure elasticity is 1.44, and price elasticity is -1.90. There are several reasons that might cause the difference in elasticities. First, Landry and Smith (2019) only consider the waste of food at home rather than examining a system of waste involving food from both at-home and away-from-home sources. While our cross-price elasticities are not statistically significant, the estimation approach is distinct from Landry and Smith and could yield different outcomes. Second, people have more food choices than forty years ago (when the data used by Landry and Smith (2019) were collected), and eating away from home has become more popular in the US. In 1970, 26 percent of total food expenditure was spent away from home. The number increased to 39 percent in 1996, and 56 percent in 2022 (Lin et al., 1999; USDA, 2023). Third, technological advances (e.g., larger refrigerators (Schwartz, 2012) and more accessible freezers) could provide households with opportunities to efficiently store purchased food and leftovers and reduce food waste (Hebrok and Boks, 2017).

The AIDS Model for Waste in Eight Food Categories

The QU-AIDS model is also used to calculate the expenditure and price elasticity for food waste in eight different food categories. Figure 5 shows the waste elasticities for eight food groups with asymptotic Taylor approximation 95% confidence intervals. As more is spent on food items intended as a buffer and subject to likely waste, the amount wasted in several categories increases proportionally (unitary elasticity), including grains, dairy products, and condiments (see Table 8 and Figure 5). The waste of several food categories increases less than proportionally (inelastically) including potatoes, proteins, snacks, and beverages, while the waste of fruits and vegetables increases more than proportionally (elastically). The differences in expenditure elasticities across categories may be related to the perishability and storage modes typical for each food category. For example, 71% of the produce items reported in the FoodAPS data are fresh, which means that as more budget is allocated for buffer foods, the share going to extra produce may be proportionally larger due to the dominance of more perishable fresh items in this category and the lack of familiarity with longer-term home storage of these items may lead to proportionally more waste. The categories where waste is expenditure inelastic tend to be dominated by shelf-stable items (snacks, beverages other than milk, potatoes) or items that are often sold as frozen or consumers have more confidence in freezing themselves (proteins, frozen potato products).

Figure 5. Waste Elasticities by Categories with Taylor Approximation 95% Confidence Intervals



Notes: Confidence intervals are normal-based and calculated based on the standard errors from asymptotic Taylor series approximation. The vertical axis is the absolute value of the own-price elasticity.

Table 8: Elasticities for Food Wastes by Categories Using QU-AIDS Model

	Expenditure Elasticity	Price Elasticity
FV	1.531***	-1.001***
	(1.382, 1.680)	(-1.072, -0.930)
Potato	0.403***	-0.646***
	(0.162, 0.644)	(-0.815, -0.477)
Grain	1.117***	-0.978***
	(0.966, 1.268)	(-1.062, -0.894)
Protein	0.606***	-3.366***
	(0.330, 0.882)	(-4.477, -2.255)
Dairy Product	1.477***	-1.453***
	(0.877, 2.077)	(-1.914, -0.992)
Condiment	1.027***	-1.046***
	(0.676, 1.378)	(-1.234, -0.858)
Snack	0.719***	-1.044***
	(0.558, 0.880)	(-1.144, -0.944)
Milk & Other Beverage	0.601***	-1.016***
	(0.503, 0.699)	(-1.114, -0.918)

Notes: Values inside the parenthesis are 95% asymptotic Taylor series approximation confidence intervals. *, **, *** represent values significantly different from 0 at 10%, 5%, and 1% level.

Price elasticities in this context refer to how the share of the budget allocated to different buffer foods responds to price changes. The own price elasticities are largely unitary with three exceptions. Protein waste is highly elastic (-3.37); dairy product waste is mildly elastic (-1.45, only significant at the 10% level), and potato waste is solidly inelastic (-0.65). The own price elasticity of these three groups follows the relative price of these groups, with proteins and dairy products the most expensive on a per unit basis, and potatoes among the least expensive categories (see Table 4, panel B).

I also explore the cross-price elasticities for food waste. The cross-price elasticity measures the responsiveness in the quantity wasted of one category if the price for the other category changes. Positive cross-price elasticities imply the waste of these two types of food are substitutes, and negative cross-price elasticities indicate that the waste of two types of food are complements. Table 9 shows that there are some positive and negative cross-price elasticities. For the first column, if FV prices increase, FV waste will decline due to the standard own-price response, but protein waste increases significantly, acting as a waste substitute. Potato and beverage waste, with a significant negative cross elasticity, acts as a complement to FV waste. Grain, dairy product, condiment, and snack waste, with insignificant cross-elasticities, are effectively unchanged. The first row shows that FV waste will decline if potato or grain prices increase, while FV waste will increase as the price of protein or snack increases. Protein, which has the largest own-price elasticity, also has some of the largest cross-price elasticities. Protein waste will increase if snack or beverage prices increase, acting as a waste substitute. The waste in some categories, such as protein and snacks, is largely a substitute to other waste categories since the cross-price elasticities are mostly positive. The waste of grain and condiment is largely independent of the prices of other categories, as there are no significant cross-price elasticities in the row 3 and 6 of Table 9. Waste in the dairy product category has only one positive and significant cross-price elasticity, acting as a substitute for the waste of protein. The potato waste significantly increases if the beverage price increases, and the beverage waste increases if the price of grain or protein increases.

Table 9: Cross-Price Elasticities for Waste by Categories Using QU-AIDS Model

	Price							
	FV	**Potato**	**Grain**	**Protein**	**Dairy**	**Condiment**	**Snack**	**Milk & Other Beverages**
FV	-1.001***	-0.092***	-0.118***	0.122**	0.006	-0.017	0.103***	-0.327
	(0.036)	(0.032)	(0.034)	(0.053)	(0.044)	(0.031)	(0.032)	(0.048)
Potato	-0.187***	-0.646***	0.108	-0.017	0.008	-0.020	0.062	0.290**
	(0.072)	(0.086)	(0.079)	(0.112)	(0.102)	(0.073)	(0.079)	(0.120)
Grain	-0.059	-0.008	-0.978***	-0.076	0.009	0.012	0.011	-0.030
	(0.043)	(0.041)	(0.043)	(0.066)	(0.056)	(0.040)	(0.043)	(0.065)
Protein	0.807***	-0.024	-0.125	-3.366***	0.104	0.008	0.505***	1.485***
	(0.231)	(0.133)	(0.144)	(0.567)	(0.176)	(0.125)	(0.171)	(0.348)
Dairy Product	0.104	-0.035	0.023	0.294*	-1.453***	0.008	-0.176	-0.241
	(0.162)	(0.136)	(0.142)	(0.163)	(0.235)	(0.134)	(0.142)	(0.227)
Condiment	-0.020	-0.068	0.098	-0.009	0.014	-1.046***	-0.010	0.014
	(0.106)	(0.099)	(0.104)	(0.148)	(0.135)	(0.096)	(0.102)	(0.156)
Snack	-0.055	0.015	0.097*	0.312***	-0.018	0.006	-1.044***	-0.032
	(0.052)	(0.049)	(0.052)	(0.057)	(0.068)	(0.049)	(0.051)	(0.079)
Milk & Other Beverages	-0.107***	0.050	0.076**	0.385***	-0.002	0.014	-0.001	-1.016***
	(0.031)	(0.031)	(0.032)	(0.033)	(0.042)	(0.031)	(0.032)	(0.050)

Notes: values inside the parenthesis are asymptotic Taylor approximation standard errors. *, **, *** represent values significantly different from 0 at 10%, 5%, and 1% level.

Heterogeneous Effects

The estimated systems control for personal and household characteristics by modeling the budget share intercepts as a linear function of these characteristics. For the two-category system (FAH vs. FAFH, Table 7), the estimated coefficients are presented in Table A.4 and the calculated impacts of the significant coefficient on the resulting elasticities are presented in Table 10. The intercepts of demographic variables are transformed to the percentage change in elasticities if the demographic variable goes from 0 to 1. Household size, gender, always shopping with a grocery list, SNAP participation, and food security, yield significant parameter estimates, where a positive parameter estimate indicates positive effects on the budget share of food waste. Households with a change in size that occurred over the last three months are more price-elastic for at-home food waste, but less price-elastic for away-from-home food waste and less expenditure-elastic for both at-home and away-from-home food waste, compared to households without any change in size. This finding reflects that household membership is important for food waste. People who are female, always shop with a list, and participate in SNAP have lower price elasticity for at-home food waste, but higher price elasticity for away-from-home food waste and higher expenditure elasticity for at-home and away-from-home food waste than other people. For example, if household food expenditure increases, the quantity increased in waste for female respondents (or people who always shop with a list, or SNAP participants) will be greater than other people. Household food security conditions also matter for waste elasticities. Households experiencing food security have lower price and expenditure elasticity for food waste, which implies food-secure households respond to changes in food expenditure and price less sensitively than food-insecure households.

Table 10. Effect of Demographics on FAH and FAFH Elasticities

	%Δ |Price Elasticity|		%Δ Expenditure Elasticity	
Variables	**AH**	**AFH**	**AH**	**AFH**
Household Size Change (<3 Months)	0.60%	-1.39%	-0.57%	-2.56%
Female	-0.40%	1.63%	0.46%	2.39%
Always Shop with List	-0.60%	2.37%	0.81%	3.79%
SNAP Participation	-0.20%	6.57%	1.27%	7.10%
Food Security	-0.50%	-1.17%	-0.11%	-0.22%

Notes: variables shown in this table are statistically significant in the QU-AIDS model (see Table A.4). Variables are dummy variables, and the %Δ is the percentage change in elasticities when the dummy variable goes from 0 to 1. Since price elasticity is negative, the %Δ in price elasticity is the percentage change of the absolute value of price elasticity. AH is an abbreviation of at-home, and AFH is an abbreviation of away-from-home. All variables other than the focal variable within a given row are evaluated at their means.

Turning to the system of eight food categories, I also find several significant demographic coefficients (Table A.5) that are translated into the impact on own-price and expenditure elasticities in Tables 11 and 12, respectively. Price elasticity for FVs is negatively influenced by several household features, such as identifying as white, college degree, food security, and living in rural areas. The only exception is that females have higher price elasticity for FV waste than males. Several demographic variables only have negative relations to the price elasticity. Households with income greater than the poverty threshold, or being self-employed, or living in rural areas, have lower price elasticity for protein foods, compared to others. Potato, snack, and beverage (including milk) are less price-elastic for food-secure households. Beverages are positively influenced by several characteristics, such as gender, higher education, employment, and home ownership. Some demographic variables positively related to price elasticities for waste in several categories, such as marital status, employment, and living in the Northeast and Midwest regions. Some demographic variables have mixed effects on price elasticity, such as gender, Hispanic or Latino, white, shopping with a list, and home ownership. For example, people who always shop with a list have higher price elasticity for the waste of dairy products, but lower price elasticity for snack waste. Finally, the effects of demographics on price elasticities are largest in absolute value terms in the food categories with the largest price elasticities and largest confidence intervals (protein and dairy), suggesting sensitivity to household characteristics may be related to confidence interval sizes.

Table 11. Effect of Demographics on Own-Price Elasticities by Category

	%Δ |Price Elasticity|							
Variables	**FV**	**Potato**	**Grain**	**Protein**	**Dairy Product**	**Condiment**	**Snack**	**Beverage**
Female	1.01%	-9.91%			-18.11%	-1.79%		1.39%
Hispanic and Latino		-16.89%	0.41%					
White	-5.92%			16.51%			-2.42%	
College	-3.04%		0.41%		8.02%			1.59%
Married				97.06%				
Income > PL				-1.42%				
Always Shop with List					16.85%		-0.69%	
Employed		4.60%						0.10%
Self Employed				-32.09%				
Food Security	-6.93%	-4.83%					-0.29%	-1.17%
Home Ownership - Own		4.11%	-0.51%	-19.58%			0.97%	7.94%
Region - NM[1]				77.96%				
Rural	-3.76%			-17.78%				

Notes: variables shown in this table are statistically significant in the QU-AIDS model (see Table A.5). Variables are dummy variables, the %Δ is the percentage change in elasticities when the dummy variable goes from 0 to 1. Since price elasticity is negative, the %Δ in price elasticity is the percentage change of the absolute value of price elasticity. Only results with statistically significant intercept coefficients are reported. [1]NM represents the Northeast and Midwest region in the US. All variables other than the focal variable within a given row are evaluated at their means.

Table 12 shows the percentage change in expenditure elasticity due to demographic differences. Some demographic variables only have a statistically negative relation to expenditure elasticity, such as female, Hispanic or Latino, married, income greater than the poverty threshold, and food security. Some demographic variables only have a positive relation to the expenditure elasticity, such as shopping with a list, employment status, and living in rural areas. The expenditure elasticity for the waste of potato, protein, and condiment is largely influenced by some demographic variables, while waste of snack only relates to the gender. For example, one of the largest effects is associated with the 48.6% decline in expenditure elasticity for potatoes among those who identify as Hispanic or Latino. This may correspond with the relatively low consumption of potatoes among these ethnic groups (about 31% less; Lin et al., 2016). The expenditure elasticity for grain waste is not largely influenced by demographic changes, with small relations to Hispanic or Latino, college, and home ownership. Several demographic variables that do not have any relation with waste elasticities at category level are not listed here, such as SNAP participation. Although SNAP participation does not statistically relate to waste elasticities at category level, it has statistical relations with at-home and away-from-home food waste elasticities (Table 10).

Table 12. Effect of Demographics on Expenditure Elasticities in Category

	%Δ |Expenditure Elasticity|							
Variables	**FV**	**Potato**	**Grain**	**Protein**	**Condiment**	**Snack**	**Beverage**	**Other**
Female	-6.27%	-25.71%			-18.49%	-1.06%		-10.46%
Hispanic and Latino		-48.62%	-0.45%					
White	0.26%			-36.98%			6.09%	
College	-4.14%		-0.45%		10.71%			-11.29%
Married				-60.76%				
Income > PL				-0.77%				
Always Shop with List					20.16%		0.50%	
Employed		14.44%						0.10%
Self Employed				10.12%				
Food Security	-1.04%	-12.79%					-0.42%	-5.03%
Home Ownership - Own		13.30%	1.71%	-24.17%				
Region - NM[1]				-				
Rural	3.30%			5.38%				

Notes: Variables shown in this table are statistically significant in the QU-AIDS model (see Table A.5). Variables are dummy variables, the %Δ is the percentage change in elasticities when the dummy variable goes from 0 to 1. All variables other than the focal variable within a given row are evaluated at their means.

Table 13 shows the waste elasticities by different waste levels, separated by the median value of household waste amount. I explore this to investigate whether the elasticity estimates are sensitive to the scale of the absolute level of waste. That is, since the AIDS model uses the share of expenditures on each type of wasted food rather than the amounts of each type of waste, it implicitly assumes that the elasticities are invariant to the scale of total waste. In Table 13 the results suggest that the elasticities are quite similar for households with above and below-median levels of wasted food, providing one source of evidence that the elasticities are invariant to the scale of waste. Table A.6 confirms that waste elasticities are invariant to the scale of waste if the sample is split between low and high shares (as opposed to levels) of waste.

Table 13. Food Waste Elasticity Using QU-AIDS Model by Waste Level (Absolute Low vs. High)

	At Home (AH)		Away from Home (AFH)	
	Expenditure	Price	Expenditure	Price
Low food waste	0.878***	-1.003***	1.453***	-1.463***
	(0.833, 0.923)	(-1.172, -0.834)	(1.200, 1.706)	(-1.896, -1.030)
High food waste	0.859***	-0.997***	1.301***	-1.295***
	(0.796, 0.922)	(-1.195, -0.799)	(1.205, 1.397)	(-1.644, -0.946)

Notes: *, **, *** represent values significantly different from 0 at 10%, 5%, and 1% level; values inside parentheses are asymptotic Taylor approximation confidence intervals.

Households with different food waste levels might also have different elasticities for food waste at the category level. Table A.7 shows that most expenditure and price elasticities are not statistically different between households with low food waste and high food waste based on asymptotic Taylor approximation standard errors. There are only a few exceptions. The price elasticity for FV is elastic in low waste group at the 10% significance level and inelastic in high waste group. The expenditure elasticities for the waste of potato and protein is not statistically different from zero in the high waste group. Moreover, the waste of dairy products increases more than proportionally (elastically) for the high waste group as the spending on food items as a buffer increases, or the price of dairy products decreases. Hence, the embedded assumption of scale invariance may be valid for this sample of consumers. Similar patterns are observed when the group is split between high and low waste rates (rather than levels, see Table A.8).

Mini-Case Study: FV Price Subsidy

A diet containing more fruits and vegetables is associated to a reduction of risk of bad health outcomes (e.g. high blood pressure and other chronic diseases) (Stanaway et al., 2022). However, some households, especially low-income households, have FV consumption below government recommendations. Some proposals that suggest a price subsidy on FV might encourage households to consume more fruits and vegetables (Dong and Lin, 2009; Engel and Ruder, 2020). As there is an increasing interest in providing FV price subsidies in recent years, we need to understand how food waste is impacted by a FV price subsidy for different households. In this section, I assume that a 10-percent subsidy is applied to FV prices, and explore the impacts of the subsidy on food waste.

The price elasticity for FV waste is very close to the unit elasticity, -1.001. Thus, a 10% discount applied to the FV price would raise the FV waste by 10.01%. Due to the cross-price elasticity, the waste of potato will increase by 1.87%, and the waste of milk and beverage will increase by 1.07%. In contrast, the waste of protein foods will decrease by 8.07%, as a substitute to FV waste. The price elasticity might be different for subgroups. Table 14 shows the price elasticity with 95% confidence intervals for households with different characteristics. The price elasticities for SNAP participants and nonparticipants are not statistically different because the elasticity for SNAP participants is within the confidence intervals, and vice versa. The price elasticity for people who are eligible for WIC and people not eligible for WIC is also not statistically different. The findings imply that a 10% discount on FV price will not have statistically different effect on people with different participation status in SNAP and WIC eligibility. The lack of sensitivity to SNAP participation aligns with Yu and Fan (2023), who find that SNAP households tend to waste less food than non-SNAP households. Price elasticities are also not statistically different for households with other different characteristics (food security vs. insecurity, female vs. male, white vs. nonwhite, college vs. no college). These findings reflect that the difference of price elasticity between two groups is not statistically significant if the effect of demographic variables shown in Table 12 is not large.

Table 14. FV Price Elasticity by Groups

	Price Elasticity	**95% Confidence Interval**
SNAP Participation	-1.034***	(-1.112, -0.956)
Non-SNAP Participation	-0.988***	(-1.066, -0.910)
WIC Eligible	-0.995***	(-1.068, -0.922)
WIC Not Eligible	-1.013***	(-1.082, -0.944)
Food Secure	-0.967***	(-1.036, -0.898)
Food Insecure	-1.039***	(-1.113, -0.965)
Female	-1.003***	(-1.070, -0.965)
Male	-0.993***	(-1.079, -0.907)
White	-0.985***	(-1.056, -0.914)
Non-white	-1.047***	(-1.121, -0.973)
College	-0.989***	(-1.054, -0.924)
No College	-1.020***	(-1.100, -0.940)
Rural	-0.973***	(-1.051, -0.895)
Urban	-1.011***	(-1.080, -0.942)

Notes: *, **, *** represent values significantly different from 0 at 10%, 5%, and 1% level. All variables other than the focal variable within a given row are evaluated at their means.

The price elasticities between two subgroups are not statistically different, but elasticities might be different by combining characteristics together. For example, compare a group containing non-white female SNAP participants with no college degree and who experience food insecurity, are living in urban areas, and are not eligible for WIC, against the group containing people with the opposite characteristics. The price elasticity for the first group is -1.107, which is elastic and statistically different than unit elasticity, with a confidence interval from -1.18 to -1.03. The elasticity for the second group is -0.883, which is inelastic and statistically different than unit elasticity, with confidence interval from -0.97 to -0.80. Thus, the price elasticities are statistically different between these two groups. Hence, there are few single factors, like SNAP or WIC status, that are associated with statistically distinct elasticities, though accumulated factors that are often occur together can often lead to distinct levels of waste responsiveness.

Conclusions

In this study, the waste behavior of households across distinct categories of food is found to be sensitive to the prices experienced for each food category and the total expenditure on food in excess of the strict caloric needs of the household. I leverage the analytical power of a well-known demand system approach to assess waste sensitivities across two ways to classify foods: foods purchased for at-home preparation and consumption vs. food purchased away from home, and for foods divided into eight types of food (e.g., proteins, potatoes, etc.). Household waste behavior is expenditure inelastic for at-home food and elastic for away-from-home food. In terms of price elasticities, the waste associated with both at-home and away-from-home food is not statistically different than unitary. These findings are distinct from those of Landry and Smith (2019), who explore at-home waste responsiveness using U.S. data from the 1970's and find behavior from this previous era to be both more expenditure and more price elastic. The differences might reflect that a smaller share of household food budgets were dedicated to food away from home 40 years ago, while there have been marked improvements in the size and efficiency of home cold storage.

This paper also extends the literature by calculating expenditure and price elasticities for away-from-home food waste and permitting the investigation of the cross-price elasticity between at-home food waste and away-from-home food waste. The fact that away-from-home waste is expenditure elastic aligns with the difficulties that consumers face in, e.g., transporting and utilizing excess purchases in restaurant and food service settings in home settings. Previous literature faced data and method limitations when considering waste in more granular food categories, which are surmounted in this work by combining the methods of Yu and Jaenicke (2020) to determine the fraction of total wasted calories at the household level with additional information about shares of waste by food category taken from recent national household food waste tracking surveys (Li et al., 2023).

I explore the elasticities for wastes of eight commonly purchased food categories, and find waste elasticities in different food categories roughly align the storage characteristics of different food categories. For example, the waste of FVs is expenditure-elastic and not statistically different than unit price-elastic. Most purchased FV products are fresh products that consumers find difficult to store for longer periods of time, and thus households might not purchase a lot if the price drops, but if more is expended on excess foods in general, the waste attributable to FV may increase more than proportionally due to perishability of these items. The difference in elasticities for food waste among different food categories implies that food waste prevention methods should also be different by category. Future studies could use the elasticities for different categories to analyze how the waste of different categories changes with relevant policies.

This paper also sheds light on food waste reduction by exploring household characteristics as factors that impact waste shares and elasticities. Food waste behaviors are statistically different with household size, gender, food shopping behaviors, SNAP participation, and food security status. Given the increasing interest in SNAP participation and food waste, our findings that SNAP participants have higher price and expenditure elasticities for away-from-home food waste might provide some implications for future research and SNAP administrators. For example, SNAP participants have similar waste elasticities for produce to non-SNAP recipients, which may assuage concerns of subsidizing the fruit and vegetable purchases will lead to disproportionate levels of waste. A single factor might not influence household waste behavior, but in the real world, accumulated factors that occur together might make a difference in waste responsiveness.

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Appendix

Table A.1. How The Combined Food Categories are Composed

Food Waste Survey Data	FoodAPS Data	Combined Category
Fresh Vegetables	64, vegetables, excluding potatoes	Fruits and Vegetables
Non-fresh Vegetables		
Fresh Fruits	60, fruits	
Non-fresh Fruits		
Potatoes	68, white potatoes (including white potatoes, baked or boiled; French fries and other fried white potatoes; mashed potatoes and white potato mixtures)	Potatoes and Potato Products
Potato Products		
Pasta	40, rice, pasta, cooked grains	Grains
Rice	32, mixed dishes - grain based	
Beans	2802, beans, peas, and legumes	
Bread	42, breads, rolls, tortillas; 44, quick breads and bread products; 55, sweet bakery products	
Cereals	46, ready-to-eat cereals; 48, cooked cereals	
Meat	20, meats; 22, poultry; 26, cold cuts and cured meats 30, mixed dishes - meat, poultry, seafood	Protein
Fish	24, seafood	
Eggs	25, eggs	
Yogurt	18, yogurt	Dairy (except milk)
Cheese	16, cheese	
Condiments	8, fats and oils, condiments, and sugars	Condiments
Candy	55, sweet bakery products 57, candy and chocolates 58, ice cream, pudding, other deserts	Snacks
Salty Snacks	50, savory snacks; 52, crackers; 54, snack/meal bars	
Alcohol Beverages	7, beverages; 10, milk; 12, flavored milk 14, dairy drinks and substitutes	Milk & Beverages
Non-alcohol beverages		

Notes: 0.79% of food in FoodAPS data is not contained in column 2, since the small portion of food is hard to match with categories in food tracking survey data.

Table A.2: Instrumental Variables First-Stage Statistics

Instrument	Endogenous Variables FAH Price	FAFH Price	Expenditure (Panel 1)	Expenditure (Panel 2)
Logged average FAH Price in other strata	-0.126***	-		
t-stat	(-9.42)	-		
F-stat	88.72	-		
R-squared	0.03	-		
Logged average FAFH price in other strata	-	-0.11***	-	
t-stat		(-8.71)	-	
F-stat	-	75.79	-	
R-squared		0.02	-	
Logged family month income in other strata	-	-	-5987.73***	-5561.20***
t-stat	-	-	(-10.31)	(-9.89)
F-stat	-	-	106.33	97.88
R-squared	-	-	0.03	0.031

Notes: *, **, *** represent values significantly different from 0 at 10%, 5%, and 1% level; values inside parentheses are 95% asymptotic Taylor approximation confidence intervals. Panel 1 is the estimation of waste elasticities for at-home and away-from-home food. Panel 2 is the estimation of waste elasticities for eight food categories.

Table A.3: Average Food Waste Amount in Different Groups (Relative Low vs. High)

	Low Food Waste Group	High Food Waste Group
FAH Waste	4539.62	6629.78
FAFH Waste	1728.05	2483.75
Overall Food Waste Percentage	20.93%	46.51%
Observations	1524	1525
FV Waste	403.32	878.25
Potato Waste	106.63	113.11
Grain Waste	474.27	597.29
Protein Waste	495.62	634.89
Dairy Product Waste	29.42	48.29
Condiment Waste	195.79	313.97
Snack Waste	343.79	482.04
Milk & Beverage Waste	4168.74	5586.36
Observations	1519	1518

Notes: The whole sample has been separated into low-waste and high-waste groups by the median value of food waste percent

Table A.4. Intercepts for Demographics Variables Using QU-AIDS Model

Variables	At-Home Budget Share	Away-from-Home Budget Share
Household Size	0.016***	-0.016***
	(0.006)	(0.006)
Household Size Change (<3 Months)	-0.038**	0.038**
	(0.017)	(0.017)
Female	0.032**	-0.032**
	(0.013)	(0.013)
Age	0.000	-0.000
	(0.000)	(0.000)
Hispanic and Latino	-0.014	0.014
	(0.015)	(0.015)
White	0.018	-0.018
	(0.014)	(0.014)
College or above	0.012	-0.012
	(0.013)	(0.013)
Married	0.013	-0.013
	(0.013)	(0.013)
Income $\geq$ Poverty Threshold	0.015	-0.015
	(0.014)	(0.014)
Always Shop with List	0.045***	-0.045***
	(0.012)	(0.012)
Employed	0.001	-0.001
	(0.012)	(0.012)
Self Employment	-0.014	0.014
	(0.014)	(0.014)
SNAP Participation	0.069***	-0.069***
	(0.018)	(0.018)
WIC Eligibility	-0.013	0.013
	(0.016)	(0.016)
Food Security	0.036***	-0.036***
	(0.012)	(0.012)
Home Ownership - Own	0.003	-0.003
	(0.012)	(0.012)
Region - Northeast & Midwest	0.006	-0.006
	(0.011)	(0.011)
Rural	0.002	-0.002
	(0.013)	(0.013)
Constant	1.409***	-1.409***
	(0.161)	(0.161)

notes: *, **, *** represent values significantly different from 0 at 10%, 5%, and 1% level; values inside () are standard errors.

Table A.5. Intercepts for Demographic Variables Estimating within QU-AIDS Model by Eight Food Categories

	Budget Share Intercept Coefficient							
	FV	Potato	Grain	Protein	Dairy Product	Condiment	Snack	Milk & Other Beverages
Household Size	-0.004	0.004**	0.006*	-0.006*	0.003***	-0.000	0.000	-0.004
	(0.004)	(0.002)	(0.004)	(0.004)	(0.001)	(0.001)	(0.002)	(0.004)
Household Size Change (<3 Months)	0.019	0.004	-0.012	0.004	-0.000	0.003	0.005	-0.023
	(0.018)	(0.007)	(0.015)	(0.015)	(0.005)	(0.005)	(0.009)	(0.018)
Female	0.038***	-0.010*	-0.011	-0.006	0.007*	0.009**	0.003	-0.030**
	(0.013)	(0.005)	(0.011)	(0.011)	(0.004)	(0.004)	(0.007)	(0.013)
Age	0.001**	0.000	0.000	0.000	-0.000	0.000	-0.000*	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Hispanic and Latino	0.009	-0.023***	0.026**	0.008	0.001	0.003	-0.013	-0.011
	(0.015)	(0.006)	(0.013)	(0.013)	(0.004)	(0.005)	(0.008)	(0.015)
White	-0.036***	-0.006	-0.000	-0.023**	0.001	-0.002	0.008	0.046***
	(0.013)	(0.006)	(0.011)	(0.011)	(0.004)	(0.004)	(0.007)	(0.013)
College or above	0.020*	-0.004	0.020**	-0.011	-0.006*	-0.001	0.004	-0.021*
	(0.012)	(0.005)	(0.010)	(0.010)	(0.003)	(0.004)	(0.006)	(0.012)
Married	-0.016	0.004	0.005	0.040***	-0.004	-0.006	-0.006	0.012
	(0.013)	(0.005)	(0.010)	(0.011)	(0.004)	(0.004)	(0.007)	(0.003)
Income $\geq$ Poverty Threshold	-0.023	0.007	0.014	-0.015	-0.004	0.013***	-0.010	0.018
	(0.014)	(0.006)	(0.012)	(0.012)	(0.004)	(0.004)	(0.008)	(0.014)
Always Shop with List	-0.003	0.002	0.003	-0.016	-0.008**	0.004	-0.003	0.021*
	(0.012)	(0.005)	(0.010)	(0.010)	(0.003)	(0.004)	(0.006)	(0.012)
Employed	-0.017	0.011**	-0.007	-0.006	0.000	-0.002	0.002	0.019
	(0.012)	(0.005)	(0.010)	(0.010)	(0.003)	(0.004)	(0.006)	(0.012)
Self Employment	-0.011	-0.005	-0.005	0.034**	0.004	-0.001	0.001	-0.017
	(0.016)	(0.007)	(0.014)	(0.014)	(0.005)	(0.005)	(0.009)	(0.016)
SNAP Participation	-0.004	0.007	-0.015	-0.001	0.001	0.002	-0.009	0.020
	(0.014)	(0.006)	(0.012)	(0.012)	(0.004)	(0.004)	(0.007)	(0.014)
WIC Eligibility	-0.012	0.001	-0.015	0.006	0.002	0.006	0.008	-0.020
	(0.016)	(0.006)	(0.013)	(0.014)	(0.004)	(0.005)	(0.008)	(0.016)
Food Security	-0.048***	0.010*	-0.002	0.010	-0.004	-0.002	0.014**	0.022*
	(0.013)	(0.005)	(0.011)	(0.010)	(0.004)	(0.004)	(0.007)	(0.013)
Home Ownership - Own	-0.006	0.016***	-0.034***	0.020*	0.000	-0.000	-0.005	0.008
	(0.013)	(0.005)	(0.011)	(0.011)	(0.004)	(0.004)	(0.007)	(0.013)
Region - Northeast & Midwest	0.016	-0.001	0.001	-0.037***	0.003	-0.002	0.004	0.018
	(0.011)	(0.005)	(0.010)	(0.010)	(0.003)	(0.003)	(0.006)	(0.011)
Rural	-0.033**	0.001	0.008	0.021*	-0.001	-0.002	0.002	0.004
	(0.013)	(0.005)	(0.011)	(0.011)	(0.004)	(0.004)	(0.007)	(0.013)
Constant	-0.194**	0.198***	0.101	-0.325***	-0.008	0.012	0.310***	0.905***
	(0.098)	(0.041)	(0.082)	(0.076)	(0.027)	(0.030)	(0.055)	(0.076)

notes: BS1-BS9 represents budget shares of food waste that originates from categories 1-9. *, **, *** represent values significantly different from 0 at 10%, 5%, and 1% level; values inside () are standard errors.

Table A.6. Food Waste Elasticity Using QU-AIDS Model with IV by Waste Level (Relative Low vs. High)

	At Home (AH)		Away from Home (AFH)	
	Expenditure	Price	Expenditure	Price
Low food waste	0.872***	-1.000***	1.382***	-1.382***
	(0.821, 0.923)	(-1.178, -0.822)	(1.225, 1.539)	(-1.796, -0.968)
High food waste	0.867***	-1.000***	1.343***	-1.344***
	(0.814, 0.920)	(-1.186, -0.814)	(1.200, 1.486)	(-1.712, -0.976)

notes: *, **, *** represent values significantly different from 0 at 10%, 5%, and 1% level; values inside () are standard errors.

Table A.7: Price Elasticity for Food Wastes by Categories Using QU-AIDS Model by Food Waste Amount (Absolute Low vs. High)

	Low Food Waste		High Food Waste	
	Expenditure	Price	Expenditure	Price
FV	1.670***	-1.100***	1.442***	-0.944***
	(1.394, 1.946)	(-1.206, -0.994)[1]	(1.352, 1.532)	(-0.995, -0.893)
Potato	0.562***	-0.734***	0.086	-0.471***
	(0.433, 0.691)	(-0.861, -0.607)	(-0.478, 0.650)	(-0.767, -0.175)
Grain	1.114***	-0.976***	1.119***	-0.979***
	(0.951, 1.277)	(-1.066, -0.886)	(0.982, 1.256)	(-1.055, -0.903)
Protein	0.931***	-3.554***	-0.081	-3.653***
	(0.721, 1.141)	(-4.691, -2.417)	(-0.914, 0.752)	(-5.474, -1.832)
Dairy Product	1.572***	-1.609***	1.410***	-1.351***
	(0.584, 2.560)	(-2.383, -0.835)	(1.018, 1.802)	(-1.676, -1.026)
Condiment	1.026***	-1.048***	1.028***	-1.045***
	(0.679, 1.373)	(-1.242, -0.854)	(0.673, 1.383)	(-1.229, -0.861)
Snack	0.755***	-1.038***	0.670***	-1.053***
	(0.643, 0.867)	(-1.124, -0.952)	(0.429, 0.911)	(-1.173, -0.933)
Milk & Other	0.675***	-1.015***	0.481***	-1.018***
Beverage	(0.614, 0.736)	(-1.091, -0.939)	(0.307, 0.655)	(-1.147, -0.889)

Notes: The low-waste group and the high-waste group are separated by using the median household total food waste amount. The high-waste group includes households with a waste percentage greater than the median waste amount, and the low-waste group includes other households. Values inside the parenthesis are asymptotic Taylor approximation 95% confidence intervals. [1]statistically different than -1 at 10% significance level.

Table A.8: Food Waste Elasticity for Categories Using QU-AIDS Model by Food Waste Amount (Relative Low vs. High)

	Low Food Waste		**High Food Waste**	
	Expenditure	**Price**	**Expenditure**	**Price**
FV	1.564***	-1.020***	1.502***	-0.984***
	(1.396, 1.738)	(-1.098, -0.942)	(1.369, 1.635)	(-1.049, -0.919)
Potato	0.452***	-0.674***	0.345**	-0.614***
	(0.240, 0.664)	(-0.829, -0.519)	(0.061, 0.629)	(-0.804, -0.424)
Grain	1.115***	-0.978***	1.119***	-0.977***
	(0.964, 1.266)	(-1.062, -0.894)	(0.968, 1.270)	(-1.059, -0.895)
Protein	0.704***	-3.302***	0.482***	-3.463***
	(0.471, 0.937)	(-4.317, -2.287)	(0.133, 0.831)	(-4.749, -2.177)
Dairy	1.413***	-1.403***	1.559***	-1.517***
Products	(0.890, 1.936)	(-1.807, -0.999)	(0.855, 2.263)	(-2.058, -0.976)
Condiment	1.026***	-1.045***	1.028***	-1.048***
	(0.687, 1.365)	(-1.227, -0.863)	(0.663, 1.393)	(-1.242, -0.854)
Snack	0.726***	-1.044***	0.710***	-1.045***
	(0.575, 0.877)	(-1.142, -0.946)	(0.538, 0.882)	(-1.149, -0.941)
Milk & Other	0.609***	-1.023***	0.593***	-1.009***
Beverages	(0.519, 0.699)	(-1.117, -0.929)	(0.489, 0.697)	(-1.109, -0.909)

Notes: The low-waste group and the high-waste group are separated by using the median household food waste percentage. The high-waste group includes households with a waste percentage greater than the median waste percentage, and the low-waste group includes other households. Values inside the parenthesis are asymptotic Taylor approximation 95% confidence intervals.