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, causing enormous economic losses and environmental damage. To effectively reduce food waste, it is important to understand how key drivers of household food demand including price and expenditures shape the amount of food that is wasted. This paper breaks new ground by offering precise 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. Through the application of the Quadratic Almost Ideal Demand System (QU-AIDS) model, I find compelling insights: at-home food waste exhibits expenditure inelasticity, while away-from-home food waste mirrors this pattern. Furthermore, at-home food waste demonstrates unitary price elasticity, contrasting with the price-elastic nature of away-from-home food waste. Upon exploring waste patterns across eight food categories, I find a prevailing trend of unitary expenditure and price elasticity across most categories, except for grain, protein, and beverage waste. Moreover, I investigate elasticity disparities among households based on various characteristics by leveraging the QU-AIDS model, including enrollment in critical nutrition programs. This nuanced examination of waste elasticity at a granular level and its intersection with household diversity offers valuable insights into forecasting food waste quantities and sheds light on how nutrition policies can influence waste generation. Ultimately, this approach fosters a more comprehensive evaluation of such policies, guiding efforts towards mitigating food waste and fostering sustainable consumption practices.

Key Words: Food waste, demand systems, price elasticity, expenditure elasticity
JEL codes: D12, Q53

Introduction

Food waste occurs within households when edible food items go unconsumed. In the United States, 30% to 40% of food is wasted with about half of the waste occurring at the household level (Buzby et al., 2014; ReFED, 2023). In 2010 alone, the United States wasted 133 billion pounds of food at the retail and consumption levels, equating to over 1249 calories per capita per day, and equavalent to more than $160 billion based on retail prices (Buzby et al., 2014). Despite the substantial waste, many individuals in the US continue to experience food insecurity issues (Coleman-Jensen et al., 2020; Gundersen, 2013; Xu et al., 2024). Addressing food waste at the household level is crucial not only for reducing waste but also for mitigating greenhouse gas emissions, as 96% of household food waste ends up in landfills, combustion facilities, or sewer systems, contributing significantly to methane emissions (EPA, 2023). In response to these challenges, the United States has set a national goal to reduce food loss and waste by 50% (USDA, 2015), prompting successive administrations to develop federal initiatives to support this objective (EPA, 2018; USDA, 2023). Despite widespread acknowledgment of the issue, many individuals are unaware of the extent of their food waste practices. For instance, research by Qi and Roe (2016) reveals that while a majority of households feel guilty about food waste, over 80% believe they waste less than other households. To effectively guide efforts to reduce household food waste, it is important to understand how food prices impact waste creation through adjustments in household budgeting processes. Price and expenditure elasticities for household food waste serve as fundamental expressions of consumer behavior, offering invaluable insights into strategies for reducing food waste.

The purpose of this paper is to estimate the household expenditure and price elasticities for food waste using recent US data. Expenditure and price elasticities for food waste measure the changes in the amount of food wasted as food expenditures and prices change. Calculating food waste elasticity holds immense significance in addressing the multifaceted challenge of food waste. By quantifying how changes in key factors such as price and expenditures affect the amount of food wasted, policymakers, researchers, and practitioners gain crucial insights into the underlying dynamics of food waste generation. Understanding waste elasticity allows for the identification of critical leverage points where interventions can be most effective in curbing waste. Moreover, it enables the development of targeted strategies to promote more sustainable consumption patterns, optimize resource allocation, and reduce the environmental, economic, and social impacts associated with food waste. Additionally, assessing food waste elasticity facilitates the evaluation of the effectiveness of various policies and initiatives aimed at mitigating waste, guiding evidence-based decision-making and fostering collaboration across sectors to build more resilient and equitable food systems that minimizes waste and maximizes societal benefit.

Estimating waste elasticities presents inherent challenges, particularly due to the difficulties of capturing and measuring food waste at the household level (Roe, 2021; Yu and Jaenicke, 2020; Elimelech et al., 2018; Bellemare et al., 2017) and pairing it with contemporaneous food price and expenditure data. Household food waste tracking surveys can capture food waste, and these innovative surveys are helpful and widely used to measure food waste and assess household attitudes toward food waste (Li et al., 2023; Qi and Roe, 2016; Roe et al., 2018). While useful waste tracking surveys typically fail to collect the contemporaneous food price and expenditure data needed to estimate waste elasticities. Hence, methods that can harness available data sources to yield waste elasticities enable analyses fundamental to understand household food waste dynamics. In this paper, I detail one example of such a method and discuss a more general approach to using more widely available food demand elasticity estimates to derive meaningful food waste elasticities.

In this study, the Quadratic Almost Ideal Demand System (QU-AIDS) model (Banks et al., 1997; Lecocq and Robin, 2015) is employed to investigate expenditure and price elasticities for food waste. The QU-AIDS model utilized in this research establishes a relationship between food prices, total expenditures on wasted food items, and the share of the household budget allocated to wasted foods across distinct categories. These categories include foods purchased for at-home preparation (FAH) and those prepared away from home (FAFH), as well as eight functional food categories (e.g., produce, proteins, beverages, etc.). Analyzing waste elasticities by category is critical due to the existence of policies and programs aimed at regulating federal nutrition funds, such as the Supplemental Nutrition Assistance Program (SNAP), which may restrict the purchase of certain types of foods for home preparation, as well as initiatives to subsidize the prices of healthy and nutritious foods like produce (Mozzaffrian et al., 2022; Niebylski et al., 2015). Additionally, different food types have varying environmental impacts, emphasizing the importance of category-specific waste elasticity assessments. By solely relying on an overall elasticity result, there is a risk of inaccurate predictions regarding the impact of interventions on waste generation in specific categories, potentially hindering the evaluation of policy effectiveness. The models are estimated using data from the 2012 National Household Food Acquisition and Purchase Survey (FoodAPS), which provides detailed food price and quantity data at the household level, along with household-wide food waste estimates derived from Yu and Jaenicke (2020). To generate categorical food waste estimates required for the QU-AIDS model, I develop categorical food waste share estimates based on data collected by Li et al. (2023). Moreover, I leverage the translating approach proposed by Pollack and Wales (1981) to model the intercepts of budget shares as a function of key demographic variables, allowing for an exploration of elasticity heterogeneity across household characteristics.

Several prior studies computed household food waste elasticity. Landry and Smith (2019) estimated price and expenditure elasticities for at-home food waste using data from the 1977-78 Nationwide Food Consumption Survey (NFCS). Their methodology employed a Working-Leser model, assuming a linear relationship between the budget share of waste and food prices and expenditures, under the presumption of constant returns to scale in household meal production (Landry and Smith, 2019). However, their analysis did not extend to estimating elasticity for away-from-home food waste or waste at the functional food category level, and it did not account for changes in U.S. household food habits over the intervening four decades since the data was collected. In a separate study, Vargas-Lopez et al. (2022) calculated expenditure and price elasticity for Mexican household food waste at the functional category level. They utilized the QU-AIDS model and computed elasticity metrics before and during the COVID period. However, their study relied on a small, convenience sample of households that retrospectively self-reported food expenditures and waste levels, and they used regional governmental statistics for price information. Moreover, the authors lacked data on food consumed away from home and did not investigate the influence of household characteristics on the resulting elasticity estimates. 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. Yu and Jaenicke (2020) calculated the calories acquired from detailed food acquisition records and then deducted food consumption, estimated using a biological model of calorie needs calibrated with known household member characteristics (e.g., age, gender). While Yu and Jaenicke (2020) examined how individual characteristics correlated with the overall level of food waste generated by a household, they did not estimate waste elasticities, nor could they explore waste discrepancies across food categories.

The analysis in this study reveals notable differences in household food waste elasticities. Specifically, I find that expenditure elasticity for at-home food waste is expenditure-inelastic, while away-from-home food waste is expenditure-elastic. Own-price elasticities for at-home food waste do not significantly deviate from unitary, whereas they are statistically elastic for away-from-home food waste. Importantly, households exhibit varying waste elasticities based on their characteristics, with SNAP participants showing greater price elasticity for away-from-home waste compared to nonparticipants. Moreover, disparities in waste elasticities are observed across food groups. Households exhibit unitary expenditure elasticity for the waste of several food categories, including fruits and vegetables (FV), potatoes, dairy products, condiments, and snacks. However, waste of grain is expenditure-elastic, while waste of protein and beverages is expenditure-inelastic. Most food categories also display unitary price elasticity, except for beverage waste. The system estimation approach also allows for the calculation of cross-price elasticities, revealing that at-home and away-from-home food waste are substitutes at a 90% confidence level. However, no waste substitutes or complements are found at the category level. The explorations on heterogenous effects highlight several household characteristics significant in estimating the model, while also revealing crucial null effects. For instance, households participating in SNAP exhibit similar price and expenditure elasticities for FVs as other households, underscoring the importance of assessing how subsidies affect FV waste rates among SNAP households, particularly given the evaluation of price subsidies for FV purchases (Durward et al., 2019).

This study contributes to the exisitng literature on household food waste in several ways. Firstly, it pioneers the exploration of household food waste elasticity using more current US data, offering insights not only into the expenditure and price elasticities for at-home food waste, as previously examined by Landry and Smith (2019), but also into household expenditure and price elasticities for away-from-home food waste and waste by functional categories. While others have used a demand system approach for assessing food waste elasticities (Vargas-Lopez et al. 2022), I am the first to provide a conceptual framing of a demand system that is theoretically cogent by assuming that households engage in a multi-stage budgeting process in which waste arises from food bought in excess of strict caloric needs to provide a buffer stock of food that facilitates the household meal production process. By employing the same demand system approach to generate elasticities for both food consumption and food waste, this study enables a comparison of the differences between waste and consumption responses within a unified econometric framework. Additionally, the study explores the heterogeneity of expenditure and price elasticities across various household characteristics and the scale of total waste generated, and offers a method to project the amount of food waste using readily available food price or purchase data associated with waste elasticities. It 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 utilizing the estimates to explore price elasticity for subgroups, such as SNAP participants versus nonparticipants, this study contributes to assessments of how different policies may impact food waste. Overall, these insights provide valuable guidance to policymakers seeking to reduce food waste by crafting more targeted and effective policies tailored to specific household dynamics and consumption patterns.

The rest of the paper is organized as follows. The first section below presents the data and summary statistics that anchor the analysis. Then the next section presents the theoretical model used to generate specific hypotheses, and then the empirical models and econometric methods are detailed. The next section 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 two brief case studies applying the elasticity estimates. The final section discusses the results and concludes.

Data

This paper relies upon two primary data sources. The first is the USDA's National Household Food Acquisition and Purchase Survey (FoodAPS) data, renowned for its national representativeness and comprehensive insights into household characteristics, food purchases, and various forms of food acquisition. While the FoodAPS data itself does not include specific information on food waste, Yu and Jaenicke (2020) creatively leverage FoodAPS data to estimate the percentage of food waste at the individual household level. Their innovative approach treats household food consumption as a production process, transforming food into the energy required for daily living based on household members' ages, weights, and BMI. Food waste is then estimated by computing the disparity between predicted household caloric needs and the total calories acquired. Their findings indicate an average food waste percentage of 31.9%. Leveraging this estimated food waste percentage, this paper exploit variations in food prices and expenditures to investigate waste elasticities pertaining to both at-home and away-from-home settings.

The FoodAPS data was collected from 4826 households spaning the period from April 2012 to January 2013. This rich dataset encompasses a wide array of information crucial for our analysis, including: 1) detailed records of quantities and expenditures for both at-home and away-from-home food purchases and acquisitions over the preceding seven days; 2) household eating occasions; 3) comprehensive demographic characteristics, encompassing individual attributes such as gender, age, and BMI, alongside broader household characteristics like income levels; 4) household food purchasing behaviors, including whether shopping occurs with or without a pre-established grocery list. In the appendix, I provide a comprehensive overview of the rigorous data cleaning and integration processes undertaken, outlining how the FoodAPS data is merged with the food waste percentage data sourced from Yu and Jaenicke (2020). This approach results in a robust dataset comprising 3,192 observations detailing the percentage of total food waste at the household level.

The food waste percentage derived from the study by Yu and Jaenicke (2020) provides an overarching view of household food waste, without exploring subcategories such as food prepared at home (FAH) versus away-from-home (FAFH), or waste by specific food categories.

To address this issue, I adopt two distinct approaches to construct food waste amounts for these categories. In the first approach, waste for FAH and FAFH is allocated by assuming an equal fraction of waste for both. Conversely, the second approach allocates food waste (regardless of FAH vs. FAFH) into eight distinct food type categories, a method elaborated upon later in the analysis. The final dataset comprises 3,192 households. As a result, the number of observations utilized to estimate expenditure and price elasticities for FAH and FAFH food waste amounts to 3,063 after the removal of price outliers beyond the 1st and 99th percentiles. Despite the exclusion of certain observations, the characteristics of the final sample closely mirror those of the original dataset, as depicted in Table A.2.

To categorize wasted food based on its type, I utilize data from a national household food waste tracking survey to estimate the proportion of wasted food originating from each category. This novel 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). Detailed survey procedures are outlined in the appendix. While some studies suggest that self-administered surveys may underestimate actual food waste amounts, they remain valuable for tracking changes and variations in waste levels over time. 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 A.3 for detailed summary statistics), and food waste for 24 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[1]. 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) condi-

[1]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.

ments, 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 46.3% of total food waste, followed by grains, which is 20.5% 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 46.3%. See Table 1 for summary statistics concerning the share of total food waste attributable to the original and the consolidated food categories from the tracking survey.

Table 1. 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 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 for the FAH and FAFH categories is shown in Figures 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 2. 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 2 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.

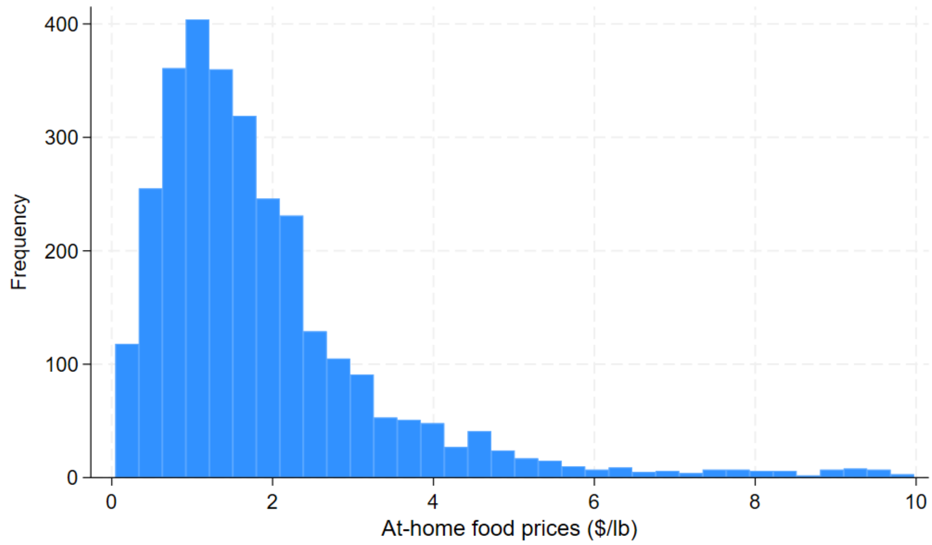


Figure 2. The Distribution of FAH Prices[1]

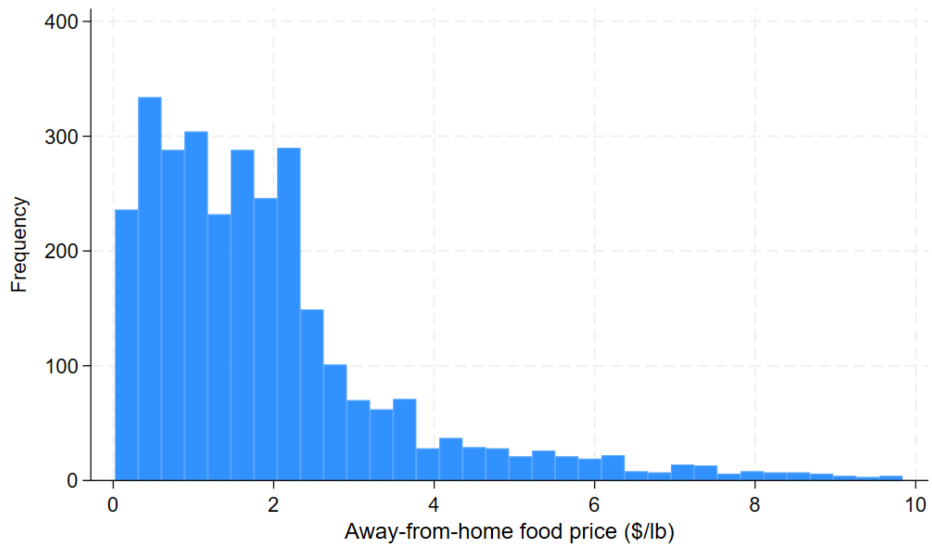


Figure 3. The Distribution of FAFH Prices[2]

[1]2989 observations with the median at 1.50 ($/lb); 74 observations (2.42% of total observations) are larger and not displayed to match the horizontal axis of FAFH prices;

[2]2989 observations with the median at 1.58 ($/lb)

Table 2. Summary Statistics for Categorical Price and Expenditure Variables

Variable	Mean	SD	Min	Max	Observations
Panel A					
FAH Price ($/lb)	2.11	2.25	0.04	22.13	3063
FAFH Price ($/lb)	2.00	1.83	0.02	13.39	3063
FAH Waste Expenditure Share	0.72	0.25	0	1	3063
FAFH Waste Expenditure Share	0.28	0.25	0	1	3063
Total Expenditure on Wasted Food ($)	26.20	27.74	0.08	340.02	3063
Panel B					
FV Price ($/lb)	3.22	3.13	0.04	45.81	3123
Potato Price ($/lb)	3.54	2.15	0.10	26.58	3123
Grain Price ($/lb)	3.73	4.54	0.03	78.88	3123
Protein Price ($/lb)	10.64	11.59	0.14	161.56	3123
Dairy Product Price ($/lb)	10.34	8.54	0.23	81.92	3123
Condiment Price ($/lb)	7.08	11.27	0.07	197.10	3123
Snack Price ($/lb)	6.00	5.56	0.08	103.32	3123
Milk & Beverage Price ($/lb)	0.77	0.72	0.00	8.81	3123
FV Waste Expenditure Share	0.24	0.28	0	1	3123
Potato Waste Expenditure Share	0.03	0.11	0	1	3123
Grain Waste Expenditure Share	0.27	0.28	0	1	3123
Protein Waste Expenditure Share	0.26	0.28	0	1	3123
Dairy Product Waste Expenditure Share	0.02	0.07	0	1	3123
Condiment Waste Expenditure Share	0.02	0.07	0	1	3123
Snack Waste Expenditure Share	0.03	0.11	0	1	3123
Milk & Beverage Waste Expenditure Share	0.12	0.26	0	1	3123
Total Expenditure on Wasted Food ($)	26.31	27.79	0.08	340.02	3123

Notes: Author calculations based upon the FoodAPS data sample.

Theory and Methods

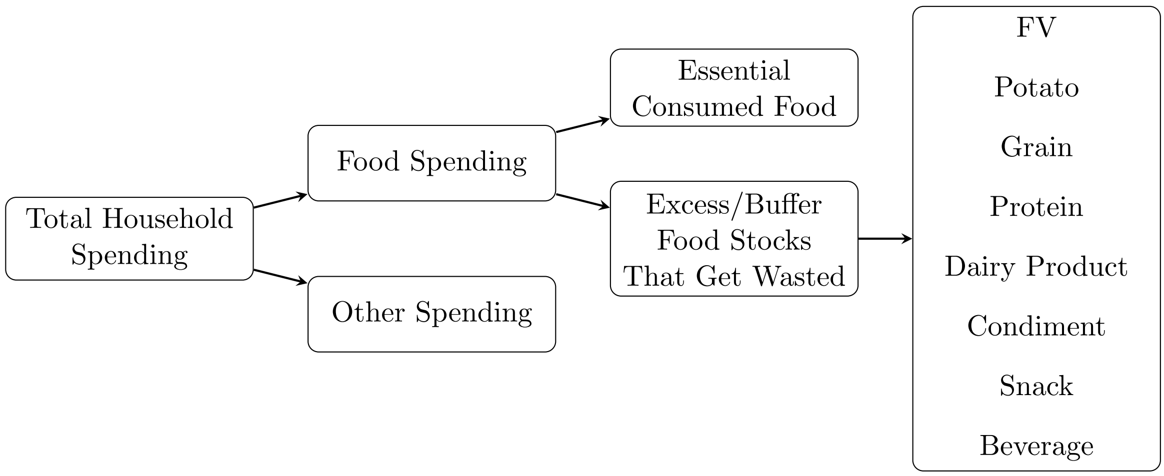
Previous studies has established frameworks to examine the economic drivers behind household food waste, primarily within the context of household production theory (Hamilton and Richards, 2019; Katare et al., 2017; Lusk and Ellison, 2017). These studies have identified factors such as food prices, policies, and various household characteristics as influential determinants of food waste. Specifically, food waste has been hypothesized to be influenced by food policies designed to impact food prices, with the amount of waste linked to household price elasticity of demand for food (Hamilton and Richards, 2019). Households are assumed to maximize their utility within budget constraints, deriving utility from food consumption (Lusk and Ellison, 2017). Katare et al. (2017) established a theoretical framework for household food waste to determine a socially-optimal food waste tax, treating food waste as an optimization problem within household decision-making processes.

Several empirical studies have employed models to investigate the determinants of food waste and household responsiveness to food prices and expenditures (Yu and Jaenicke, 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, this paper utilizes the QU-AIDS model along with demographic variables to assess the responsiveness of food waste to food prices and household food expenditures, providing insights that can inform pertinent government policies aimed at reducing 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:

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

$$\boldsymbol{\alpha} = \boldsymbol{A}\boldsymbol{s} \tag{3a}$$

$$\boldsymbol{A} = \boldsymbol{\alpha}'_i \tag{3b}$$

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 with key restrictions that are imposed upon these parameters during estimation detailed in the appendix.

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(4). 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).

$$w_i = \frac{E_{fw,\,i}}{E_{fw,\,total}} = \frac{Q_{fw,\,i} * p_i}{Q_{fw,\,total} * p_{total}} \tag{4a}$$

$$p_{total} = \frac{E_{total}}{Q_{total}} \tag{4b}$$

$$w_i = \frac{Q_{fw,i} * p_i}{Q_{fw,\,total} * \frac{E_{total}}{Q_{total}}} = QS_{fw,\,i} * \frac{p_i}{\frac{E_{total}}{Q_{total}}} \tag{4c}$$

Where $E_{fw,i}$ is the expenditure on food from category i that is wasted, $E_{fw,total}$ is the amount spent on total 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(4b) into Eq(4a), and get Eq(4c). In Eq(4c), $QS_{fw,i}$ 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.

$$QS_{fw,i} = \frac{Q_{fw,i}}{Q_{fw,total}} \tag{4d}$$

Where $Q_{fw,i}$ is the quantity of food waste for category i, and $Q_{fw,total}$ is the total gram weight of food waste. Then I use Eq(5d) to calculate the $QS_{fw,i}$.

However, the share $QS_{fw,i}$ may not be the same for all households. For example, households with more members might have less waste of fruits and vegetables. Thus, I use cluster analysis to separate households in the food waste tracking survey data into six[2] clusters based on eight household characteristics variables: gender, race, ethnicity, education, household size, region, employment, and household income. Then I use multinomial logit regressions to get the marginal effect of each household's characteristic variable. Based on these marginal effects, I separate households in the FoodAPS data into six clusters. The waste share of each food category in each cluster within the FoodAPS data is assigned to equal the shares for the same cluster within the Food Waste Tracking Survey data.

[2]The number of clusters is determined by the Pseudo F Index (Calinski and Harabasz, 1974). The pseudo-F statistic is commonly used to determine the number of clusters since it describes the ratio of between-cluster variance to within-cluster variance. Each cluster has a waste share of each food category.

The function "aidsills"[3] 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 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. I use the asymptotic Taylor series approximations of elasticity standard errors to get the confidence interval of the elasticity (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 as it is calculated as expenditure divided by quantity, and 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

[3] 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-series approximation standard errors.

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 greater 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. 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.

Results

The AIDS Model for FAH and FAFH Waste

The expenditure and price elasticities for at-home and away-from-home food waste, derived from the QU-AIDS model, are presented in Table 3. These elasticities are estimated under the assumption that the rates of at-home and away-from-home food waste are identical to the overall household-level food waste rate calculated by Yu and Jaenicke (2020). The table also includes the asymptotic Taylor-series approximation 95% confidence intervals. The expenditure elasticities indicate that at-home food waste is expenditure-inelastic, as evidenced by the upper bound of the confidence interval being less than 1, the unit elasticity threshold. In contrast, away-from-home food waste is expenditure-elastic. This implies that food waste increases with higher expenditures on surplus or buffer foods, yet the change in waste quantity does not perfectly align with the change in household expenditure on surplus food. Specifically, a 10% increase in expenditure results in a 9.5% rise in at-home food waste and an 11.5% increase in away-from-home food waste. Moreover, the expenditure elasticity for away-from-home food waste is statistically greater than that for at-home food waste, as evidenced by the 95% confidence interval for away-from-home expenditure elasticity surpassing that for at-home expenditure elasticity.

Table 3. Elasticities for Food Waste with 95% Asymptotic Taylor Approximation Confidence Intervals

	Expenditure	FAH Price	FAFH Price
FAH Waste	0.95***	-1.16***	0.21**
	(0.92, 0.97)	(-1.35, -0.97)	(0.04, 0.38)
FAFH Waste	1.15***	0.46*	-1.61***
	(1.07, 1.24)	(-0.09, 1.00)	(-2.10, -1.13)

Notes: the estimation is based on 3057 households, with demographics contained in the analysis. R^2 is 0.16. *, **, *** 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 stands at -1.16, with a 95% confidence interval ranging from -1.35 to -0.97. This suggests that at-home food waste exhibits unitary responsiveness to fluctuations in the price of at-home foods. The finding of unit price elasticity indicates that changes in waste quantity are directly proportional to alterations in price. Conversely, the price elasticity for away-from-home food waste surpasses unit elasticity in statistical significance. Moreover, the standard error associated with away-from-home waste elasticities exceeds that of at-home elasticities. The relative lack of precision in away-from-home food waste elasticities may arise from data challenges inherent in away-from-home settings, particularly considering established difficulties in accurately quantifying FAFH within the FoodAPS dataset (refer to Yu and Jaenicke, 2020). Cross-price elasticities exhibit statistical significance different from zero, indicating that changes in at-home (or away-from-home) food waste will correspond to increases in FAFH (or FAH) prices.

Food waste elasticities are computed under the assumption that at-home and away-from-home food waste rates align with the overall food waste rate determined by Yu and Jaenicke (2020). Given the absence of empirical evidence regarding the relative rates of at-home and away-from-home waste, I present estimates across various relative waste rate scenarios in Table A.8 to assess the robustness of these key findings to this pivotal assumption. Table A.8 shows that elasticities demonstrate minimal variation across a wide spectrum of ratios between at-home and away-from-home food waste rates. Regardless of the relative rates of at-home and away-from-home waste, at-home food waste maintains its status as expenditure-inelastic and unit-price-elastic. Similarly, away-from-home food waste retains its attributes of being expenditure-elastic and price-elastic despite changes in the relative rates.

The elasticity results yield several implications. As households spend more on food intended as a buffer for food production, it is unsurprising 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. The percentage change of food waste in response to the change in food expenditure remains consistent across various settings. These findings align partially with those of Landry and Smith (2019), who observed unit-elastic expenditure and price responses for at-home food waste using data from the 1970s. However, there are several factors that may account for differences in elasticities. First, Landry and Smith (2019) solely examined food waste at home, whereas our analysis considers a broader waste system encompassing both at-home and away-from-home sources. Additionally, our estimation approach differs from that of Landry and Smith, potentially yielding disparate 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 enhanced capabilities to efficiently store purchased food and leftovers, thereby potentially mitigating food waste (Hebrok and Boks, 2017).

The AIDS Model for Waste in Eight Food Categories

The QU-AIDS model is also used to estimate the expenditure and price elasticity for food waste across eight distinct food categories. However, the FoodAPS dataset lacks specific waste quantities for each food category. Consequently, cluster analysis leveraging data from the Food Waste Tracking Survey is utilized to estimate categorical waste within the FoodAPS dataset. Under the assumption that the waste share $QS_{fw,i}$ might vary across households, households are segmented into six clusters based on their characteristics. Table 4 delineates the waste share for each food category across the six clusters, drawing from the Food Waste Tracking Survey data. Each cluster comprises households with diverse characteristics, thus exhibiting varying waste shares for each food category. For instance, households in Cluster 1 exhibit the highest average condiment waste share relative to total household food waste among the six clusters, while those in Cluster 2 display the highest average protein waste share. Additionally, households in the FoodAPS dataset are segmented into six clusters based on the marginal effects of household characteristics, as depicted in Table A.13. The distribution of households across these clusters is detailed in Table A.15, with the majority falling into clusters 2, 3, and 4. Then the waste shares $QS_{fw,i}$ for food categories in six clusters are utilized to derive budget share w_i (see Eq 5c).

Table 4. Average Waste Share in Each Cluster (Food Waste Tracking Survey Data)

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
FV	44.59%	44.95%	51.12%	42.74%	53.36%	46.65%
Potato	8.58%	9.04%	8.10%	7.43%	3.54%	9.12%
Grain	21.74%	22.14%	15.90%	24.32%	16.81%	19.59%
Protein	8.27%	9.53%	7.19%	8.54%	8.96%	8.55%
Dairy Product	4.71%	3.56%	6.11%	5.75%	5.43%	5.02%
Condiment	4.21%	2.49%	3.12%	3.01%	3.48%	3.25%
Snack	1.69%	1.09%	1.00%	1.02%	2.23%	1.06%
Milk & Other Beverages	6.20%	7.20%	7.47%	7.18%	6.19%	6.75%
Observations	1231	377	393	436	295	856

Table 5 presents waste elasticities for eight food categories along with asymptotic Taylor approximation 95% confidence intervals. The majority of categories exhibit unit expenditure elasticity and unit price elasticity, including fruits and vegetables (FVs), potatoes, dairy products, condiments, and snacks. When more expenditure is allocated to food items intended as a buffer and likely to be wasted, the waste in these categories increases proportionally, demonstrating unitary elasticity. Conversely, waste in protein and beverage categories increases less than proportionally, indicating inelasticity, while waste in the grain category increases more than proportionally, reflecting elasticity. These differences in expenditure elasticities may be attributed to various factors such as human nutrition needs, food perishability, and typical storage modes for each category. For instance, grains, typically foundational in nutrition pyramids advocating a balanced diet, are recommended for consumption in larger quantities due to their essential nutrient content. Consequently, as more budget is allocated to buffer foods, a greater proportion may be devoted to extra produce, driven by nutritional priorities, potentially leading to a corresponding increase in waste. Additionally, categories with expenditure inelastic waste, such as beverages, often comprise shelf-stable items.

Table 5. Elasticities for Food Wastes (8-Category Case)

	Expenditure Elasticity	**Price Elasticity**
FV	1.05***	-1.23***
	(0.93, 1.16)	(-1.52, -0.95)
Potato	0.87***	-0.87***
	(0.52, 1.22)	(-1.44, -0.29)
Grain	1.20***	-1.25***
	(1.09, 1.31)	(-1.67, -0.83)
Protein	0.83***	-0.77***
	(0.73, 0.93)	(-1.28, -0.25)
Dairy Product	1.17***	-0.82***
	(0.67, 1.66)	(-1.17, -0.46)
Condiment	1.11***	-0.82***
	(0.78, 1.44)	(-1.20, -0.45)
Snack	1.08***	-1.90***
	(0.71, 1.45)	(-2.86, -0.94)
Milk & Other Beverage	0.71***	-0.60
	(0.45, 0.96)	(-2.39, 1.19)

Notes: numbers inside the parentheses 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 allocation of the budget across various buffer foods adjusts in response to price fluctuations. Own-price elasticities for the waste of all food groups except beverages are generally unitary. These price elasticities for waste align closely with those of food groups overall, as detailed in Table A.17, with a few notable exceptions. For instance, the waste of fruits and vegetables (FV) is unit expenditure-elastic, evidenced by a 95% confidence interval containing 1, whereas FV consumption is expenditure-elastic, with a 95% confidence interval ranging from 1.18 to 1.64. Moreover, protein consumption exhibits expenditure elasticity, while protein waste demonstrates expenditure inelasticity. This may suggest that a household's responsiveness to purchasing buffer stocks of key food categories in reaction to expenditure changes may align with their sensitivity to immediate consumption quantities.

Furthermore, I investigate cross-price elasticities for food waste. Cross-price elasticity measures the responsiveness in the quantity wasted of one category when the price of another category changes. Positive cross-price elasticities imply substitutability between the wasted food categories, while negative values indicate complementarity. Table 6 illustrates that the waste of commonly purchased food categories remains largely unaffected by the prices of other categories, as evidenced by the absence of statistically significant cross-price elasticities.

Table 6. Cross-Price Elasticities for Waste by Categories Using QU-AIDS Model

	Price							
	FV	**Potato**	**Grain**	**Protein**	**Dairy**	**Condiment**	**Snack**	**Milk & Other Beverages**
FV	-1.23***	0.01	0.13	-0.09	-0.01	0.03	0.06	0.07
	(0.15)	(0.09)	(0.27)	(0.30)	(0.04)	(0.07)	(0.16)	(0.43)
Potato	0.10	-0.87***	0.83	0.45	-0.11	0.01	-0.32	-0.97
	(0.45)	(0.29)	(0.84)	(0.93)	(0.14)	(0.21)	(0.49)	(1.37)
Grain	0.06	0.08	-1.25***	-0.19	0.02	0.01	0.08	-0.01
	(0.11)	(0.08)	(0.22)	(0.25)	(0.03)	(0.05)	(0.12)	(0.33)
Protein	-0.03	0.05	-0.10	-0.77***	-0.02	0.01	0.02	0.01
	(0.13)	(0.08)	(0.24)	(0.26)	(0.04)	(0.06)	(0.14)	(0.39)
Dairy Product	-0.14	-0.23	0.35	-0.46	-0.82***	-0.06	0.25	-0.05
	(0.60)	(0.40)	(1.12)	(1.24)	(0.18)	(0.28)	(0.65)	(1.82)
Condiment	0.30	0.01	0.15	-0.01	-0.04	-0.82***	-0.06	-0.64
	(0.41)	(0.27)	(0.76)	(0.84)	(0.12)	(0.19)	(0.44)	(1.24)
Snack	0.44	-0.33	0.80	0.11	0.12	-0.04	-1.90***	-0.29
	(0.45)	(0.29)	(0.84)	(0.92)	(0.13)	(0.21)	(0.49)	(1.35)
Milk &	0.24	-0.31	0.13	0.05	-0.00	-0.14	-0.08	-0.60
Other Beverages	(0.31)	(0.20)	(0.56)	(0.63)	(0.09)	(0.14)	(0.33)	(0.91)

Notes: numbers inside the parentheses are asymptotic Taylor approximation standard errors. *, **, *** represent values significantly different from 0 at 10%, 5%, and 1% level. The standard error of price elasticity for Snack waste is missing due to the singular price.

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 3), the estimated coefficients are presented in Table A.8 and the calculated impacts of the coefficient on the resulting elasticities are presented in Table 8. The intercepts of demographic variables are transformed to the percentage change in elasticities if the demographic variable goes from 0 to 1. A positive parameter estimate indicates positive effects on the budget share of food waste.

Households with larger sizes exhibit greater expenditure elasticity for away-from-home food waste but less expenditure and price elasticity for at-home food waste, compared to single-member households. This finding underscores the significance of household composition in influencing food waste behaviors, where shifts in household size, potentially disrupting food preparation and shopping routines, reverberate throughout the core food waste elasticities. Moreover, other household characteristic variables, such as gender, adherence to a grocery list, participation in SNAP, and eligibility for WIC, also yield statistically significant impacts on waste elasticities. For instance, households enrolled in SNAP display higher expenditure elasticity for at-home food waste, lower expenditure elasticity for away-from-home food waste, and higher price elasticity for both at-home and away-from-home food waste.

Table 7. Effect of Demographics on FAH and FAFH Waste Elasticities

	%Δ Expenditure Elasticity		%Δ |Price Elasticity|	
Variables	**AH**	**AFH**	**AH**	**AFH**
Household Size (base: 1)				
2	-1.16%	3.25%	-1.87%	-0.91%
3	-0.84%	1.67%	-1.45%	-2.92%
>3	-0.21%	0.26%	-1.28%	-3.04%
Female	0.11%	1.31%	-1.03%	1.95%
Always Shop with List	-0.42%	3.77%	-1.80%	4.14%
SNAP Participation	2.45%	-2.33%	0.95%	9.29%
WIC Eligibility	0.11%	-1.38%	0.09%	-3.28%

Notes: The variables shown in this table are control variables that are statistically significant in the QU-AIDS model (see Table A.8). Variables are dummy variables (except household size), and the %Δ is the percentage change in elasticities when the dummy variable goes from 0 to 1. 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 find several significant demographic coefficients (Table A.9) that are translated into the respective impacts on own-price and expenditure elasticities, detailed in Tables 8 and 9, respectively. The price elasticity for fruits and vegetables (FVs) is adversely affected by various household attributes, including female gender identification, possession of a college degree, residence in specific geographical regions, and rural residency. Certain demographic variables exhibit solely negative associations with price elasticity, such as Hispanic or Latino ethnicity, adherence to shopping lists, and residence in the Northeast or Midwest regions. Moreover, most characteristic variables yield mixed effects on price elasticities for food waste, encompassing factors like gender identification, educational attainment, marital status, employment status, participation in SNAP, and homeownership. Significant impacts are observed particularly for the waste of dairy products, snacks, and beverages. For instance, households that consistently adhere to grocery lists demonstrate lower price elasticity for dairy product waste compared to their counterparts. 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 (snacks and beverages), suggesting sensitivity to household characteristics may be related to confidence interval sizes.

Table 8. Effect of Demographics on Own-Price Elasticities by Category

	$\%\Delta$ |Price Elasticity|							
Variables	**FV**	**Potato**	**Grain**	**Protein**	**Dairy Product**	**Condiment**	**Snack**	**Beverage**
Household Size (base: 1)								
2		2.05%			28.19%			
3		4.33%			38.42%			
>3		6.38%			46.14%			
Female	-3.85%					6.65%	-25.86%	
Hispanic and Latino		-7.20%						
White					8.74%		14.65%	8.87%
College	-5.02%		1.49%					
Married		2.79%					24.60%	-36.13%
Income > PL						7.30%	27.38%	
Always Shop with List			-0.88%		-10.37%			
Employed			-2.54%		1.72%			
Self Employed				1.97%				
SNAP Participation							-5.85%	25.05%
Home Ownership - Own		1.98%	-4.32%	0.26%			26.48%	
Region - NM[1]	-2.25%			-4.25%				
Rural	1.71%							

Notes: variables shown in this table are statistically significant in the QU-AIDS model (see Table A.9). Variables are dummy variables, the $\%\Delta$ is the percentage change in elasticities when the dummy variable goes from 0 to 1. Since price elasticity is negative, the $\%\Delta$ in price elasticity is the percentage change of the absolute value of price elasticity. [1]NM represents the Northeast and Midwest regions in the US. All variables other than the focal variable within a given row are evaluated at their means.

Table 9 presents the percentage change in expenditure elasticity attributed to demographic disparities. Several demographic variables exhibit statistically negative associations with expenditure elasticity, notably gender identification as female, Hispanic or Latino ethnicity, college attendance, and residence in the Northeast or Midwest regions. Most demographic variables display mixed relationships with expenditure elasticities across various waste categories, and certain demographic variables demonstrate solely positive associations with expenditure elasticity, such as employment status and rural residency. The expenditure elasticity for waste in dairy products, snacks, and beverages is largely influenced by certain demographic variables. For instance, one of the most pronounced effects is observed in the 28.94% increase in expenditure elasticity for beverage waste among individuals identifying as white. The expenditure elasticity for fruits and vegetables (FV) waste exhibits minimal sensitivity to demographic variations, with only marginal associations with select characteristic variables. Participation in the

Supplemental Nutrition Assistance Program (SNAP) correlates with expenditure elasticity for waste in snacks and beverages. However, SNAP participation does not statistically correlate with waste elasticities across most food categories.

Table 9. Effect of Demographics on Expenditure Elasticities in Category

	%Δ |Expenditure Elasticity|							
Variables	**FV**	**Potato**	**Grain**	**Protein**	**Dairy Product**	**Condiment**	**Snack**	**Beverage**
Household Size (base: 1)								
2		4.63%			-9.49%			
3		6.33%			-14.63%			
>3		9.14%			-17.43%			
Female	-0.67%					-2.90%		-15.33%
Hispanic and Latino		-9.37%						
White					-3.41%		5.48%	28.94%
College	-0.38%							
Married				2.44%			7.34%	-8.90%
Income > PL						-3.25%	6.65%	
Always Shop with List			-1.33%		8.20%			
Employed			0.08%		-0.77%			
Self Employed			1.81%					
SNAP Participation							-3.67%	1.57%
Home Ownership - Own		6.64%	-2.63%	0.36%			8.04%	
Region - NM[1]	-0.29%			-3.45%				
Rural	0.67%							

Notes: Variables shown in this table are statistically significant in the QU-AIDS model (see Table A.9). 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 10 shows the waste elasticities by different waste scales, 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 10 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. The only exception is that expenditure elasticity for at-home food waste is statistically higher in the low-waste group, compared to the high-waste group.

Table A.10 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 10. 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	0.97***	-1.20***	1.08***	-1.68***
	(0.95, 1.00)	(-1.39, -1.01)	(1.00, 1.16)	(-2.12, -1.24)
High food waste	0.92***	-1.12***	1.21***	-1.51***
	(0.88, 0.95[1])	(-1.32, -0.91)	(1.15, 1.28)	(-1.99, -1.02)

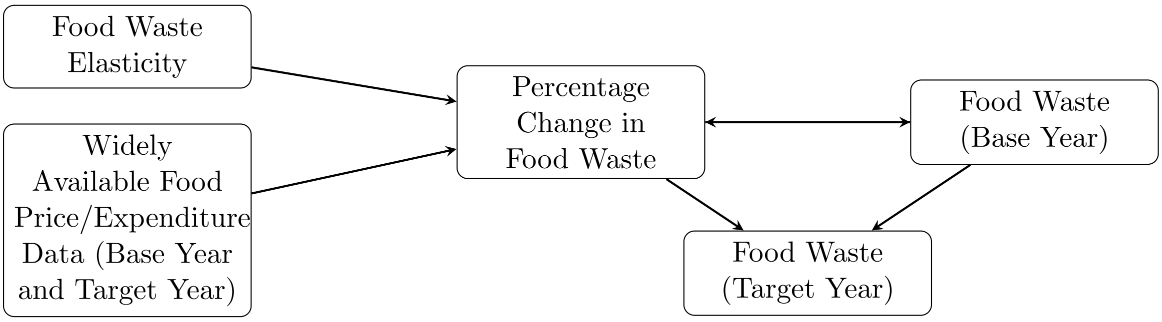
Notes: *, **, *** represent values significantly different from 0 at 10%, 5%, and 1% level; values inside parentheses are asymptotic Taylor approximation confidence intervals. [1]0.95 is rounded from 0.949, smaller than the lower bound of the expenditure elasticity for at-home food waste in the low waste group.

Households with different food waste scales might also demonstrate different elasticities for waste at the category level. In Table A.11, expenditure and price elasticities for households categorized into absolute low- and high-waste groups, distinguished by the median quantity of food waste, are listed. These elasticities are not statistically different between the groups, as per asymptotic Taylor approximation standard errors. 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.12).

Mini-Case Study I: Predicting Food Waste Using Waste Elasticity

Waste elasticity offers a predictive tool for estimating the quantity of food wasted. When coupled with readily accessible food price or expenditure data, waste elasticity enables the calculation of the percentage change in food waste. The percentage change facilitates the determination of food waste quantities in the target year (refer to Figure 5), by integrating the baseline food waste data obtained through waste tracking surveys.

Figure 5. Food Waste Projection Using Elasticity



The percentage change in the amount of waste ($\%\Delta Q$) is a function of waste elasticity (E) and the percentage change in price($\%\Delta P$), based on the elasticity formula (eq. 7a). To account for price fluctuations, the percentage change in price has been adjusted using the Consumer Price Index (CPI) and GDP deflator.

$$\%\Delta Q = E \times \%\Delta P \tag{7a}$$

$$\%\Delta P = \frac{CPI_{target}}{CPI_{base}} / \frac{\text{GDP } \textit{deflator}_{target}}{\text{GDP } \textit{deflator}_{base}} - 1 \tag{7d}$$

As an illustrative example, let's predict the amount of fruit and vegetable (FV) waste in 2022. In 2021, the CPI for fruits and vegetables in the city averaged 314.81, rising to 350.18 in 2022 (FRED Economic Data, 2024). Based on tracking survey data, the average amount of FV waste per week was 416.79 grams in 2021, with a price elasticity for FV waste estimated at -1.23. The GDP deflator is 110.19 in 2021 and 117.97 in 2022. Applying the formula, a 3.90% increase in real price corresponds to a -4.80% change in quantity. Thus, the predicted amount of FV waste in 2022 is approximately 397 grams. However, the actual average amount of FV waste reported in the tracking survey for 2022 is 466.34 grams weekly, deviating from the predicted value. Several factors may contribute to this discrepancy. Firstly, the formulated model assumes all other conditions remain constant, which may not hold true in reality. Additionally, the COVID-19 pandemic affected households during 2021 and 2022, potentially influencing food waste behaviors. For instance, the prevalence of home cooking due to COVID-19 restrictions may have reduced overall food waste during this period. While predictive models offer valuable insights, real-world complexities and external factors such as the COVID-19 pandemic underscore the importance of considering broader contextual factors when interpreting predictions and data outcomes.

Mini-Case Study II: FV Price Subsidy

A diet containing more fruits and vegetables is associated with a reduction in the 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 has been an increasing interest in providing FV price subsidies in recent years, we need to understand how an FV price subsidy for different households impacts food waste. 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, -1.23, with 95% confidence interval between -1.52 to -0.95. Thus, a 10% discount applied to the FV price would raise the FV waste by 12.3%. The price elasticity might be different for subgroups. Table 11 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 findings imply that a 10% discount on FV price will not have a statistically different effect on people with different participation statuses in SNAP. 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, living in the Northeast and Midwest vs. other regions, college vs. no college, rural vs. urban). These findings reflect that the difference in price elasticity between the two groups is not statistically significant if the effect of demographic variables shown in Table 11 is not large.

Table 11. FV Price Elasticity by Groups

	Price Elasticity	95% Confidence Interval
Female	-1.23***	(-1.50, -0.95)
Male	-1.27***	(-1.61, -0.94)
Attending College	-1.21***	(-1.46, -0.96)
Not Attending College	-1.28***	(-1.61, -0.94)
SNAP Participation	-1.27***	(-1.60, -0.94)
Non-SNAP Participation	-1.22***	(-1.49, -0.96)
Food Secure	-1.22***	(-1.49, -0.95)
Food Insecure	-1.25***	(-1.55, -0.95)
Living in Northeast or Midwest Regions	-1.22***	(-1.48, -0.95)
Living in Other Regions	-1.25***	(-1.55, -0.95)
Rural	-1.25***	(-1.55, -0.95)
Urban	-1.23***	(-1.51, -0.95)

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 the two subgroups are not statistically different, and elasticities for FV waste by combining characteristics are also not statistically different. One reason is that the effects of demographics on the price elasticity of FV waste are small. These findings might reflect that a potential FV price subsidy will not cause more FV waste.

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 waste, and expenditure-elastic for away-from-home food waste. In terms of price elasticities, the waste associated with at-home food is not statistically different than unitary, and statistically elastic for away-from-home food waste. These findings are partially consistent with those of Landry and Smith (2019), who explore at-home waste responsiveness using U.S. data from the 1970s and find behavior from this previous era to be both unitary expenditure and 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 contributes to the literature by expanding the scope of analysis to include expenditure and price elasticities for away-from-home food waste, thus enabling the examination of cross-price elasticity between at-home and away-from-home food waste.The fact that away-from-home waste is unit expenditure-elastic with a large standard error aligns with the difficulties of collecting waste data in the away-from-home setting and 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).

The categorical food waste elasticities provide insights into how different types of food respond to changes in prices and expenditures, allowing for a nuanced understanding of household waste behaviors. Policymakers can tailor interventions more effectively, targeting specific food groups where waste reduction efforts would yield the greatest impact by examining waste elasticity at the category level. This study finds waste elasticities in different food categories roughly align the storage characteristics of different food categories. For example, the waste of FVs has unitary expenditure and price elasticity. Most purchased FV products are fresh products that households might purchase the amount that is roughly enough to support the family, instead of purchasing a lot more than their need when FV price drops due to the perishability of these FV 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.

Understanding categorical food waste elasticity also helps identify potential substitutes or complements in waste behavior across different food categories, which is invaluable for designing policies aimed at reducing waste while promoting healthier and more sustainable food choices. For instance, identifying that certain food categories are waste substitutes suggests that policies targeting waste reduction in one category may inadvertently lead to increased waste in another. Policymakers can implement more holistic and effective waste reduction strategies by anticipating and addressing such dynamics. This study finds no statistically significant cross-price elasticity across categories. However, the cross-price elasticities may exist in subgroups.

This paper also sheds light on food waste reduction by exploring household characteristics as factors that impact waste shares and elasticities, and provide insights on how demographic factors influence waste behaviors within different food categories. This socio-demographic dimension is crucial for designing targeted interventions that consider the diverse needs and behaviors of various population groups. For example, understanding how waste elasticity differs between SNAP participants and nonparticipants can inform policies aimed at reducing waste among vulnerable populations. Given the increasing interest in SNAP participation and food waste, our findings that SNAP participants have smaller expenditure elasticities for away-from-home food waste and larger for at-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 that subsidizing the fruit and vegetable purchases for SNAP participants 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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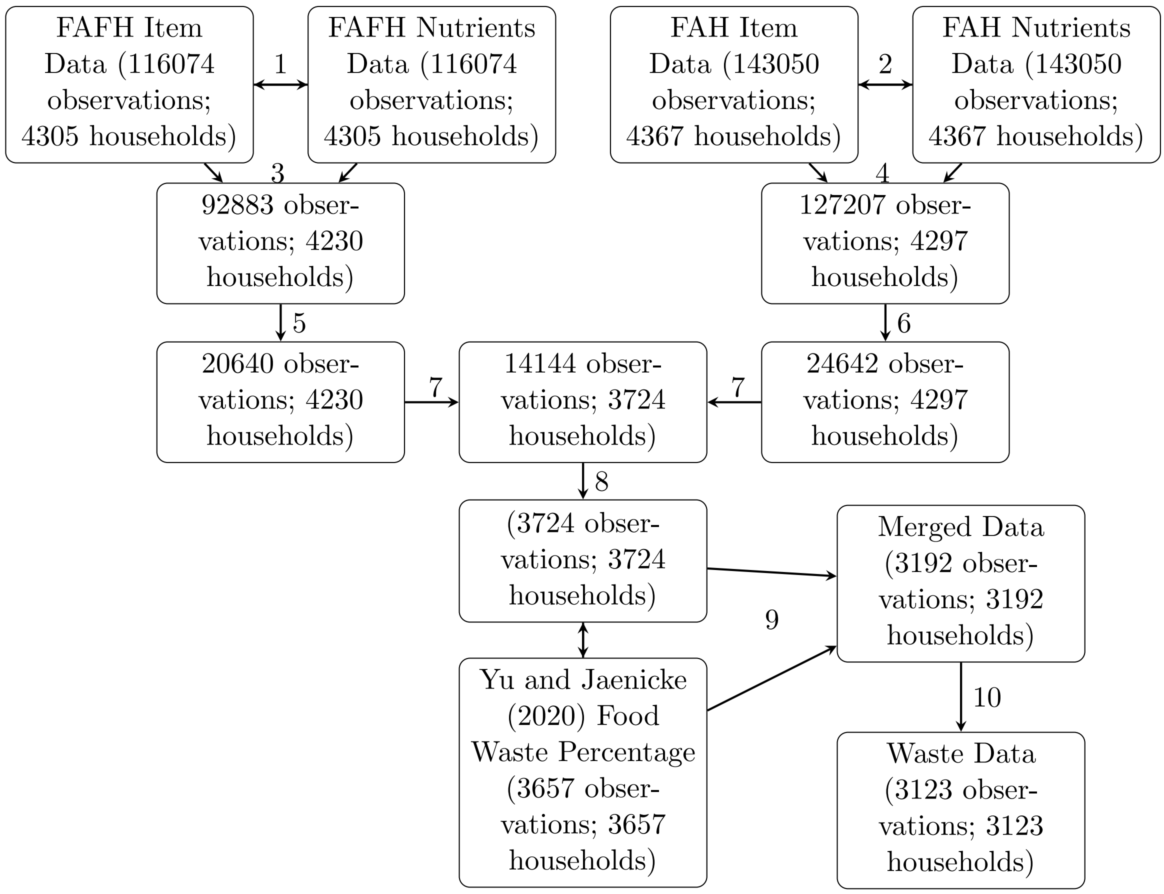
Appendix I. Figures

Figure A.1 Sample Selection Process[1]



[1]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.

Figure A.2 The Distribution of Expenditure Elasticities for Eight Categories

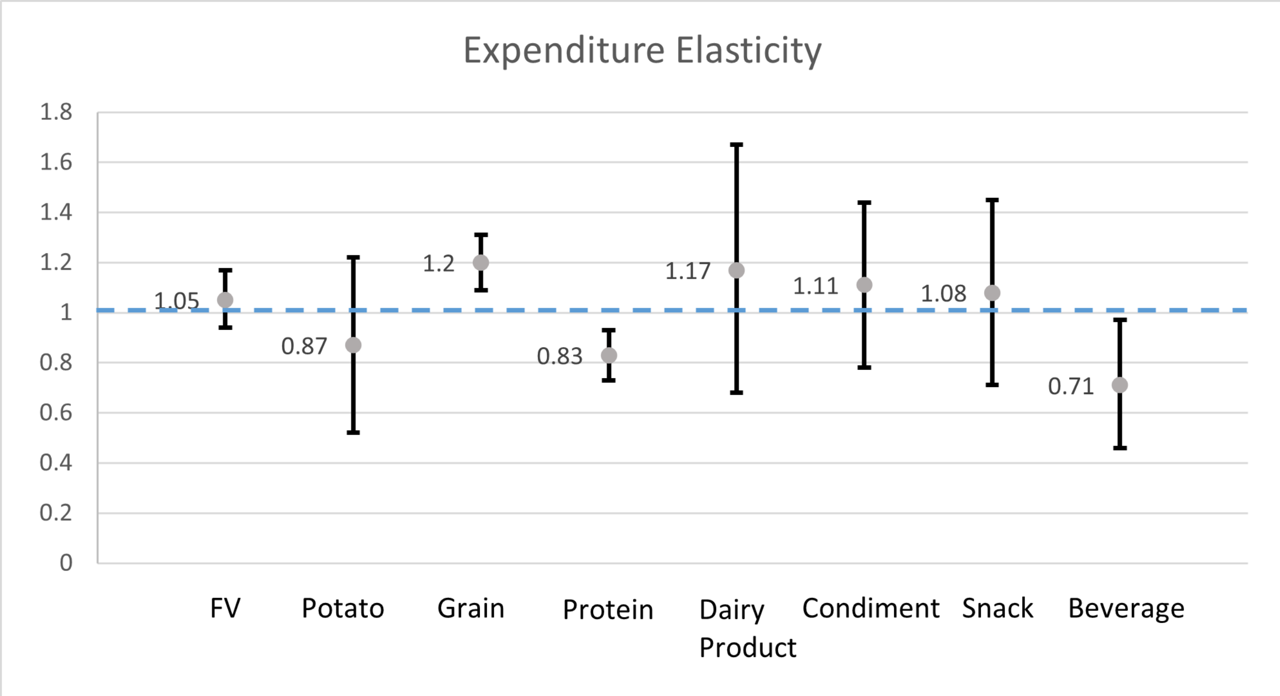
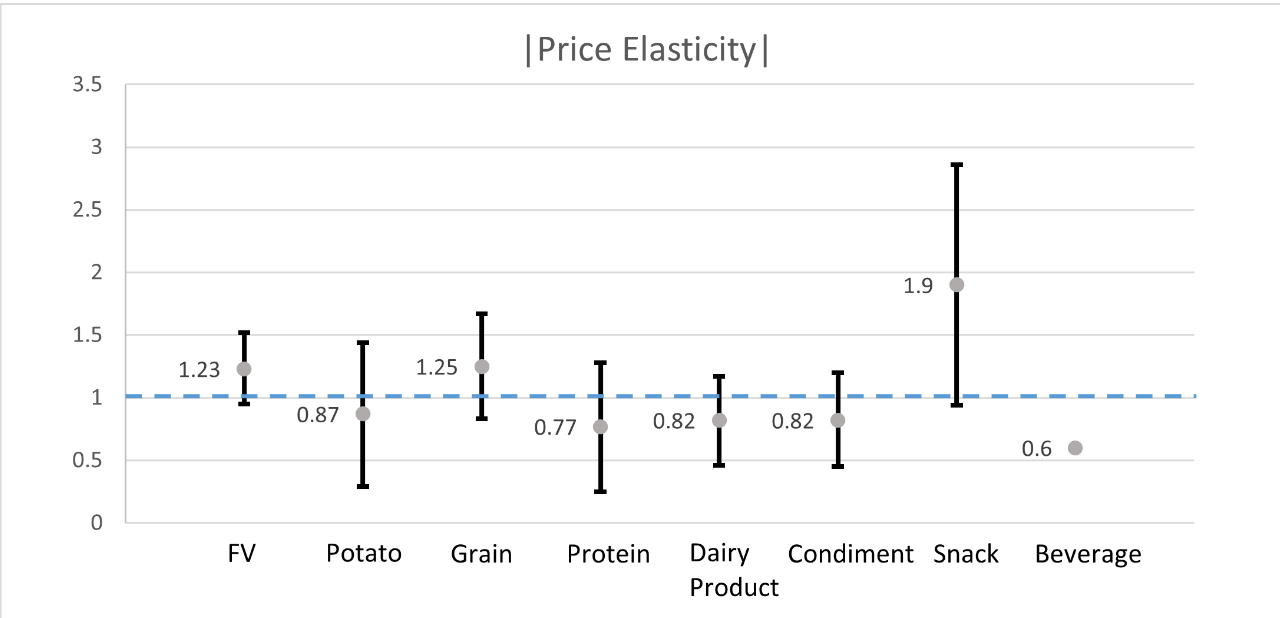


Figure A.3 The Distribution of Price Elasticities for Eight Categories



Appendix II. QU-AIDS Model Restrictions

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 indicates eighteen demographic variables.

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

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

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

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

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

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

Appendix III. Tables

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 32, mixed dishes - grain based	Grains
Rice		
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	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 Summary Statistics (FoodAPS Sample)

Variables	Mean/Proportion	SD	Min	Max	Observations
Household Size	3.16	1.67	1	14	3123
Household Size Change (Within the Last 3 Months)	0.11	0.31	0	1	3122
Household Monthly Income	4088.98	3610.65	106.20	25650	3123
Age	45.59	16.04	16.50	85	3121
Hispanic or Latino	19.73%	0.40	0	1	3122
Rural	28.56%	0.45	0	1	3123
Gender:					3123
Female	76.14%				
Male	23.86%				
Region:					3123
Northeast	16.11%				
Midwest	24.91%				
South	37.50%				
West	21.49%				
Employment Status:					3121
Work at A Job	49.41%				
Not Working at A Job	39.57%				
With A Job but Not at Work	2.82%				
Look for Work	7.37%				
Worked, but Look for A Job	0.83%				
Education:					3119
10th Grade or Less	9.43%				
11th or 12th Grade, No Diploma	5.45%				
High School Diploma	28.28%				
Some College	34.27%				
Bachelor's Degree	15.87%				
Master's Degree or Above	6.70%				
Race:					3118
White	72.96%				
Black	12.19%				
American Indian	0.90%				
Asian or Pacific Islander	3.98%				
Other	7.92%				
Multiple Race	2.05%				
Marital Status:					3118
Married	48.43%				
Widowed	5.71%				
Divorced	17.00%				
Separated	4.71%				
Never Married	24.15%				
SNAP Participation:					3122
SNAP	30.30%				
Non-SNAP, Income<100%PT	5.54%				
Non-SNAP, 100%PT<Income<185%PT	17.65%				
Non-SNAP, Income>185%PT	46.51%				
WIC Eligibility:	65.39%				3123

Table A.3 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	56.9%				
Male	42.4%				
Race:					4364
White	77.5%				
Black	8.7%				
Asian	7.4%				
Other	6.5%				
Household Income:					4365
<50k	39.8%				
50-99k	34.5%				
>100k	25.7%				
Age:					4365
18-44	45.1%				
45-64	30.0%				
65 or Older	24.8%				
Employment Status:					4363
Full Time	44.6%				
Part Time	13.9%				
Retired	24.4%				
Student	3.0%				
Unable to Work	2.9%				
Unemployed	11.2%				
Region:					4365
Northeast	21.9%				
Midwest	23.3%				
South	30.7%				
West	24.2%				
Education:					4364
Bachelor	35.2%				
Below Bachelor	47.3%				
Above Bachelor	17.5%				

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

Table A.4 Instrumental Variables First-Stage Statistics (two-good system)

	Endogenous Variables		
Instrument	FAH Price	FAFH Price	Expenditure
Logged average FAH Price in the same strata	0.004***		
t-stat	(7.320)		
F-stat	57.600		
R-squared	0.017		
Logged average FAFH price in the same strata		0.003***	
t-stat		(8.750)	
F-stat		76.59	
R-squared		0.024	
Logged family month income in the same strata			29.645***
t-stat			(10.340)
F-stat			106.870
R-squared			0.034

Notes: *, **, *** represent values significantly different from 0 at 10%, 5%, and 1% level.

Table A.4 Instrumental Variables First-Stage Statistics (eight-good system)

	Endogenous Price Variables				
Instrument	FV	Potato	Grain	Protein	Dairy Product
Logged average FV Price in the same strata	0.006***				
t-stat	(13.240)				
F-stat	175.180				
R-squared	0.050				
Logged average Potato price in the same strata		0.008***			
t-stat		(29.210)			
F-stat		853.410			
R-squared		0.215			
Logged average Grain price in the same strata			0.007***		
t-stat			(8.160)		
F-stat			66.580		
R-squared			0.021		
Logged average Protein price in the same strata				0.020***	
t-stat				(10.980)	
F-stat				120.550	
R-squared				0.037	
Logged average Dairy Product price in the same strata					0.025***
t-stat					(76.460)
F-stat					5845.450
R-squared					0.652

Notes: *, **, *** represent values significantly different from 0 at 10%, 5%, and 1% level.

Table A.4 Instrumental Variables First-Stage Statistics (eight-good system, Continued)

	Endogenous Price/Expenditure Variables			
Instrument	Condiment	Snack	Beverage	Expenditure
Logged average Condiment Price in the same strata	0.018***			
t-stat	(39.290)			
F-stat	1543.560			
R-squared	0.331			
Logged average Snack price in the same strata		0.014***		
t-stat		(27.170)		
F-stat		738.030		
R-squared		0.191		
Logged average Beverage price in the same strata			0.002***	
t-stat			(12.180)	
F-stat			148.270	
R-squared			0.045	
Logged average Income in the same strata				29.659***
t-stat				(10.350)
F-stat				107.110
R-squared				0.033

Notes: *, **, *** represent values significantly different from 0 at 10%, 5%, and 1% level.

Table A.5 Average Food Waste Amount in Different Groups (Absolute Low vs. High)

	High Food Waste Group	Low Food Waste Group
FAH Waste	8691.60	2174.66
FAFH Waste	2993.78	1205.18
Observations	1532	1531
FV Waste	5312.69	1485.48
Potato Waste	946.79	273.71
Grain Waste	2510.88	732.62
Protein Waste	1019.11	292.31
Dairy Product Waste	563.41	157.70
Condiment Waste	332.01	92.94
Snack Waste	128.72	35.20
Milk & Beverage Waste	835.61	237.85
Overall Food Waste Percentage	36.08%	31.01%
Observations	1523	1522

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.

Table A.6 Average Food Waste Amount in Different Groups (Relative Low vs. High)

	High Food Waste Group	Low Food Waste Group
FAH Waste	6348.45	4519.34
FAFH Waste	2467.83	1731.47
Observations	1532	1531
FV Waste	4026.84	2772.17
Potato Waste	705.69	514.96
Grain Waste	1849.17	1394.78
Protein Waste	753.88	557.72
Dairy Product Waste	435.66	285.53
Condiment Waste	254.21	170.79
Snack Waste	97.31	66.64
Milk & Beverage Waste	627.00	446.59
Overall Food Waste Percentage	46.18%	20.91%
Observations	1552	1552

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

Table A.7 Food Waste Elasticities Under Different Ratios of At-Home and Away-from-Home Waste Rates

	Expenditure Elasticity		Own Price Elasticity		Cross Price Elasticity	
$\frac{AH\ FoodWaste\ Rate}{AFH\ FoodWaste\ Rate}$	**AH**	**AFH**	**AH**	**AFH**	$\frac{P_{afh}}{BS_{ah}}$	$\frac{P_{ah}}{BS_{afh}}$
25%	0.73***	1.06***	-1.05***	-1.07***	0.32**	0.01
	(0.64, 0.82)	(1.04, 1.08)	(-1.30, -0.80)	(-1.12, -1.02)	(0.10, 0.54)	(-0.04, 0.07)
50%	0.87***	1.07***	-1.12***	-1.14***	0.25**	0.07
	(0.84, 0.90)	(1.05, 1.09)	(-1.31, -0.92)	(-1.25, -1.03)	(0.05, 0.44)	(-0.05, 0.18)
75%	0.84***	1.21***	-1.15***	-1.39***	0.31***	0.19
	(0.74, 0.93)	(1.08, 1.33)	(-1.43, -0.87)	(-1.63, -1.15)	(0.12, 0.50)	(-0.16, 0.53)
100%	0.95***	1.15***	-1.16***	-1.61***	0.21**	0.46*
	(0.92, 0.97)	(1.07, 1.24)	(-1.35, -0.97)	(-2.10, -1.13)	(0.04, 0.38)	(-0.08, 1.00)
125%	0.96***	1.16***	-1.12***	-1.61***	0.16**	0.45
	(0.94, 0.98)	(1.07, 1.24)	(-1.26, -0.98)	(-2.10, -1.12)	(0.03, 0.28)	(-0.09, 1.00)
150%	0.96***	1.18***	-1.09***	-1.62***	0.13**	0.44
	(0.94, 0.98)	(1.09, 1.28)	(-1.20, -0.98)	(-2.12, -1.13)	(0.03, 0.23)	(-0.11, -0.99)
175%	0.97***	1.16***	-1.07***	-1.60***	0.10**	0.44
	(0.96, 0.99)	(1.06, 1.26)	(-1.17, -0.98)	(-2.10, -1.10)	(0.02, 0.19)	(-0.10, 0.98)
200%	0.98***	1.16***	-1.06***	-1.59***	0.09**	0.44
	(0.96, 0.99)	(1.04, 1.27)	(-1.14, -0.98)	(-2.09, -1.09)	(0.01, 0.16)	(-0.11, 0.98)

Table A.8 Intercepts for Demographics Variables Using QU-AIDS Model

Variables	At-Home Budget Share	Away-from-Home Budget Share
Household Size	0.02***	-0.02***
	(0.01)	(0.01)
Household Size Change (<3 Months)	-0.03	0.03
	(0.02)	(0.02)
Female	0.03**	-0.03**
	(0.01)	(0.01)
Age	-0.00	0.00
	(0.00)	(0.00)
Hispanic and Latino	-0.02	0.02
	(0.02)	(0.02)
White	0.01	-0.01
	(0.01)	(0.01)
College or above	0.01	-0.01
	(0.01)	(0.01)
Married	0.01	-0.01
	(0.01)	(0.01)
Income $\geq$ Poverty Threshold	0.01	-0.01
	(0.01)	(0.01)
Always Shop with List	0.04***	-0.04***
	(0.01)	(0.01)
Employed	-0.01	0.01
	(0.01)	(0.01)
Self Employment	-0.02	0.02
	(0.02)	(0.02)
SNAP Participation	0.07***	-0.07***
	(0.02)	(0.02)
WIC Eligibility	-0.03*	0.03*
	(0.02)	(0.02)
Food Security	0.02	-0.02
	(0.01)	(0.01)
Home Ownership - Own	-0.01	0.01
	(0.01)	(0.01)
Region - Northeast & Midwest	0.01	-0.01
	(0.01)	(0.01)
Rural	0.01	-0.01
	(0.01)	(0.01)
Constant	0.05	-0.05
	(0.08)	(0.08)
Observation	3057	3057

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

Table A.9 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	-0.003	0.004**	0.000	-0.001	0.002**	-0.001	0.002	-0.004
	(0.004)	(0.002)	(0.004)	(0.004)	(0.001)	(0.001)	(0.002)	(0.004)
Household Size Change	0.004	0.009	0.012	-0.004	-0.001	0.007	0.006	-0.033**
(<3 Months)	(0.018)	(0.007)	(0.018)	(0.017)	(0.005)	(0.005)	(0.007)	(0.017)
Female	0.044***	-0.008	0.001	-0.001	0.005	0.006*	0.000	-0.047***
	(0.013)	(0.005)	(0.013)	(0.012)	(0.003)	(0.003)	(0.005)	(0.012)
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	0.003	-0.014**	0.002	0.008	0.000	-0.001	-0.005	0.007
	(0.016)	(0.007)	(0.017)	(0.015)	(0.004)	(0.004)	(0.007)	(0.015)
White	0.005	-0.008	-0.002	-0.016	0.008**	0.000	-0.010*	0.023*
	(0.014)	(0.006)	(0.016)	(0.013)	(0.004)	(0.004)	(0.006)	(0.013)
College or above	0.048***	-0.003	-0.003	-0.015	0.001	0.002	-0.006	-0.025
	(0.018)	(0.007)	(0.020)	(0.017)	(0.005)	(0.005)	(0.007)	(0.016)
Married	0.006	-0.003	-0.010	0.045***	0.001	-0.004	-0.010**	-0.024**
	(0.012)	(0.005)	(0.013)	(0.012)	(0.003)	(0.003)	(0.005)	(0.011)
Income $\geq$ Poverty Threshold	0.002	-0.001	0.015	-0.004	0.000	0.008**	-0.018***	-0.001
	(0.014)	(0.006)	(0.014)	(0.013)	(0.004)	(0.004)	(0.006)	(0.013)
Always Shop with List	0.017	-0.003	-0.025**	-0.005	-0.007**	0.005	0.005	0.013
	(0.012)	(0.005)	(0.012)	(0.011)	(0.003)	(0.003)	(0.005)	(0.011)
Employed	0.000	0.005	-0.027**	0.011	-0.001	0.000	0.004	0.008
	(0.011)	(0.005)	(0.012)	(0.011)	(0.003)	(0.003)	(0.005)	(0.011)
Self Employment	0.004	-0.006	-0.021	0.032*	0.006	-0.001	0.003	-0.017
	(0.018)	(0.007)	(0.018)	(0.017)	(0.005)	(0.005)	(0.007)	(0.016)
SNAP Participation	-0.018	0.007	0.002	-0.004	0.001	-0.001	-0.010*	0.023*
	(0.013)	(0.006)	(0.014)	(0.013)	(0.004)	(0.004)	(0.005)	(0.012)
WIC Eligibility	0.005	-0.002	0.011	-0.001	0.004	0.003	-0.002	-0.017
	(0.018)	(0.007)	(0.018)	(0.017)	(0.005)	(0.005)	(0.007)	(0.017)
Food Security	0.001	0.000	-0.007	0.012	0.000	-0.001	0.003	-0.008
	(0.012)	(0.005)	(0.013)	(0.011)	(0.003)	(0.003)	(0.005)	(0.011)
Home Ownership - Own	0.028	0.009*	-0.029**	0.023*	-0.002	-0.001	-0.013***	-0.016
	(0.012)	(0.005)	(0.013)	(0.012)	(0.003)	(0.003)	(0.005)	(0.012)
Region - Northeast & Midwest	0.024*	0.001	0.004	-0.036***	0.004	-0.001	-0.008	0.012
	(0.014)	(0.006)	(0.014)	(0.014)	(0.004)	(0.004)	(0.006)	(0.013)
Rural	-0.027*	0.002	0.000	0.015	-0.002	-0.003	0.004	0.011
	(0.015)	(0.006)	(0.015)	(0.014)	(0.004)	(0.004)	(0.006)	(0.013)
Constant	0.211	0.078	-0.955***	0.512*	-0.003	-0.029	0.128	1.059***
	(0.242)	(0.102)	(0.208)	(0.262)	(0.067)	(0.068)	(0.101)	(0.229)
Observation	3117	3117	3117	3117	3117	3117	3117	3117

notes: BS1-BS8 represents budget shares of food waste that originates from categories 1-8. *, **, *** represent values significantly different from 0 at 10%, 5%, and 1% level; values inside () are standard errors.

Table A.10 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	0.95***	-1.17***	1.14***	-1.65***
	(0.93, 0.98)	(-1.35, -0.98)	(1.06, 1.22)	(-2.15, -1.14)
High food waste	0.94***	-1.15***	1.16***	-1.58***
	(0.91, 0.97)	(-1.35, -0.96)	(1.08, 1.24)	(-2.04, -1.12)

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

Table A.11 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	1.03***	-1.25***	1.06***	-1.22***
	(0.91, 1.15)	(-1.56, -0.94)	(0.95, 1.16)	(-1.48, -0.96)
Potato	0.84***	-0.88***	0.92***	-0.85***
	(0.55, 1.12)	(-1.41, -0.35)	(0.52, 1.32)	(-1.47, -0.23)
Grain	1.30***	-1.40***	1.13***	-1.13***
	(1.17, 1.44)	(-1.89, -0.91)	(1.03, 1.22)	(-1.51, -0.74)
Protein	0.85***	-0.79***	0.81***	-0.74***
	(0.76, 0.93)	(-1.26, -0.31)	(0.68, 0.93)	(-1.30, -0.18)
Dairy Product	1.17***	-0.78***	1.16***	-0.85***
	(0.53, 1.81)	(-1.22, -0.34)	(0.77, 1.55)	(-1.15, -0.55)
Condiment	1.12***	-0.81***	1.10***	-0.84***
	(0.75, 1.49)	(-1.21, -0.41)	(0.80, 1.40)	(-1.19, -0.48)
Snack	1.02***	-1.86***	1.14***	-1.90***
	(0.67, 1.36)	(-2.79, -0.93)	(0.78, 1.50)	(-2.89, -0.91)
Milk & Other	0.67***	-0.77	0.80***	-0.33
Beverage	(0.52, 0.82)	(-2.13, 0.59)	(0.40, 1.19)	(-2.67, 2.01)

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.

Table A.12 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	1.05***	-1.25***	1.05***	-1.22***
	(0.92, 1.17)	(-1.56, -0.94)	(0.94, 1.15)	(-1.48, -0.96)
Potato	0.87***	-0.88***	0.88***	-0.85***
	(0.55, 1.19)	(-1.41, -0.34)	(0.49, 1.26)	(-1.48, -0.23)
Grain	1.21***	-1.28***	1.19***	-1.22***
	(1.11, 1.32)	(-1.69, -0.86)	(1.07, 1.30)	(-1.65, -0.79)
Protein	0.84***	-0.77***	0.82***	-0.76***
	(0.74, 0.93)	(-1.27, -0.27)	(0.72, 0.93)	(-1.28, -0.23)
Dairy	1.14***	-0.84***	1.20***	-0.79***
Products	(0.70, 1.58)	(-1.15, -0.53)	(0.63, 1.77)	(-1.20, -0.44)
Condiment	1.11***	-0.83***	1.11***	-0.82***
	(0.78, 1.44)	(-1.19, -0.46)	(0.78, 1.44)	(-1.20, -0.44)
Snack	1.06***	-1.86***	1.10***	-1.94***
	(0.71, 1.41)	(-2.78, -0.93)	(0.71, 1.49)	(-2.95, -0.93)
Milk & Other	0.68***	-0.64	0.74***	-0.56
Beverages	(0.44, 0.92)	(-2.40, 1.12)	(0.47, 1.00)	(-2.40, 1.27)

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.

Table A.13 Average Marginal Effects of Household Characteristics Variables (Food Waste Tracking Survey Data)

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
Household Size	-0.03***	0.07***	-0.04***	0.05***	-0.02***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
White	0.02**	-0.23***	0.07***	0.03***	0.09***	0.02*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Hispanic	-0.01	0.02*	-0.02	0.01	0.01	-0.01
	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Bachelor	0.19	0.15	0.59	0.22	-1.26	0.12
	(2.65)	(7.42)	(17.31)	(15.43)	(46.51)	(3.70)
Region (Northeast	-0.02	0.07	-0.79	0.19	0.39	0.15
& Midwest)	(0.40)	(8.42)	(23.32)	(0.30)	(13.90)	(0.31)
Employed	-0.07***	0.21***	-0.04***	-0.01	-0.16***	0.08***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Incomegeq100k	0.18	0.22	-0.81	-0.09	0.47	0.04
	(0.54)	(11.48)	(31.80)	(0.41)	(18.95)	(0.42)

Table A.14 Determine The Number of Clusters

# Clusters	Calinski/Harabasz Pseudo-F	Duda/Hart Pseudo-T
1	-	1639.59
2	1639.59	33.90
3	842.92	873.63
4	965.53	50.13
5	737.78	2353.86
6	1378.95	5.95
7	1151.38	225.15
8	1073.17	7.12

Table A.15 Number of Households in 6 Clusters

Cluster	Number of Households
1	21
2	1387
3	425
4	1153
5	59
6	90

Table A.16 Food Elasticities with 95% Asymptotic Taylor Approximation Confidence Intervals

	Expenditure	FAH Price	FAFH Price
FAH	0.71***	-0.70***	-0.01
	(0.63, 0.78)	(-0.78, -0.62)	(-0.06, 0.04)
FAFH	1.90***	0.93***	-0.97***
	(1.62, 2.18)	(-1.22, -0.65)	(-1.13, -0.81)

Notes: the estimation is based on 3098 households, with demographics contained in the analysis. R^2 is 0.05. *, **, *** represent values significantly different from 0 at 10%, 5%, and 1% level; values inside parenthesis are 95% asymptotic Taylor approximation confidence intervals.

Table A.17 Elasticities for Food by Categories Using QU-AIDS Model

	Expenditure Elasticity	**Price Elasticity**
FV	1.41***	-1.35***
	(1.18, 1.64)	(-2.16, -0.54)
Potato	0.69	-0.21
	(-2.79, 4.18)	(-4.59, 4.17)
Grain	0.73***	-1.15**
	(0.05, 1.40)	(-2.04, -0.26)
Protein	1.33***	-1.44***
	(1.24, 1.41)	(-1.96, -0.91)
Dairy Product	1.13***	-1.12***
	(0.57, 1.68)	(-1.44, -0.79)
Condiment	1.14***	-0.88***
	(0.96, 1.32)	(-1.02, -0.75)
Snack	1.12***	-1.82***
	(0.55, 1.68)	(-3.49, -0.14)
Milk & Other Beverage	0.76***	-0.85***
	(0.48, 1.04)	(-1.43, -0.26)

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.