GLP-1 Use and Protein Demand

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Abstract

The use of glucagon-like peptide-1 (GLP-1) receptor agonists for weight loss is reshaping food demand, particularly for protein. This research estimates how GLP-1 use alters protein demand curves using methods of causal inference applied to structural demand modeling. Data from a public survey are balanced via matching to address endogenous selection into GLP-1 treatment. Demand shifts and rotations are then estimated using a discrete choice model and an Almost Ideal Demand System. GLP-1 use increases willingness-to-pay for most evaluated protein products, though the effects vary by product and outlet. Own-price elasticities for several retail products become up to 0.22 more inelastic. Our findings of shift effects of GLP-1 use on protein demand indicate externalities that are internal to the U.S. food system and that extend beyond simple consumption changes.

Keywords: AIDS, demand transformation, GLP-1, protein, random utility

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1 Introduction

Changes in food demand can reflect i) a pure shift where consumers purchase more or less at any given price (or, conversely, spend more or less for any given quantity), ii) a pure, mean-preserving rotation where price responsiveness changes, or iii) both (Johnson & Myatt, 2006). The emergence of glucagon-like peptide-1 (GLP-1) receptor agonists represents such a demand shock. Shift effects may arise from GLP-1 users' reduced appetites and desire to purchase less at prevailing prices, while rotation effects may occur if users seek nutrient density and become less price sensitive when purchasing foods that are "GLP-1 friendly." Thus, we examine how GLP-1 use alters protein demand, considering both shifts and rotations while accounting for endogenous selection into treatment.

Originally developed to treat type 2 diabetes, GLP-1 medications are now widely used for weight loss, promoting satiety and suppressing appetite (Latif et al., 2024; Mayo Clinic, 2024). By spring 2024, six to twelve percent of U.S. adults had used these medications (Montero et al., 2024; Witters & Maese, 2024), and usage continues to grow (Gratzl et al., 2024; Hristakeva et al., 2025). Thus, a large and growing group of consumers are self-selecting into a medical treatment that directly affects their desire to eat.

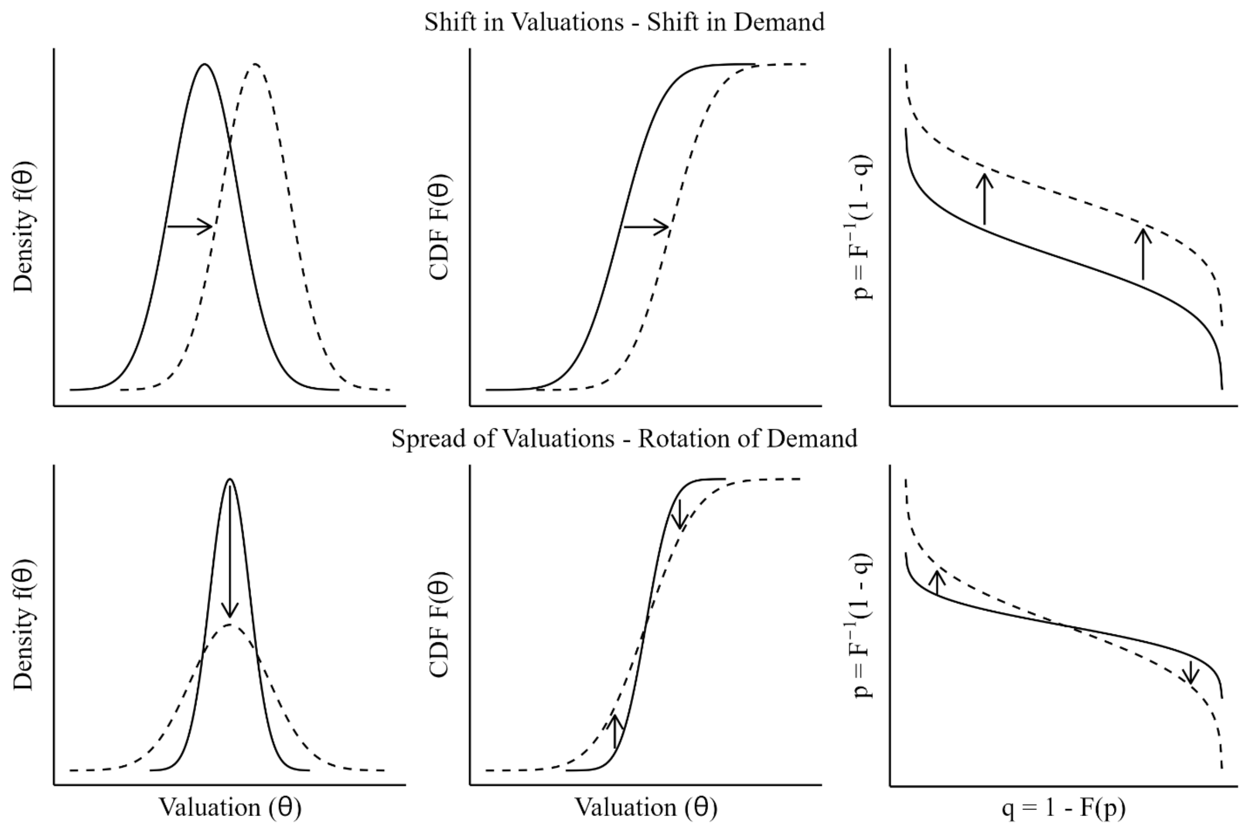
Industry responses have been swift. Conagra Brands now labels certain high-protein items as "On Track" to signal GLP-1 compatibility, while Nestlé has introduced high-protein, portion-aligned meals and beverages (Conagra Brands, Inc., 2024; Naidu, 2024; Nestlé, 2024). These initiatives share the common message that GLP-1 users should favor protein-dense foods. Yet, empirical evidence on actual demand changes is mixed. Some research finds users reduce their consumption of various protein sources even as desirability of protein-dense products remains the same or increases (Dilley et al., 2025), while others show equal shares of users increasing and decreasing their meat consumption (Roe, 2025). This ambiguity, combined with protein's economic importance, warrants further investigation.

To address this, we evaluate two dimensions. "Study 1" estimates causal effects of GLP-1 use on willingness-to-pay (WTP) for protein products, reflecting pure demand shifts [i.e., changes in what users will spend for a given quantity]. Prior research linking high-protein diets to improved weight loss outcomes (Leidy et al., 2015; Westerterp-Plantenga et al., 2012) and dieticians' recommendations that users consume lean proteins (Mozaffarian et al., 2025) suggests that GLP-1 adoption may raise protein valuations. Such shifts in protein demand influence both industry economic performance and consumer welfare as aggregate prices adjust to GLP-1 users' altered demand.

"Study 2" examines demand rotations, or changes in price sensitivity following GLP-1 adoption. Prior findings indicate that GLP-1 users prioritize high-protein foods (Circana, 2024) and that fitness-conscious consumers exhibit lower price sensitivity for protein (Bina & Tonsor, 2024). Hence, there is some industry and empirical backing that GLP-1 medications may reduce sensitivity to own-price changes, making demand for various protein products more inelastic. This can occur if some users prioritize protein consumption per dietary recommendations (Mozaffarian et al., 2025) and, thus, find a protein-dense product to be highly desirable while other users avoid fatty or satiating foods [such as those high in protein or fiber (Holt et al., 1995)] and, thus, find the same product to be highly undesirable. This ultimately lowers users' willingness to adjust quantities as prices change.

We illustrate Study 1 and 2 demand transformation concepts in Figure 1, following Johnson and Myatt (2006). Suppose a consumer will pay up to θ for a protein product, where θ is drawn from distribution $F(\theta)$. Given a price $p \geq 0$, a portion of consumers $q = 1 - F(p)$ will buy the product. If q units are to be sold, the inverse demand curve is then $p = F^{-1}(1 - q)$.

Figure 1. Demand Transformations



Note: The left panel depicts probability density functions, the middle panel depicts cumulative distribution functions, and the right panel depicts inverse demand curves.

A unanimous change in consumers' valuations for a protein product as they begin GLP-1 use reflects a shift in users' probability density function of valuations, the associated cumulative distribution function (CDF), and the inverse demand curve (which is equivalent to the inverse CDF). Conceptually, GLP-1 use and associated dietary recommendations to consume lean protein sources (Mozaffarian et al., 2025) may act in a similar way to Johnson and Myatt (2006) advertising "hype" in that users become aware of various protein products and any objective qualities those products may possess (e.g., protein density that may be valued by all users). In this simple case, users' demand for these products shifts outwards (Figure 1, top panel).

However, the assumption that GLP-1 medications will uniformly increase users' demand is strong. Again following the Johnson and Myatt (2006) taxonomy, GLP-1 therapy and dietary recommendations (or individuals' independent research) may consist of "real information" that allows users to discern their own personal matches with various protein products. For example, one user, upon receiving dietary advice, may purely prioritize protein intake regardless of other product characteristics, while another user may elect to limit consumption of fattier red meats. If we consider a product like ribeye steak, which is high in both protein and fat, the two users will move toward opposite ends of the distribution of valuations, increasing the dispersion of valuations among users. This results in a clockwise rotation of users' inverse demand curve for ribeye steak and reduced price sensitivity [i.e., more inelastic demand] (Figure 1, bottom panel).

Because GLP-1 use is endogenous, methods of causal inference are essential to identifying these protein demand transformations. We use matching methods to balance covariates between GLP-1 users and non-users (Hristakeva et al., 2025) and then quantify the impacts of GLP-1 use on demand for protein products using structural demand estimation. Results indicate that GLP-1 use increases WTP for most retail and foodservice protein products, with magnitudes of effects varying across products and outlet. Own-price sensitivity decreases for some retail products, making demand up to 0.22 more inelastic.

This research adds to conversation around GLP-1 medications by improving policymakers' awareness of externalities related to subsidized GLP-1 use. Since users exhibit higher WTP for protein, subsidized insurance coverage may elevate adoption rates and lead to increases in average protein prices, straining lower-income consumers' access to protein. If adoption rates continue to rise, expanded interagency collaboration and data access will likely be needed to balance economic and public health outcomes. Moreover, GLP-1 medications are a potential opportunity for sustainability as they reduce aggregate meat consumption (Dilley et al., 2025; Hristakeva et al., 2025) while raising consumers' valuations, thus reflecting a premiumization of meat protein. The shift from quantity to quality may reduce agriculture's environmental footprint, but this is only economically viable if food producers can capture higher protein valuations through labeling and value-added marketing. Thus, government-subsidized and GLP-1-focused labeling may help maintain economic outcomes while advancing social (i.e., reduced obesity prevalence) and environmental goals.

2 Data

2.1 The Meat Demand Monitor

This research uses data from the Meat Demand Monitor (MDM), launched in February 2020 through funding from the U.S. Beef and Pork Checkoff programs (Tonsor, 2020). The MDM tracks U.S. retail and foodservice meat demand through monthly, online surveys distributed by Dynata to a nationally representative sample.[1] Roughly 3,000 usable responses are obtained each month, forming a pooled cross-sectional dataset. Participants receive redeemable "points" to incentivize quality responses.

[1] The MDM survey tracks retail demand for ribeye steak, ground beef, pork chops, bacon, chicken breast, plant-based patties, shrimp, and beans and rice; and foodservice demand for ribeye steak, hamburger, pork chops, baby back ribs, chicken breast, plant-based patties, shrimp, and salmon entrées.

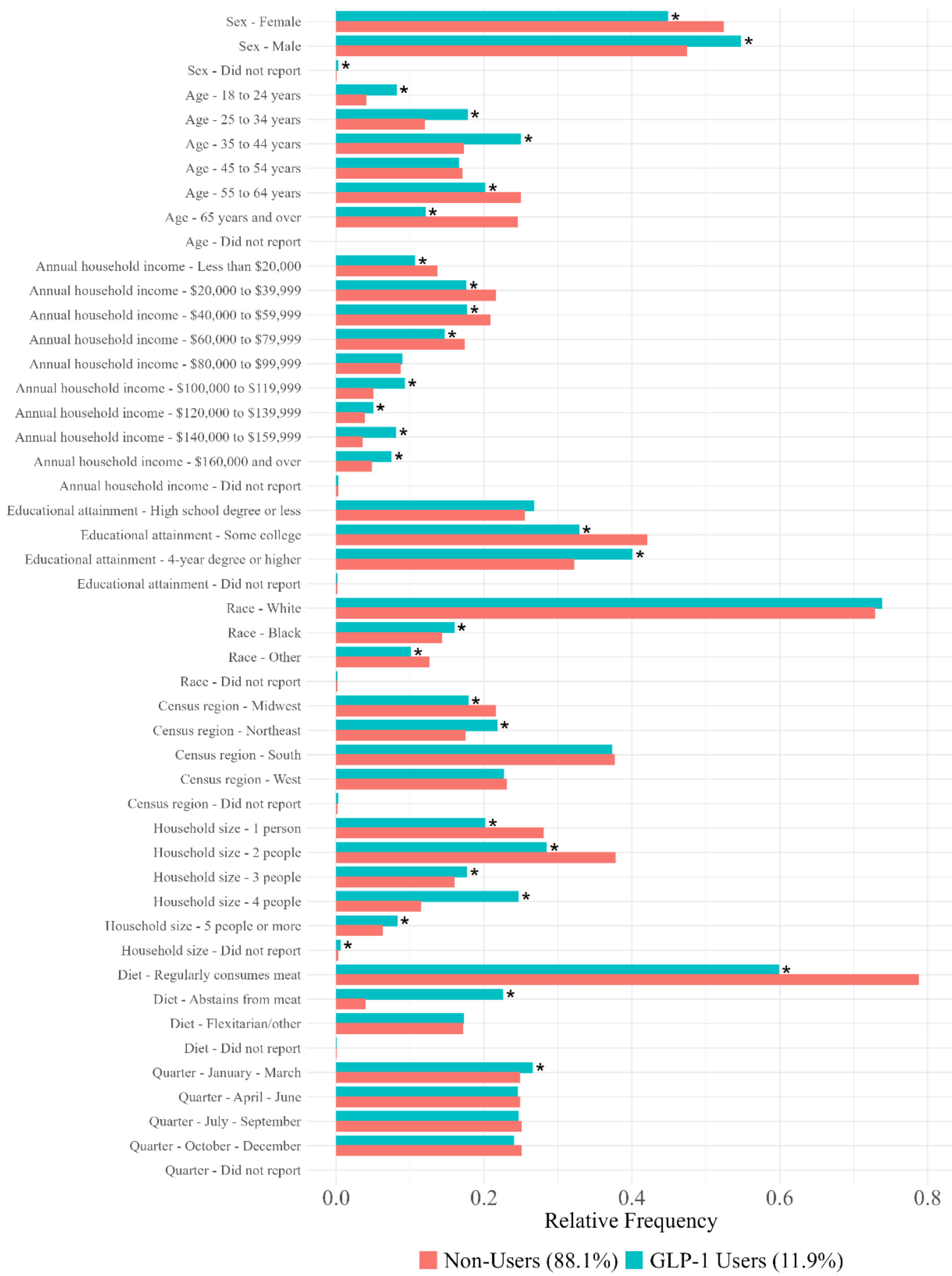
Since July 2024, the MDM has included questions on GLP-1 use, enabling assessment of how the medications influence consumers' protein preferences (Tonsor, 2024). Participants are asked: "*Are you currently taking GLP-1 medications (such as Ozempic, Mounjaro, etc.) to aid in weight loss, treat diabetes, or meet another personal health goal?*" The survey also includes discrete choice experiments (DCE) measuring preferences for retail and foodservice protein products, and an "open-ended" choice experiment (OECE) capturing retail preferences. These experiments precede GLP-1 questions, reducing potential framing bias.

2.2 Descriptive Statistics

We analyze MDM responses from July 2024 through June 2025. Respondents are excluded if they are under 18, fail attentiveness checks, or are not their household's primary grocery shopper (Tonsor, 2020), leaving 36,406 observations, whose descriptive statistics are reported in Figure 2. Excluding non-primary shoppers (1,475 of the omitted responses) ensures accuracy for retail demand but may be inappropriate for foodservice assessments. However, sensitivity analyses confirm that including them yields similar results. Missing sociodemographic data is rare and roughly balanced between GLP-1 users and non-users, reducing concerns about nonresponse bias related to sensitive topics (e.g., income). Consequently, participants with missing sociodemographic information are further omitted from the analyses.[2]

[2] The final number of observations used in each study is further dependent on completion of all DCE and OECE choice tasks and a series of matching procedures.

Figure 2. Descriptive Statistics of Meat Demand Monitor Sample



Note: Asterisks (*) indicate proportions in the GLP-1 user group that are statistically different than the non-user group at the five percent level or lower using two-proportions *z*-tests. GLP-1 use status and age are forced responses in the MDM survey, while time of completion (i.e., quarter) is automatically captured.

Around 11.9 percent of participants report current GLP-1 use (4,347 of 36,406 participants), which exceeds the 3 to 6 percent reported in spring 2024 (Montero et al., 2024; Witters & Maese, 2024) and 8.3 percent in July 2024 (Hristakeva et al., 2025) but is consistent with rising adoption (Gratzl et al., 2024; Hristakeva et al., 2025).[3] Among GLP-1 users, 54.8 percent are male, 51.0 percent are between the ages of 18 and 44, and 29.9 percent have annual household incomes of at least $100,000. This is compared to non-users, of which 47.5 percent are male, 33.4 percent are between the ages of 18 and 44, and 17.3 percent have annual household incomes of at least $100,000. Users also differ in education, race, region, household size, and diets.

3 Establishing Causality

3.1 Matching Methods

Current GLP-1 use is treated as the exposure variable. Because characteristics correlated with GLP-1 adoption (Figure 2) also influence meat consumption (Daniel et al., 2011; Wang et al., 2010; Zeng et al., 2019), there is a clear endogeneity issue. Thus, matching techniques are used to correct for non-random selection into treatment. Our primary method is coarsened exact matching (CEM), which balances observed covariates between GLP-1 users and non-users without relying on functional form assumptions (Cochran, 1968; Iacus et al., 2011; Stuart, 2010).

Using CEM, GLP-1 users and non-users are placed into strata where individuals in each are identical across sex, age, annual household income, education, region, household size, and diet. Although subgroup differences are not sizable in magnitude, we also stratify by race and quarter

[3] We acknowledge that the MDM survey data underrepresents younger and higher-income individuals, which may yield an understated GLP-1 adoption rate. However, our objective is not to provide precise estimates of GLP-1 use in the broader population. Rather, we seek to obtain consistent estimates of our model parameters and tests of the hypothesis we explain in the narrative. To this end, our identification strategy does not rely on representativeness of the sample.

of survey response to reduce variance in estimated treatment effects (Brookhart et al., 2006). However, we avoid stratifying on bodyweight and exercise habits, as these are likely impacted by treatment, creating selection bias if included in the matching process (Greenland, 2003; Stuart, 2010).

Two alternative matching methods are used for sensitivity analysis. The first is 1:1 nearest neighbors matching (1:1 NNM) using propensity scores from a logistic regression and a caliper of 0.25 standard deviations of the propensity score to improve match quality (Rosenbaum & Rubin, 1985; Stuart, 2010). The second is generalized full matching [GFM] (Sävje et al., 2021), which is a generalization of the full matching stratification method that minimizes within-group covariate heterogeneity based on the average distances between treated and control individuals (Hansen, 2004; Stuart, 2010).

Matching is conducted separately for each study because some participants lack complete responses for either the DCE or OECE choice tasks. Covariate balance across 1:1 NNM and GFM samples is evaluated using absolute standardized mean differences, depicted in Appendix Figures A1 through A6. CEM assures perfect balance across treated and control subgroups; thus, further diagnostics are unnecessary.

3.2 Sensitivity to Selection on Unobservables

Matching relies on the selection on observables assumption. This assumption is that, after controlling for all observed confounders, the decision to adopt GLP-1 medications is effectively random. Violations of this assumption cannot be directly tested, which is a limitation of matching techniques. Moreover, the absence of panel data and valid instrumental variables limits our ability to fully address endogeneity.

To assess sensitivity to unobserved confounders, we use the Rosenbaum bounds framework (DiPrete & Gangl, 2004; Rosenbaum, 1987, 2002). This method uses outcomes for treated and control groups and a Wilcoxon signed-rank test to derive a sensitivity parameter, Γ, representing the potential influence of an unobserved variable on treatment assignment. The critical Γ value is the smallest potential hidden bias that would cause the estimated treatment effect to lose statistical significance. Values of 2.0 or greater are generally considered as strong evidence that the estimated treatment effect is robust to unobserved bias (Proserpio & Zervas, 2017). Although initially designed for matched case studies (Rosenbaum, 1987), this framework has since been extended to stratification methods (Rosenbaum, 2018).

4 Study 1—Impacts of GLP-1 Use on Willingness-to-Pay for Protein

4.1 Methods

We estimate the causal effect of GLP-1 use on WTP for protein using the MDM's retail- and foodservice-framed DCEs. Participants are randomly assigned to one of the two DCEs, which each present eight protein products and an "opt-out" option (Tonsor, 2020). The protein products and price levels of these DCEs are depicted in Appendix Table A1. The choice tasks are blocked into three groups such that each MDM participant is randomly assigned to one set of nine choice tasks (after being assigned to either the retail- or foodservice-framed DCE).

We use a random utility framework and the multinomial logit (MNL) model (McFadden, 1973). Utility for individual i and alternative j is $U_{ij} = V_{ij} + e_{ij}$, where e_{ij} is the stochastic portion of utility that is not observed by the analyst. The observable portion of utility is defined as:

(1) $$V_{ij} = \theta_{ij} + \gamma_i p_j$$

where θ_{ij} is an alternative-specific constant (ASC) that reflects the marginal utility of alternative j relative to the opt-out option (which is normalized to zero), γ_i is the marginal utility of a price change, and p_j is the price of alternative j. The ratio $-\theta_{ij}/\gamma_i$ is consumer i's WTP for alternative j relative to no purchase.

GLP-1 users may desire protein-dense foods relatively more than non-users or may have a preference for some protein sources over others to meet their perceived dietary needs. Thus, we let preference parameters vary across individuals. Let $\theta_{ij} = \delta_j + \sum_{k=1}^{K} \delta_{jk} z_{ik} + \pi_j GLP_i$, where δ_j is the marginal utility obtained from product j (over the opt-out option) when all covariates are set equal to zero; z_{ik} is the vector of survey participant characteristics that is used in the matching procedures (reflected in Figure 2) and that influence choice through the parameters δ_{jk}; and GLP_i is a treatment indicator that is equal to one if a participant is currently using a GLP-1 medication and that influences choice through the parameters π_j. Further, GLP-1 users may be less sensitive to price changes than non-users considering their investment in weight loss goals. Thus, we let $\gamma_i = \alpha + \omega GLP_i$, where α is the price responsiveness of non-adopters and where GLP-1 use is allowed to alter price responsiveness through the parameter ω.[4] Additionally, we assess sensitivity of our findings to this specification by i) restricting GLP-1 impacts on ASCs to zero (i.e., $\pi_j = 0\ \forall_j$) and ii) restricting the GLP-1 impact on price responsiveness to zero (i.e., $\omega = 0$).

Equation (1) is estimated separately for retail and foodservice choice data via maximum likelihood and using the Apollo package (S. Hess & Palma, 2019) in R version 4.4.1. Matching weights are incorporated into estimation to ensure that GLP-1-using and non-using subgroups are

[4] Price responsiveness may vary by characteristics other than GLP-1 use. However, this level of flexibility yields marginal utility from a price increase (rather than disutility) and nonsensical WTP estimates for many participants.

balanced across the confounding characteristics. Post-estimation, we implement a doubly robust standardization procedure (Chatton & Rohrer, 2024; Funk et al., 2011; Snowden et al., 2011; Vansteelandt & Keiding, 2011). This entails i) predicting θ_{ij} and γ_i among GLP-1 users assuming that $GLP_i = 1$, ii) predicting θ_{ij} and γ_i among GLP-1 users assuming that $GLP_i = 0$, iii) estimating individual-specific WTP in each counterfactual, iv) calculating an average of WTP across all GLP-1 users in each counterfactual, and v) calculating the difference in the averages. This provides an average treatment effect on the treated (ATT) that is unbiased if either the outcome model (equation [1]) is correctly specified or the matching procedure sufficiently reduces imbalance in covariates between GLP-1 users and non-users (Chatton & Rohrer, 2024; Funk et al., 2011).

There is debate whether uncertainty in the matching process should be considered in variance estimation (Stuart, 2010). Further, bootstrap confidence intervals around matching and outcome estimation are not practical in this application. We instead construct Krinsky and Robb (1986) confidence intervals by resampling from the original parameter estimates. This considers uncertainty in outcome estimation but not uncertainty in the matching procedures.

4.2 Results

Table 1 reports unmatched mean WTP estimates for GLP-1 users and non-users, along with ATT estimates derived using CEM, 1:1 NNM, and GFM. Bracketed values show Rosenbaum bounds critical Γ values, where values of 2.0 or greater indicate robustness to confounding from unobserved factors. Appendix Tables A2 and A3 summarize key parameter estimates and model fit measures.

Table 1. Mean Willingness-to-Pay and Effects of GLP-1 Use

Retail WTP ($/lb)

				Doubly Robust Average Treatment Effect on the Treated		
Product	Users	Non-Users	Difference	Coarsened Exact Matching	1:1 Nearest Neighbors Matching	Generalized Full Matching
Ribeye steak	22.99	16.00	6.99	2.30* [>100]	5.53* [13.4]	5.45* [11.7]
Ground beef	14.76	7.64	7.12	1.69* [>100]	5.72* [60.8]	6.12* [>100]
Pork chop	12.67	6.34	6.33	1.19* [>100]	5.02* [31.9]	5.51* [73.0]
Bacon	10.20	5.40	4.80	1.30* [>100]	4.04* [16.4]	4.25* [21.2]
Chicken breast	12.80	7.56	5.24	1.52* [>100]	4.16* [28.2]	4.54* [84.0]
Plant-based patty	9.42	6.96	2.46	1.55* [>100]	1.73* [2.5]	1.41* [<2.0]
Shrimp	12.64	9.22	3.42	1.06* [>100]	2.94* [6.4]	2.90* [6.6]
Beans and rice	5.38	2.87	2.51	0.14 [<2.0]	1.39* [3.8]	1.26* [3.5]

Foodservice WTP ($/meal)

				Doubly Robust Average Treatment Effect on the Treated		
Product	Users	Non-Users	Difference	Coarsened Exact Matching	1:1 Nearest Neighbors Matching	Generalized Full Matching
Ribeye steak	37.84	25.19	12.66	3.87* [>100]	9.75* [44.0]	10.94* [61.5]
Hamburger	31.31	18.41	12.89	3.73* [>100]	9.35* [50.1]	10.92* [82.5]
Pork chop	24.55	15.11	9.43	2.34* [86.2]	7.09* [13.1]	7.38* [11.7]
Baby back ribs	26.20	17.82	8.38	3.07* [>100]	7.19* [19.6]	7.96* [26.9]
Chicken breast	25.30	17.41	7.90	3.22* [>100]	6.55* [24.1]	7.31* [56.0]
Plant-based patty	12.33	10.86	1.47	-0.23 [<2.0]	-0.10 [<2.0]	-0.46 [<2.0]
Shrimp	25.02	17.18	7.84	3.20* [>100]	6.62* [20.8]	7.64* [53.4]
Salmon	25.04	18.64	6.40	1.42* [11.8]	4.90* [8.3]	5.78* [12.6]

Note: Asterisks (*) denote statistical significance using Krinsky and Robb (1986) 95 percent confidence intervals. We use 10,000 draws in the Krinsky and Robb (1986) resampling procedure. Values in brackets are critical Γ values from Rosenbaum bounds sensitivity testing.

CEM estimates show GLP-1 use yields a $1.06 (shrimp) to $2.30 (ribeye steak) per pound premium for retail protein, holding other traits constant. These correspond to 9.6 (shrimp) to 38.1 (chicken breast) percent increases in WTP over midpoint retail DCE prices (Appendix Table A1). Further, the CEM-derived "GLP-1 premiums" for protein reflect 18.8, 26.7, 27.7, 18.0, and 36.1 percent increases over August 2025 national average prices for beef steaks, ground beef, pork chops, bacon, and chicken breast, respectfully (Federal Reserve Bank of St. Louis, 2025a). With retail food spending fixed, this may imply higher WTP for proteins and lower WTP for other foods.

Alternatively, users may value protein more per unit but prefer smaller quantities, broadly consistent with Dilley et al. (2025). Thus, higher-margin, GLP-1-focused products may offset volume reductions, though premium capture depends on effective communication of GLP-1-friendly attributes and precise market targeting.

Foodservice effects are similarly substantial, with WTP increases of $1.42 (salmon) to $3.87 (ribeye steak) per meal using CEM. These estimates reflect 8.4 (salmon) to 31.1 (hamburger) percent increases over midpoint foodservice DCE prices (Appendix Table A1). This suggests potential for second-degree price discrimination, such as offering smaller, protein-dense and "GLP-1-friendly" meals sold at higher prices. Menus trading portion size for protein density or other GLP-1-friendly attributes may help mitigate risks of reduced appetites, though profitability of any price discrimination strategy depends on standard single-crossing and monotone hazard conditions, among others (Anderson & Dana, 2009).

Relative to prior research, Van Loo et al. (2011) find 35 to 104 percent WTP premiums for organic chicken breast labels, while Van Loo et al. (2014) report 12 to 93 percent premiums for various sustainability labels likewise placed on chicken breast. Lusk et al. (2018) document smaller premiums, finding up to a 23 percent premium for a "USDA Good, Better, Best" quality labeling scheme for pork chops and noting considerable heterogeneity in WTP across consumers. Last, Yang and Renwick's (2019) meta-analysis on WTP for credence attributes of livestock products reports mean premiums of 26 percent (environmentally-friendly labels) to 63 percent (food safety labels). Overall, our CEM estimates rest at the lower end of these findings, though direct comparison is limited by differing research objectives.

Using multiple matching methods, doubly robust standardization, and Rosenbaum bounds sensitivity analysis strengthens confidence in the positive GLP-1 effects. Results are robust to specification of ASCs and price responsiveness, and the inclusion of non-primary shoppers (Appendix Table A4).

4.3 Sensitivity to Unobserved Preference and Price Heterogeneity

Random parameters logit (RPL) models test Study 1's sensitivity to preference and price heterogeneity. We compare four specifications (Table 2) that each include normally and independently distributed ASCs (with mean θ_j and standard deviation σ_j), but that vary in price responsiveness (i.e., common versus product-specific price terms; fixed versus zero-bounded and triangularly distributed price terms). Price response that follows a zero-bounded and triangular distribution (with mean γ) ensures marginal disutility from a price increase across all consumers and aids in convergence compared to a negative lognormal distribution.

Table 2. Random Parameters Logit Specifications

Model	Utility Specification
1	$U_{nj} = (\theta_j + \sigma_j d_{nj}) + \gamma p_j + \varepsilon_{nj};\ d_{nj} \sim N(0,1)$
2	$U_{nj} = (\theta_j + \sigma_j d_{nj}) + \gamma_j p_j + \varepsilon_{nj};\ d_{nj} \sim N(0,1)$
3	$U_{nj} = (\theta_j + \sigma_j d_{nj}) + \left(\gamma + \gamma * \frac{b_n + c_n}{2}\right) p_j + \varepsilon_{nj};\ d_{nj} \sim N(0,1), b_n \sim U(0,1), c_n \sim U(0,1)$
4	$U_{nj} = (\theta_j + \sigma_j d_{nj}) + \left(\gamma_j + \gamma_j * \frac{b_{nj} + c_{nj}}{2}\right) p_j + \varepsilon_{nj};\ d_{nj} \sim N(0,1), b_{nj} \sim U(0,1), c_{nj} \sim U(0,1)$

We estimate the RPL models via simulated maximum likelihood separately for GLP-1 users and non-users with CEM samples. Thus, sixteen models are estimated across 4 specifications, 2 outlets (i.e., retail and foodservice), and 2 groups (i.e., GLP-1 users and non-users). CEM weights are applied in each to facilitate estimation of ATT. Each model uses 500 individual-specific Modified Hypercube Sampling Draws, which avoid correlation patterns and outperform Halton draws in higher-dimension integration (S. Hess et al., 2006).

These complex models (incorporating up to 16 random coefficients) preclude use of sociodemographic controls and the doubly robust standardization procedure. Instead, GLP-1 effects are assessed via simulated WTP estimates and Poe et al. (2005) hypothesis testing. Following Hensher and Greene (2003), we take 1,000 Krinsky and Robb (1986) draws for statistical variation and, within each, a subsequent 1,000 drawings for preference heterogeneity. Means and standard deviations of WTP are identified within each Krinsky and Robb (1986) draw, generating empirical distributions. We then construct Poe et al. (2005) complete combinatorials defined as GLP-1 users' mean WTP (or standard deviation of WTP) *less* non-users'. That is, we take the difference between each combination of users' and non-users' WTP estimates (1,000 * 1,000 = 1,000,000 total differences). From this procedure, 95 percent confidence intervals around the mean differences are easily identified.

Table 3 shows RPL-derived ATT estimates alongside primary, MNL-derived CEM results. For brevity, RPL models 2 and 4 (with product-specific price response) are excluded, as they produce implausible WTP estimates for some products. This is likely due to the MDM design, which includes widely varying price ranges for each product and only three price levels.

Table 3. GLP-1 Effects on Means and Standard Deviations of Willingness-to-Pay

	Retail Average Treatment Effects on the Treated		
Product	MNL (primary)	RPL fixed price term	RPL random price term
Ribeye steak	2.30*	2.45*	2.10*
		(0.48)	(0.80)
Ground beef	1.69*	1.51*	1.63*
		(0.05)	(0.07)
Pork chop	1.19*	1.46*	1.40*
		(-0.32)	(-0.42)
Bacon	1.30*	1.40*	1.34*
		(-0.86*)	(-0.82*)
Chicken breast	1.52*	1.27*	1.18*

		(0.64*)	(0.65*)
Plant-based patty	1.55*	0.95	1.78*
		(1.31*)	(0.06)
Shrimp	1.06*	1.41*	0.89*
		(-0.13)	(0.18)
Beans and rice	0.14	0.55	0.52
		(-0.90*)	(-0.66)

	Foodservice Average Treatment Effects on the Treated		
		RPL	RPL
Product	MNL (primary)	fixed price term	random price term
Ribeye steak	3.87*	2.72*	3.61*
		(1.35*)	(0.59)
Hamburger	3.73*	2.68*	2.63*
		(1.32*)	(0.83*)
Pork chop	2.34*	3.23*	2.49*
		(-0.55)	(-0.43)
Baby back ribs	3.07*	2.65*	2.45*
		(0.44)	(0.36)
Chicken breast	3.22*	1.21*	1.73*
		(2.00*)	(1.73*)
Plant-based patty	-0.23	0.84	0.25
		(-0.26)	(0.45)
Shrimp	3.20*	2.05*	2.21*
		(1.58*)	(1.26*)
Salmon	1.42*	0.61	0.09
		(1.00)	(1.54*)

Note: Asterisks (*) denote statistical significance at the five percent level or lower. Treatment effects from RPL models are obtained via simulation and Poe et al. (2005) complete combinatorials. Values in parentheses are standard deviation of WTP.

GLP-1 effects on mean WTP remain consistent with primary results when accounting for preference and price heterogeneity. Effect sizes vary by specification, though directions and significance generally hold. Exceptions include non-significant effects for retail plant-based patties (fixed-price RPL model) and foodservice salmon (both RPL models).

4.4 Industry Implications

Study 1 shows GLP-1 users have higher WTP for protein-rich foods in both retail and foodservice, much of which reflects GLP-1 use rather than income or other factors. However, effects are selective in the sense that they are consistent for animal proteins but inconsistent or absent for plant-based options (i.e., plant-based patties and beans and rice). Similar selectivity may extend to other protein categories, such as dairy or meat snacks, warranting further study. Moreover, if food budgets remain fixed, increased protein spending necessitates reduced spending elsewhere, underscoring the need to examine substitution patterns both across and within all food groups.

These findings support a "protein premium" among GLP-1 users ranging from 18.0 to 36.1 percent over August 2025 retail prices (Federal Reserve Bank of St. Louis, 2025a) and, further, supports the initial industry pivot toward protein-focused products (Conagra Brands, Inc., 2024; Naidu, 2024, 2024). Thus, developing higher-protein items may be economically sound given GLP-1's positive effects on WTP. Nonetheless, food manufacturers must balance research and development expenses, input costs, and competitor's strategies. Future research should evaluate firms' equilibrium response to GLP-1 use in price and attribute spaces to inform product reformulation and marketing decisions. Importantly, research and industry efforts to make GLP-1 demand forecasts and craft appropriate business strategies should recognize the role of confounders, as shown by differences in Table 1 associations and treatment effects.

5 Study 2—GLP-1 Effects on Retail Protein Demand Elasticities

5.1 Methods

Differences in price sensitivity for retail protein between GLP-1 users and non-users is assessed using the MDM's OECE. Participants complete one choice task showing eight retail protein items (matching the retail DCE), with prices randomly drawn from product-specific ranges (Appendix

Table A5). Given these prices, they select which goods to buy and their quantities from “zero” to “five or more pounds.” This multi-product, multi-quantity design allows for complementary goods and traditional demand estimation (Bina & Tonsor, 2024; Dennis et al., 2021).

Retail protein demand is estimated using the popular AIDS framework (Deaton & Muellbauer, 1980). The budget share for good j is described as:

(2)
$$w_j = \bar{\alpha}_j + \sum_{l=1}^{8} \gamma_{jl} \ln{(p_l)} + \beta_j \ln{({}^{X}/_{P})}$$

where p_l is the price of the lth good, X is the total expenditure across the eight goods, P is a price index defined by:

(3)
$$\ln{(P)} = \alpha_0 + \sum_{j=1}^{8} \bar{\alpha}_j \ln(p_j) + \frac{1}{2}\sum_{j=1}^{8}\sum_{l=1}^{8} \gamma_{jl} \ln(p_j) \ln{(p_l)}$$

and γ_{jl} and β_j are parameters to be estimated. Non-price factors are included in the intercept terms $\bar{\alpha}_j$ such that $\bar{\alpha}_j = \alpha_j + \sum_{k=1}^{K} \delta_{jk} z_k$, where z_k is again the vector of participant characteristics used in the matching procedures (reflected in Figure 2) that shift demand through δ_{jk}. We use the notation of Coffey et al. (2011), but note that observations are at the participant level (i.e., indexed by i). Weak separability of the eight OECE goods is a maintained assumption and homogeneity, adding-up, and symmetry are imposed as: $\sum_{j=1}^{8} \alpha_j = 1$, $\sum_{j=1}^{8} \delta_{jk} = 0 \ \forall_k$, $\sum_{j=1}^{8} \beta_j = 0$, $\sum_{j=1}^{8} \gamma_{jl} = 0$, and $\gamma_{jl} = \gamma_{lj}$. Expenditure and price elasticity calculation follows Green and Alston (1990).

Estimation of equation (2) must address the censored nature of the OECE data. We apply the expectation maximation (EM) algorithm to obtain consistent estimates (Dempster et al., 1977). This method avoids the issues with i) the Kuhn-Tucker approach, which struggles with identifying estimable utility functions and ensuring probabilities of purchase regimes sum to one, and ii) twostep Amemiya-Tobin approaches that impose adding-up only on latent, not observed, budget shares (Dong et al., 2004; Nava & Dong, 2022).

The EM method entails iteratively estimating the demand system, replacing zero budget shares with positive predicted shares until parameter estimates stabilize. This is done separately for GLP-1 users and non-users using iterative seemingly unrelated regression via SAS 9.4's MODEL procedure.[5] As before, matching weights are applied in demand estimation to balance confounders. We halt the EM process when the change in all parameter estimates from one iteration to the next is less than 0.0001. Elasticity estimates and differences in elasticities between GLP-1 users and non-users are calculated using the final sets of parameter estimates. Confidence intervals around the differences are constructed using 500 bootstrap samples (i.e., matching and demand estimation is conducted for each sample) and Poe et al. (2005) hypothesis testing.

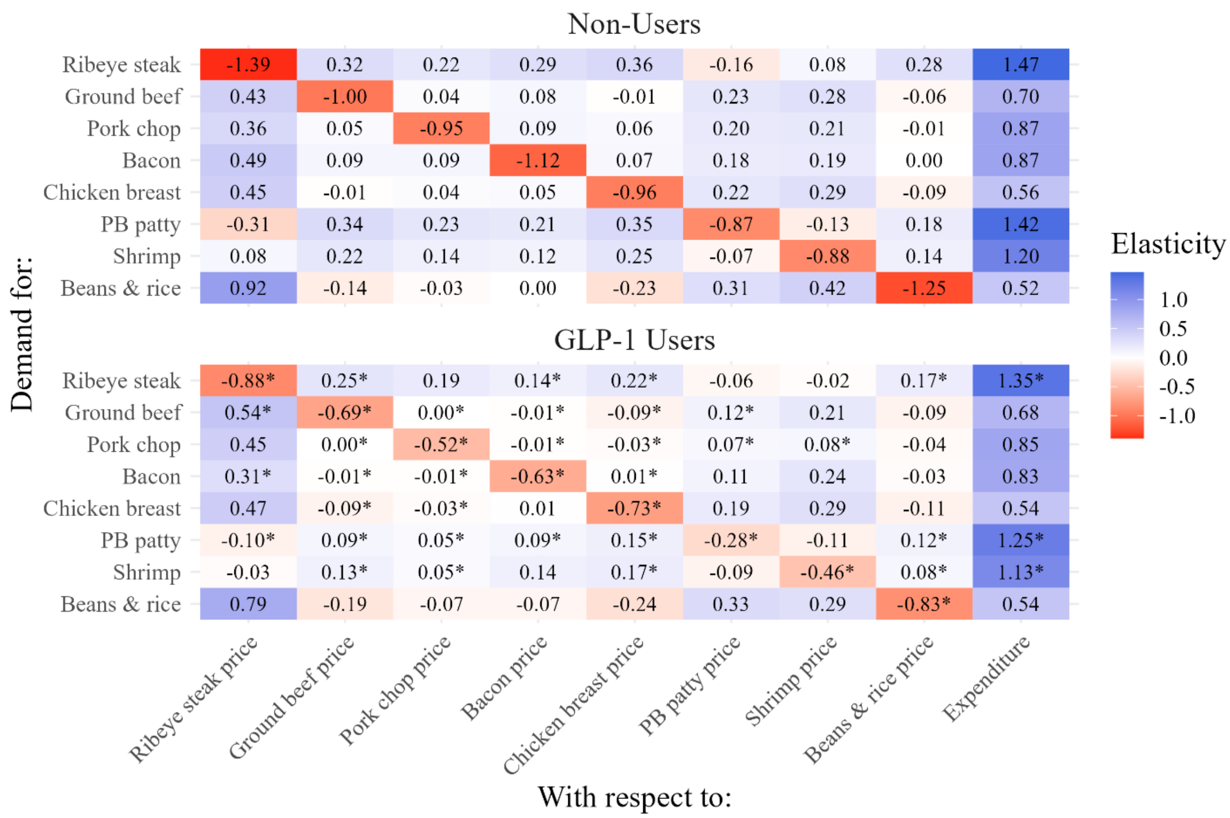
5.2 Results

Unweighted, full sample AIDS model results are in Appendix Table A6. Since these contain hundreds of parameters, we present only price and expenditure effects and model fit measures. We focus on differences in elasticities between GLP-1 users and non-users, comparing traditional and causal inference methods. Figure 3 presents elasticities from the full, unmatched sample, which do not account for subgroup covariate imbalances. Differences are calculated as user *less* non-user elasticities, with significance tested via bootstrap resampling and the Poe et al. (2005) method. For interpretation, non-users reduce quantity demanded of ribeye steak by 1.39 percent following a ribeye steak price increase of 1 percent (top left corner, top panel), whereas users reduce their

[5] Prices in the OECE are randomly generated and can be treated as exogenous. Instrumental variable methods are not necessary.

quantity demanded by 0.88 percent (top left corner, bottom panel). Thus, GLP-1 use is associated with a 0.51 reduction in own-price sensitivity (-0.88 less -1.39).

Figure 3. GLP-1 User and Non-User Expenditure and Compensated Price Elasticities—Full Sample

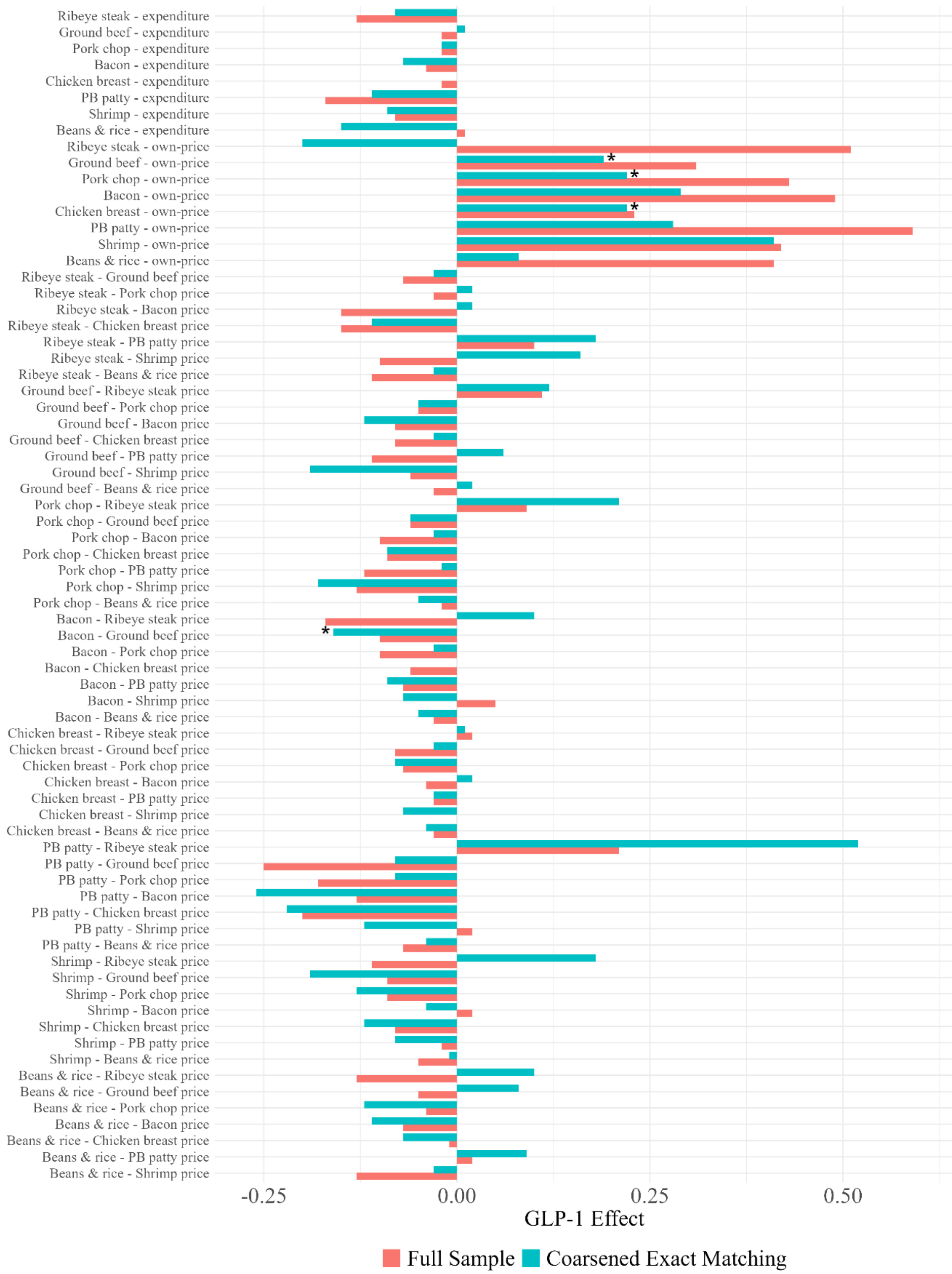


Note: Elasticities are calculated at the mean values of the budget shares obtained from the final iteration of the EM estimation. Asterisks (*) denote GLP-1 user elasticities that are statistically different than non-user elasticities using 500 bootstrap samples and Poe et al. (2005) 95 percent confidence intervals.

GLP-1 users are slightly less responsive to expenditure than non-users in their demand for ribeye steak, plant-based patties, and shrimp, with expenditure elasticities 0.12, 0.17, and 0.07 lower, respectively. Other products show no significant subgroup differences. Substitution patterns are largely similar, as cross-price elasticities differ little in magnitude between groups. The largest difference occurs in plant-based patty quantity response to ground beef price, where the cross-price elasticity is 0.25 lower for users. Notably, GLP-1 users are less own-price sensitive, with own-price elasticities between 0.23 (chicken breast) and 0.51 (ribeye steak) closer to zero than non-users. Similar patterns appear among fitness-motivated consumers (Bina & Tonsor, 2024), though prior work does not address potential confounding, which we do next.

Figure 4 reports ATT estimates from the CEM approach (i.e., differences in elasticities between users and non-users using CEM samples and weighted demand estimation) and the differences in elasticities from traditional estimation discussed above. For interpretation, GLP-1 use reduces own-price sensitivity for ground beef by 0.19 (i.e., the ground beef own-price elasticity moves closer to zero by 0.19), which is statistically significant at the five percent level. This is compared to the simple association, which is 0.31. Unlike Study 1, Rosenbaum bounds are infeasible here, so results may reflect unobserved confounders influencing both GLP-1 use and protein demand. Nonetheless, robust treatment effects observed in Study 1 using the same survey data increase confidence in the following estimates.

Figure 4. GLP-1 Effects on Expenditure and Compensated Price Elasticities



Note: Asterisks (*) denote coarsened exact matching-derived GLP-1 effects that are statistically significant. Significance is assessed using 500 bootstrap samples and Poe et al. (2005) 95 percent confidence intervals.

Utilizing matching to balance covariates, GLP-1 use yields lower ribeye steak and shrimp expenditure sensitivity by 0.06 to 0.10 using 1:1 NNM and GFM (Appendix Figure A7), however these effects lose statistical significance in our primary use of CEM depicted in Figure 4. Further, treatment effects on cross-price elasticities are slight and only occasionally statistically significant across product combinations and matching methods. For instance, using CEM, GLP-1 use alters only bacon quantity response to ground beef prices, reducing the cross-price elasticity by 0.16 and making the goods more complementary.

GLP-1 use exhibits smaller effects on own-price sensitivity than implied by the standard heterogeneity assessment. Ribeye steak and plant-based patty own-price elasticities do not differ significantly between groups across any matching method (see Appendix Figure A7 for 1:1 NNM and GFM results). Further, only chicken breast, ground beef, and pork chop differ using CEM. Differences in CEM-derived own-price elasticities for ground beef and pork chops are smaller than the associations, whereas chicken breast is similar. Specifically, users' own-price elasticities for ground beef and pork chops are 0.19 and 0.22 greater (i.e., closer to zero) than non-users', respectively, using CEM but 0.31 and 0.43 greater using the unmatched sample. Still, CEM results indicate meaningful demand-rotation effects for these three protein sources, with own-price elasticities between 0.19 and 0.22 greater for GLP-1 users.

Although these estimated 0.19 to 0.22 reductions in price sensitivity appear modest, they are economically meaningful relative to prior benchmarks. Meta-analyses report mean own-price elasticities for beef, pork, and poultry of -0.75, -0.72, and -0.68 (Andreyeva et al., 2010) and medians of -0.87, -0.78, and -0.65 (Gallet, 2010), respectively. Thus, a roughly 0.20 upward move represents a 23 to 31 percent reduction in price sensitivity compared to historical averages, acknowledging methodological and aggregation differences. More recent demand estimation using household scanner data finds fresh ground beef, chicken, and pork median own-price elasticities of -1.34, -0.97, and -0.65, respectively (Nouve et al., 2025). Our CEM effect estimates are still sizable relative to these most recent findings, representing between 14 (ground beef) and 34 (pork chops) percent reductions in price sensitivity, again acknowledging aggregation differences. In a practical sense, roughly 0.20 own-price elasticity increases imply that a 10 percent retail price increase would lead GLP-1 users to reduce purchases by about 2 percentage points less than non-users (independent of sociodemographic differences between groups). This is non-trivial given adoption has risen from 5.5 percent of U.S. adults in October 2023 to 8.3 percent in July 2024 per external estimates (Hristakeva et al., 2025). Going forward, research should incorporate supply-side behavior to evaluate how these elasticity changes impact price pass-through, equilibrium outcomes, and aggregate welfare.

5.3 Industry Implications

Study 2 reveals several implications. First, null or inconsistent effects of GLP-1 use on expenditure elasticities indicate that protein demand responds similarly to total food budgets across users and non-users (holding other consumer traits fixed). Thus, purchase volatility for premium items like ribeye steak and shrimp (with expenditure elasticities over 1.0) amid economic cycles or income shifts is unlikely to change as GLP-1 adoption grows.

Second, minimal effects of GLP-1 use on cross-price elasticities suggest adoption does not meaningfully alter substitution patterns between popular meat products. Bina and Tonsor (2024) note consumers may avoid substitutions misaligned with perceived health goals, which may explain this result. However, it is important to recognize that MDM data, and our associated separability assumptions, precludes demand shifts toward other proteins or food categories potentially more aligned with GLP-1 users' preferred substitutions.

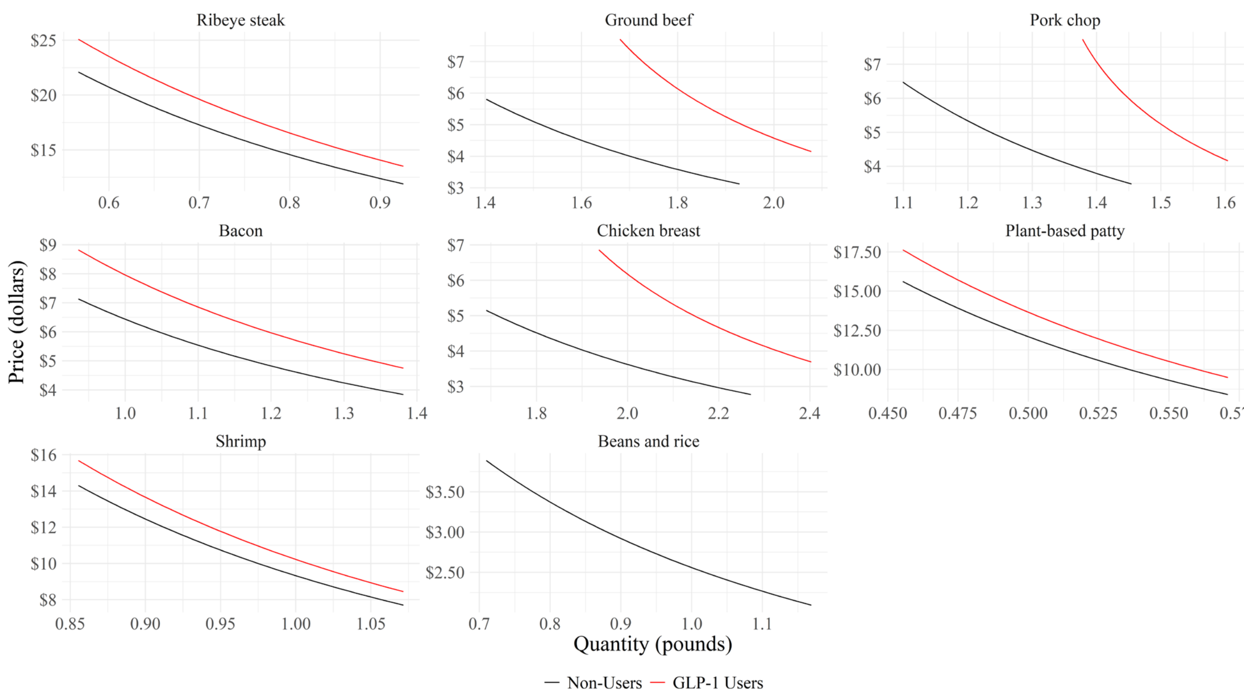
Third, GLP-1 users exhibit lower own-price sensitivity for protein (Figure 3), meaning their purchase volumes respond less to price changes. Thus, price reductions may not incentivize greater consumption. Instead, as Study 1 suggests, capturing users' elevated WTP through value-added offerings may be a more effective response to GLP-1 adoption, though more research is needed to inform marketing and product development strategies. Lower price sensitivity also implies GLP-1 users will represent a larger share of protein purchases (in terms of aggregate quantities purchased) as prices increase and non-users disproportionately reduce purchases, echoing Lusk and Tonsor (2016) comments on relatively inelastic meat demand among higher-income consumers and underscoring the importance of monitoring shifts in buyer composition as GLP-1 adoption rises and prices fluctuate.

Further, matching methods reveal that much of users' apparent insensitivity to own-price changes stems from sociodemographic characteristics rather than GLP-1 effects. Nonetheless, CEM estimates show GLP-1 use reduces own-price sensitivity for chicken breast, ground beef, and pork chops by up to 0.22. Thus, rising GLP-1 adoption may smooth aggregate purchases of these proteins as prices fluctuate seasonally or through economic booms and downturns. This would further explain steady per capita red meat and poultry disappearance in recent years despite rising prices (Bina, 2025; A. Hess, 2025).

6 Discussion

GLP-1 use is reshaping U.S. food demand, creating uncertainty throughout the food system and requiring improved understanding of potential consequences. Industry responses indicate the protein sector is especially important (Conagra Brands, Inc., 2024; Naidu, 2024; Nestlé, 2024). This study quantifies GLP-1's impact on protein demand, finding positive effects on WTP for meat products in retail and foodservice. GLP-1 use also reduces price sensitivity for select retail products with own-price elasticities becoming up to 0.22 more positive. A summary of retail results is depicted in Figure 5. Compensated demand curves from the full (unmatched) non-user sample are in black, whereas CEM-derived rightward shifts (Study 1) and clockwise rotations (Study 2) are in red. We emphasize here that Figure 5 is illustrative only and intended to convey economic intuition. Demand shifts and rotations were quantified separately using different choice experiments and empirical methods.

Figure 5. Summary of Retail Demand Transformations



These findings raise key policy considerations. First, future GLP-1 coverage under private health insurance and subsidized healthcare is uncertain, as are costs (Office of Health Policy Assistant Secretary for Planning and Evaluation, 2024). Over 40 percent of privately insured U.S. adults could receive coverage if prescribed for diabetes or weight-related health issues (McGough et al., 2024). Further, the medications remain uncovered under Medicare and Medicaid if prescribed for weight loss. A late-2024 proposal by the Centers for Medicare and Medicaid Services would have extended coverage to obesity treatment, potentially benefiting 7.4 million adults (Office of Health Policy Assistant Secretary for Planning and Evaluation, 2024). However, the proposed extension was rescinded in spring 2025 amid various federal budget cuts (Park, 2025).

Beyond healthcare impacts, subsidizing GLP-1 coverage will generate externalities throughout the food system. Broader adoption will alter food purchasing patterns, ultimately changing quantities, WTP, and price sensitivity. Further policy discussions should therefore weigh economic as well as public health outcomes. Importantly, policymakers should remain cognizant that GLP-1 users have higher WTP (Table 1). Thus, increased adoption may widen dietary divides as higher-WTP users drive up national protein prices, limiting lower-income consumers' access to protein. This is especially important given the current high-price environment for red meat and poultry (Federal Reserve Bank of St. Louis, 2025b) and lower-income consumers' relatively elastic demand for these products (Lusk & Tonsor, 2016). Any government initiative that yields elevated GLP-1 adoption rates and (indirectly) increases protein prices may progressively push lower earners out of the market for red meat and poultry.

Second, GLP-1 use is rising rapidly (Gratzl et al., 2024; Hristakeva et al., 2025) and will increasingly shape U.S. food demand, requiring monitoring and management of related shifts. The USDA Economic Research Service (ERS) has historically shared proprietary data for policy-relevant research (U.S. Department of Agriculture Economic Research Service, 2025), including Circana retail and household scanner data. Precedent exists for granting access to special datasets, such as Circana Household COVID-19 Response Data, to study consumer behavior during abnormal market periods. Our findings show that GLP-1 therapies substantially affect protein demand, which, along with rapid increases in adoption, suggest that ERS should acquire GLP-1 use data (Circana, 2025) and offer access to researchers via standard third-party agreements. This would enhance understanding of GLP-1's economic and dietary impacts while helping identify how food manufacturers can offset reduced consumption through product reformulation or other strategies.

Third, GLP-1 medications significantly shift protein demand independent of income and other factors, highlighting a key link between pharmaceutical and food sectors. Interagency collaboration related to food consumption is well established, as the USDA Food Safety and Inspection Service and the Food and Drug Administration's Department of Health and Human Services co-manage food safety. Extending on prior interagency efforts, new GLP-1-focused workgroups could help integrate pharmaceutical trends into dietary and agricultural policymaking. Such coordination would support research on medication-driven food spending and improve dietary guidance during GLP-1 therapy. Further, the medications demonstrate how health and food systems interact endogenously: GLP-1 use alters diets, influencing broader health outcomes. For instance, higher protein demand may increase red meat's share of the diet, which has been linked to chronic diseases (Ekmekcioglu et al., 2018; Wolk, 2017). Thus, research and policy groups working in this intersection are key to balancing the economic and health impacts of rising GLP-1 use.

Last, previous research shows GLP-1 users consume less meat (Dilley et al., 2025; Hristakeva et al., 2025), yet our results reveal higher WTP for meat products. This apparent contradiction reflects a shift from quantity to quality, where users buy less but value each unit more highly. This behavior aligns with a premiumization pattern, in which individuals reduce total intake while seeking greater satisfaction, quality, or nutrient profiles compatible with successful GLP-1 therapy. Because livestock, especially cattle, account for a disproportionate share of agricultural greenhouse gas emissions (Pelton et al., 2024; U.S. Department of Agriculture Agricultural Research Service, 2023), this shift may contribute to a lower environmental footprint for the sector. The feasibility of these sustainability gains, however, depends on producers' ability to capture elevated per-unit valuations through value-added activities, such as transparent labeling or the development of GLP-1-friendly product attributes. Policymakers could support this alignment of economic, environmental, and social (i.e., reduced obesity prevalence) outcomes by subsidizing credible labeling efforts and tightening oversight to prevent misleading "GLP-1-friendly" claims on products whose attributes are inherently GLP-1 friendly (i.e., lean proteins).

Though this study has important implications for the food system and policymaking, it has several limitations. Our identification of GLP-1 effects on protein demand relies on matching methods that cannot address unobserved confounders. Since the MDM survey lacks data on participants' motivation for GLP-1 use, selecting into treatment for diabetes versus weight management may confound our effect estimates if those motivations likewise influence protein demand. For instance, being diagnosed with diabetes increases the likelihood of using a GLP-1 medication while realistically lowering demand for certain protein products (e.g., red meat), creating a negative bias in our effect estimates. Further, other behavioral factors, such as pre-adoption health focus and concurrent lifestyle changes, may also influence outcomes and cannot be disentangled from medication effects. As with Hristakeva et al. (2025), we thus document *overall* adjustments to GLP-1 adoption across related behavioral changes.

Second, the cross-sectional and meat-centric MDM data precludes analysis of how GLP-1 effects vary over time and across foods. Future research should use longitudinal household scanner data to capture temporal and substitution patterns, and to enable panel data-based causal inference methods that better address unobserved confounders. Still, our extensive sensitivity analyses related to data exclusion criteria, matching approaches, utility specifications, and unobserved confounding and heterogeneity consistently show positive GLP-1 effects on WTP for meat proteins.

Last, this study focuses on U.S. consumers' GLP-1 use and protein demand, so global applicability is uncertain. The U.S. remains the largest market for GLP-1 medications, but international adoption could reach 10 percent of the obese population by 2035 (Flynn, 2025). Great Britain is already experiencing such increases, with current users rising from 2.3 to 4.1 percent of the adult population from March 2024 to August 2025 (Kennaugh & Pattni, 2025), while Australia has observed elevenfold increases in adoption from 2014 to 2022 [though largely for diabetes treatment] (Lin et al., 2023). Since global per capita consumption of red meat and poultry is generally increasing over time (Godfray et al., 2018; Milford et al., 2019), GLP-1 effects on protein demand may span globally. More research is needed to determine if the magnitudes of effects differ across countries for cultural or institutional reasons. However, we believe we identify a general finding in that weight loss medications that place a premium on protein consumption will change both the shape and location of demand as we describe here.

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Appendix

Figure A1. Study 1 1:1 Nearest Neighbors Matching Covariate Balance—Retail DCE

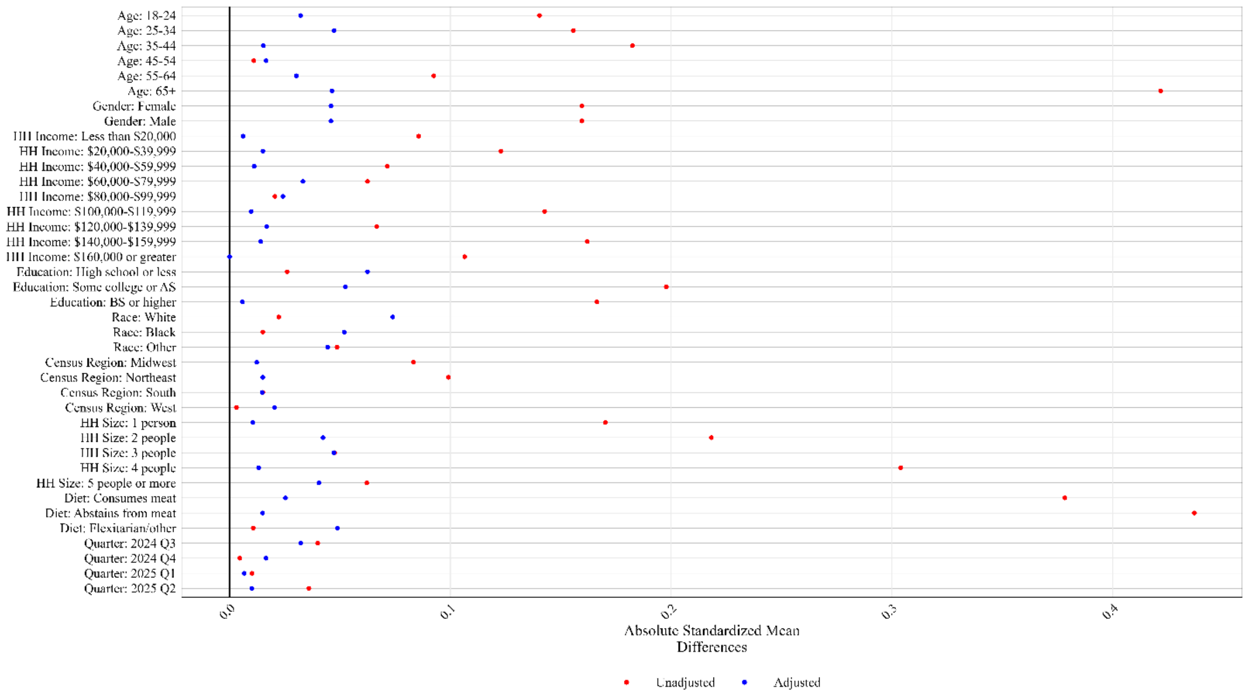


Figure A2. Study 1 Generalized Full Matching Covariate Balance—Retail DCE

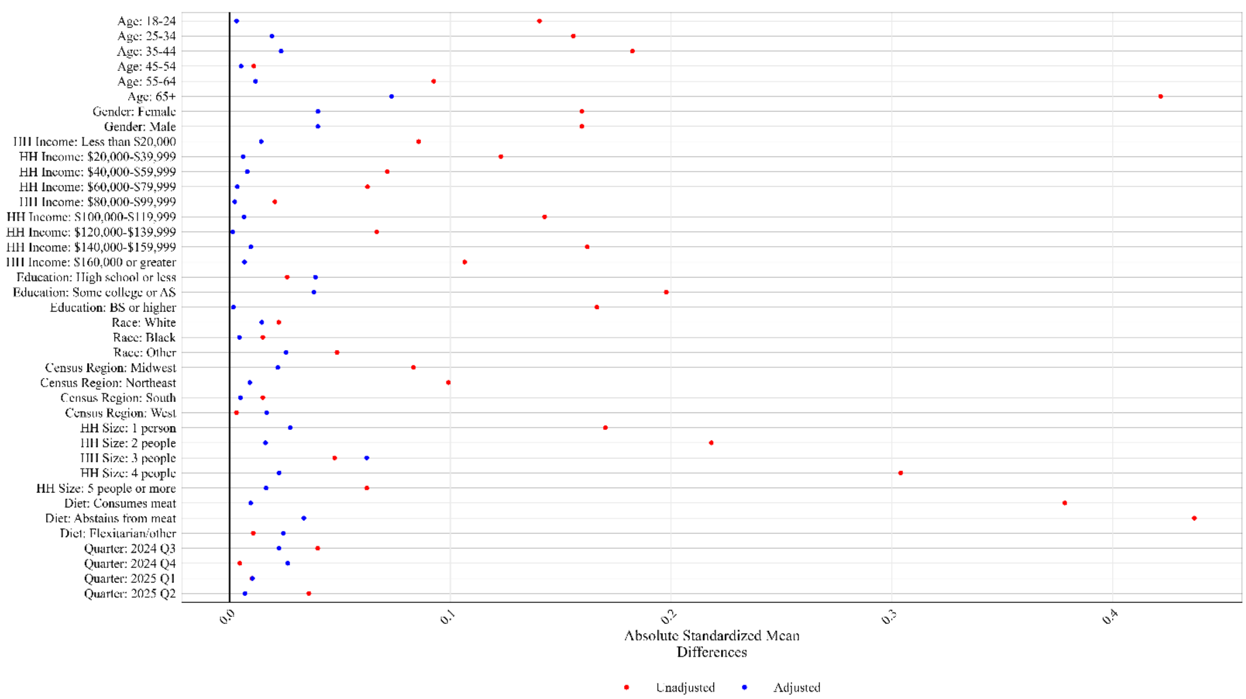


Figure A3. Study 1 1:1 Nearest Neighbors Matching Covariate Balance—Foodservice DCE

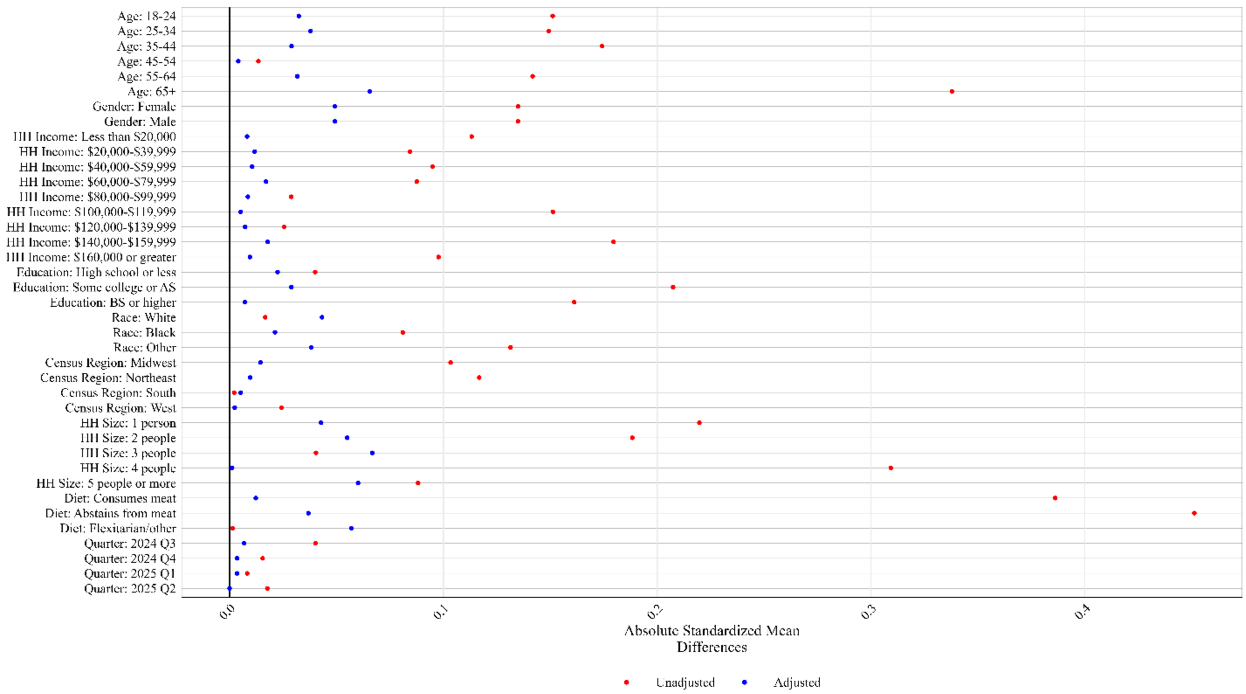


Figure A4. Study 1 Generalized Full Matching Covariate Balance—Foodservice DCE

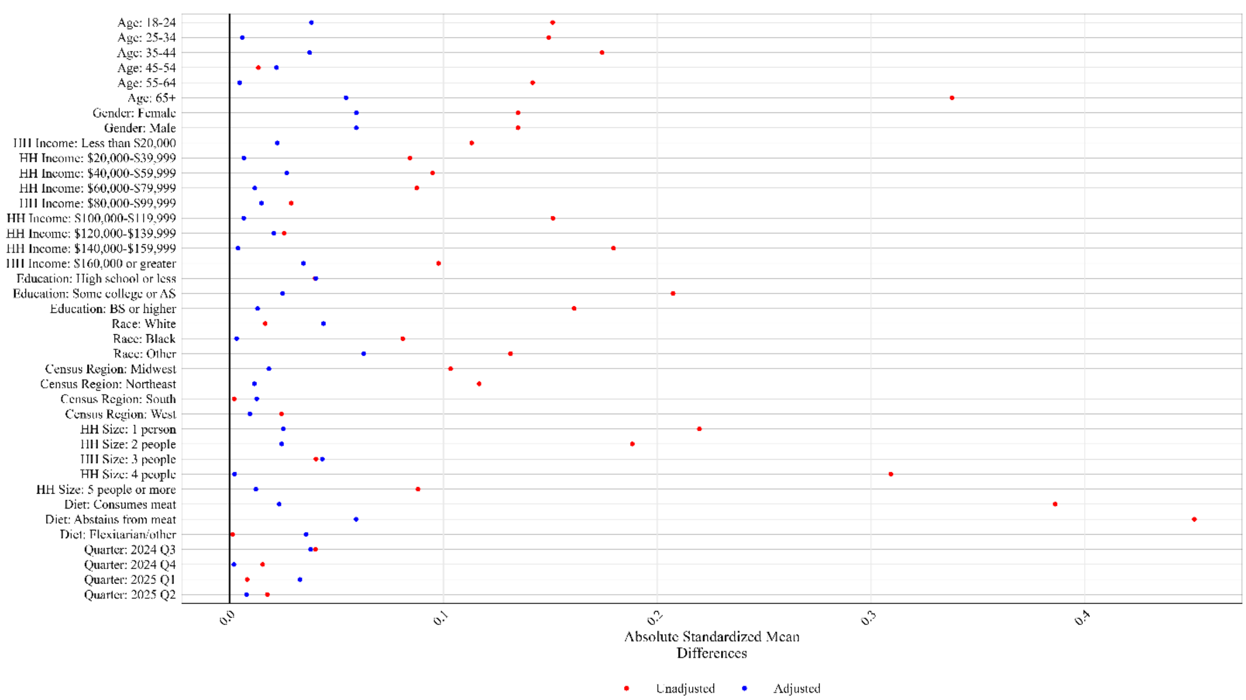


Figure A5. Study 2 1:1 Nearest Neighbors Matching Covariate Balance

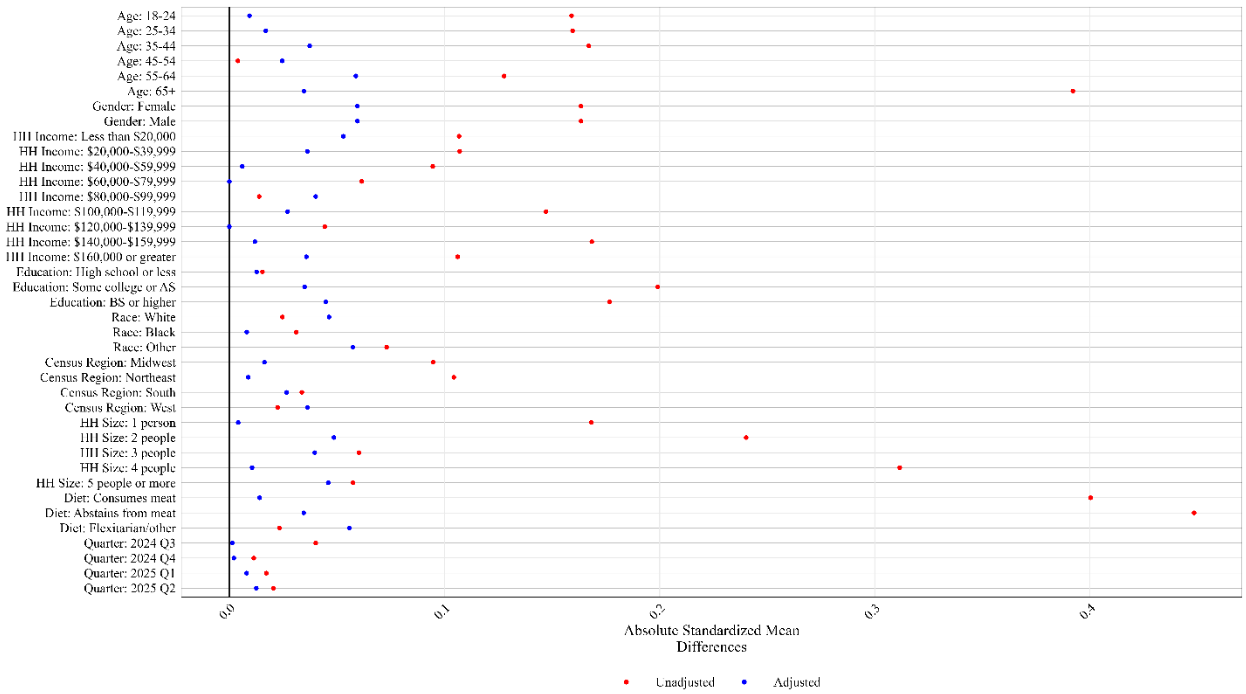


Figure A6. Study 2 Generalized Full Matching Covariate Balance

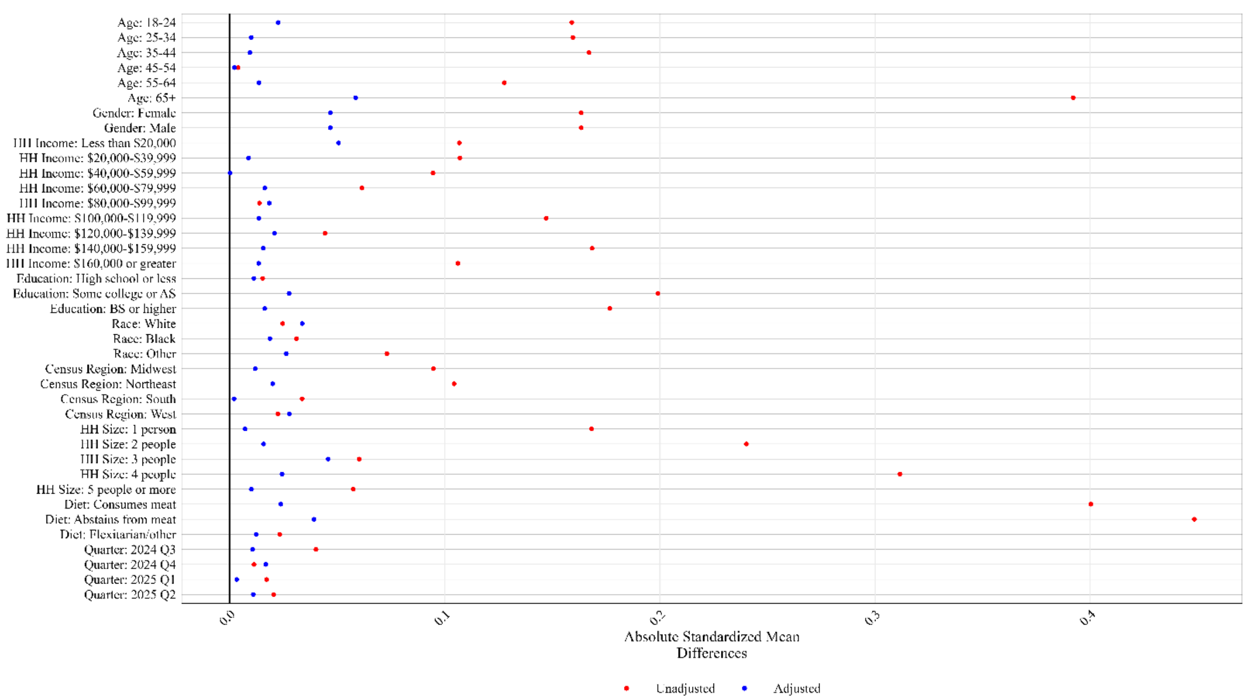


Table A1. Discrete Choice Experiment Alternatives and Price Levels

	Retail DCE ($/lb)							
	Ribeye Steak	Ground Beef	Pork Chop	Bacon	Chicken Breast	Plant-Based Patty	Shrimp	Beans & Rice
Price level 1	14.49	1.99	2.49	2.99	1.49	9.49	8.49	0.49
Price level 2	16.99	4.49	4.99	5.49	3.99	11.99	10.99	2.99
Price level 3	19.49	6.99	7.49	7.99	6.49	14.49	13.49	5.49

	Foodservice DCE ($/meal)							
	Ribeye Steak	Hamburger	Pork Chop	Baby Back Ribs	Chicken Breast	Plant-Based Patty	Shrimp	Salmon
Price level 1	18.99	9.49	14.49	12.99	10.49	12.49	10.99	14.49
Price level 2	21.49	11.99	16.99	15.49	12.99	14.99	13.49	16.99
Price level 3	23.99	14.49	19.49	17.99	15.49	17.49	15.99	19.49

Table A2. Parameter Estimates from Retail MNL Models

Variable	Full Sample	Coarsened Exact Matching	1:1 Nearest Neighbors Matching	Generalized Full Matching
Linear price effect (α)	-0.38*	-0.37*	-0.29*	-0.30*
GLP-1 use price effect (ω)	0.20*	0.05*	0.10*	0.11*
GLP-1 use preference parameters (π_j)				
$\pi_{\text{ribeye steak}}$	-2.33*	-0.17	-0.60*	-0.93*
$\pi_{\text{ground beef}}$	-0.23*	0.06	0.23*	0.16
$\pi_{\text{pork chop}}$	-0.18*	-0.04	0.23*	0.21*
π_{bacon}	-0.31*	0.07	0.18	0.11
$\pi_{\text{chicken breast}}$	-0.44*	0.03	-0.04	-0.10
$\pi_{\text{plant-based patty}}$	-1.65*	0.16	-0.53*	-0.72*
π_{shrimp}	-1.45*	-0.19	-0.39*	-0.57*
$\pi_{\text{beans and rice}}$	-0.36*	-0.15	-0.15	-0.23*
Number of individuals	17,944	2,238	4,208	17,896
Total choice tasks completed	161,496	20,142	37,872	161,064
Log-likelihood	-278,393	-34,105	-70,091	-292,786
AIC	557,303	68,726	140,698	586,087
BIC	559,881	70,767	142,902	588,665

Note: Asterisks (*) denote statistical significance at the five percent level using robust standard errors. Untreated individuals with generalized full matching weights greater than 20.0 are trimmed before MNL estimation to ensure convergence.

Table A3. Parameter Estimates from Foodservice MNL Models

Variable	Full Sample	Coarsened Exact Matching	1:1 Nearest Neighbors Matching	Generalized Full Matching
Linear price effect (α)	-0.23*	-0.23*	-0.17*	-0.18*
GLP-1 use price effect (ω)	0.12*	0.05*	0.05*	0.07*
GLP-1 use preference parameters (π_j)				
$\pi_{\text{ribeye steak}}$	-1.60*	-0.59	-0.31	-0.61*
$\pi_{\text{hamburger}}$	-0.72*	-0.29	-0.03	-0.17
$\pi_{\text{pork chop}}$	-0.95*	-0.39	-0.05	-0.33*
$\pi_{\text{baby back ribs}}$	-1.05*	-0.37	-0.16	-0.38*
$\pi_{\text{chicken breast}}$	-1.01*	-0.33	-0.23	-0.43*
$\pi_{\text{plant-based patty}}$	-1.69*	-0.61*	-0.79*	-1.00*
π_{shrimp}	-0.93*	-0.34	-0.18	-0.34*
π_{salmon}	-1.43*	-0.72*	-0.48*	-0.69*
Number of individuals	18,043	1,974	3,996	17,999
Total choice tasks completed	162,387	17,766	35,964	161,991
Log-likelihood	-309,337	-33,626	-70,000	-313,582
AIC	619,190	67,769	140,515	627,680
BIC	621,769	69,777	142,706	630,259

Note: Asterisks (*) denote statistical significance at the five percent level using robust standard errors. Untreated individuals with generalized full matching weights greater than 20.0 are trimmed before MNL estimation to ensure convergence.

Table A4. Sensitivity Analysis of GLP-1 Effects on Willingness-to-Pay

	Retail Doubly Robust Average Treatment Effects on the Treated			
Product	(1)	(2)	(3)	(4)
Ribeye steak	2.30* [>100]	2.28* [>100]	2.01* [>100]	2.24* [>100]
Ground beef	1.69* [>100]	1.22* [>100]	0.80* [>100]	1.63* [>100]
Pork chop	1.19* [>100]	1.06* [>100]	0.52* [>100]	1.17* [>100]
Bacon	1.30* [>100]	0.89* [>100]	0.89* [>100]	1.27* [>100]
Chicken breast	1.52* [>100]	1.15* [>100]	0.66* [>100]	1.47* [>100]
Plant-based patty	1.55* [>100]	0.87* [19.6]	2.12* [>100]	1.48* [>100]
Shrimp	1.06* [>100]	1.32* [>100]	0.99* [>100]	0.98* [>100]
Beans and rice	0.14 [<2.0]	0.48* [52.9]	-0.13 [<2.0]	0.14 [<2.0]

	Foodservice Doubly Robust Average Treatment Effects on the Treated			
Product	(1)	(2)	(3)	(4)
Ribeye steak	3.87* [>100]	2.86* [>100]	2.01* [>100]	3.67* [>100]
Hamburger	3.73* [>100]	2.17* [>100]	1.32* [>100]	3.57* [>100]
Pork chop	2.34* [86.2]	1.81* [>100]	1.90* [>100]	2.18* [64.3]

Baby back ribs	3.07* [>100]	2.06* [>100]	1.68* [>100]	2.95* [>100]
Chicken breast	3.22* [>100]	2.05* [>100]	1.32* [>100]	3.02* [>100]
Plant-based patty	-0.23 [<2.0]	1.20* [>100]	0.36 [>100]	-0.29 [<2.0]
Shrimp	3.20* [>100]	2.06* [>100]	1.35* [>100]	3.20* [>100]
Salmon	1.42* [11.8]	2.14* [>100]	0.33 [>100]	1.23* [7.3]

Note: Asterisks (*) denote statistical significance using Krinsky and Robb (1986) 95 percent confidence intervals. We use 10,000 draws in the Krinsky and Robb (1986) resampling procedure. Values in brackets are critical Γ values from Rosenbaum bounds sensitivity testing. Column (1) reflects the primary effect estimates derived using coarsened exact matching (CEM); column (2) reflects CEM-derived estimates when GLP-1 use is omitted from preference parameters; column (3) reflects CEM-derived estimates when GLP-1 use is omitted from price responsiveness; and column (4) reflects CEM-derived estimates when we relax the restriction on primary grocery shopper status.

Table A5. Open-Ended Choice Experiment Price Ranges ($/lb)

	Minimum	Maximum
Ribeye steak	14.49	19.49
Ground beef	1.99	6.99
Pork chop	2.49	7.49
Bacon	2.99	7.99
Chicken breast	1.49	6.49
Plant-based patty	9.49	14.49
Shrimp	8.49	13.49
Beans and rice	0.49	5.49

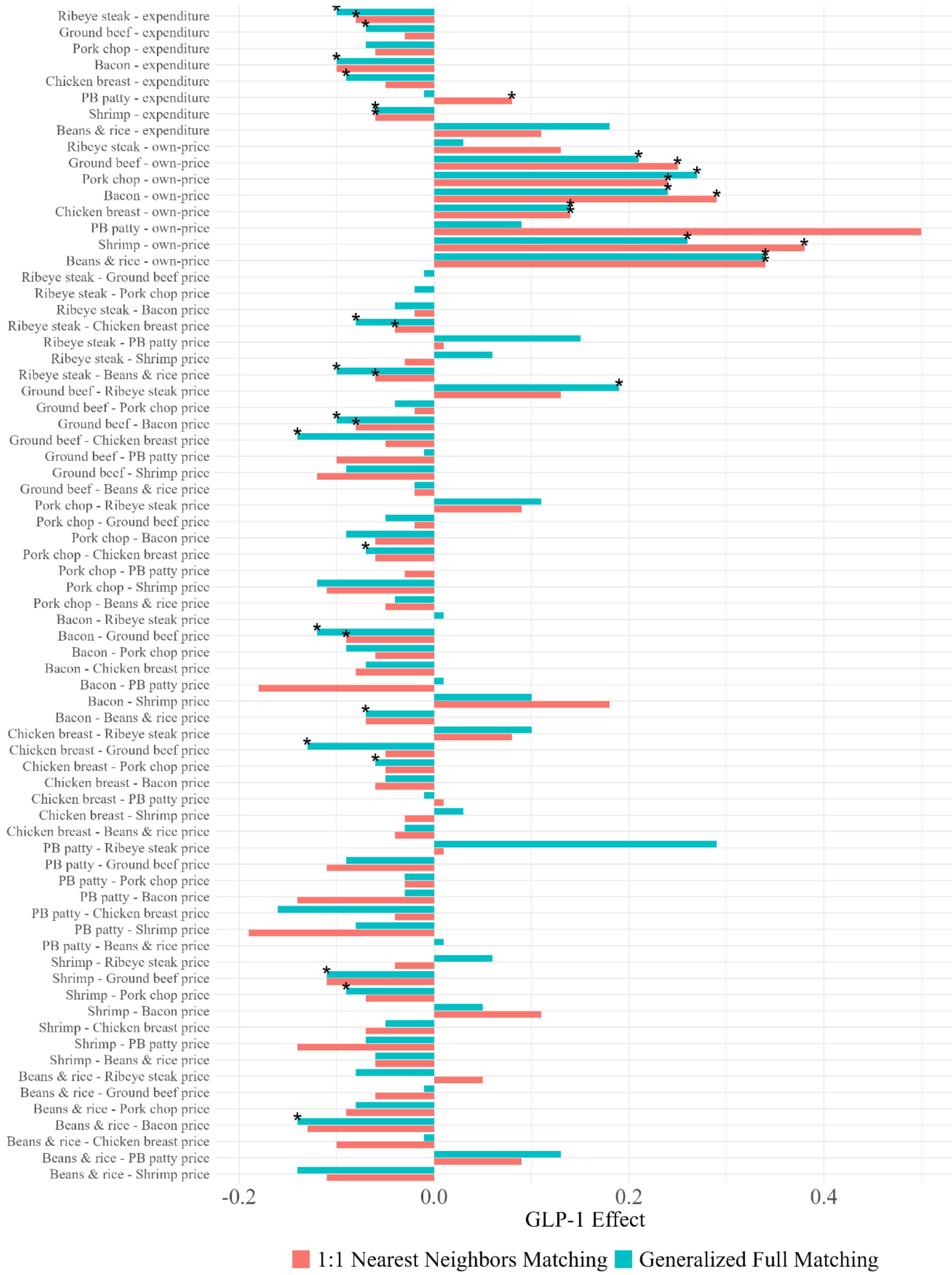
Table A6. Expectation Maximation Estimates of AIDS Parameters—Full Sample

	Share Equation							
Parameter	Ribeye Steak	Ground Beef	Pork Chop	Bacon	Chicken Breast	Plant-Based Patty	Shrimp	Beans & Rice
				Users				
βj	0.080*	-0.034*	-0.014*	-0.018*	-0.048*	0.034*	0.022*	-0.022*
Price effects								
Ribeye steak ($/lb.)	0.014							
Ground beef ($/lb.)	0.016*	0.029*						
Pork chop ($/lb.)	0.014*	-0.008*	0.039*					
Bacon ($/lb.)	0.000	-0.008*	-0.010*	0.030*				
Chicken breast ($/lb.)	0.002	-0.010*	-0.009*	-0.004*	0.031*			
Plant-based patty ($/lb.)	-0.028*	-0.009*	-0.009*	-0.006	-0.005	0.087*		
Shrimp ($/lb.)	-0.033*	0.000	-0.011*	0.004	0.005	-0.035*	0.067*	
Beans & rice ($/lb.)	0.016*	-0.009*	-0.006*	-0.006*	-0.010*	0.005	0.002	0.009*
Number of observations	3,185							

Parameter	Ribeye Steak	Ground Beef	Pork Chop	Bacon	Chicken Breast	Plant-Based Patty	Shrimp	Beans & Rice
	Share Equation							
Mean share	0.23	0.10	0.10	0.11	0.10	0.14	0.17	0.05
Adj. R-squared	0.42	0.39	0.19	0.16	0.47	0.48	0.09	
Log-likelihood	-32,776							
				Non-Users				
βj	0.086*	-0.041*	-0.015*	-0.014*	-0.064*	0.039*	0.034*	-0.026*
Price effects								
Ribeye steak ($/lb.)	-0.051*							
Ground beef ($/lb.)	0.008*	-0.006*						
Pork chop ($/lb.)	0.010*	-0.005*	-0.005*					
Bacon ($/lb.)	0.025*	-0.001	-0.001	-0.024*				
Chicken breast ($/lb.)	0.000	-0.002	-0.003*	-0.002	0.014*			
Plant-based patty ($/lb.)	-0.022*	0.008*	0.007*	0.006*	0.000	0.014*		
Shrimp ($/lb.)	0.005	0.005*	0.001	-0.001	0.001	-0.018*	0.000	
Beans & rice ($/lb.)	0.024*	-0.007*	-0.005*	-0.003*	-0.009*	0.004*	0.007*	-0.012*
Number of observations	22,859							
Mean share	0.18	0.13	0.11	0.11	0.15	0.09	0.17	0.05
Adj. R-squared	0.51	0.28	0.09	0.08	0.41	0.42	0.16	
Log-likelihood	-197,525							

Note: Asterisks (*) denote statistical significance using 95 percent bootstrap confidence intervals. We use 500 bootstrap samples.

Figure A7. GLP-1 Effects on Expenditure and Compensated Price Elasticities—1:1 NNM and GFM



Note: Asterisks (*) denote GLP-1 effects that are statistically significant. Significance is assessed using 500 bootstrap samples and Poe et al. (2005) 95 percent confidence intervals.