Effects of Aerobic and Strength-Based Exercise on Consumer Preference for Protein

Abstract

The role of protein consumption in adaptations to physical exercise is well documented in prior research. However, little is known about how physical exercise and associated protein needs impact consumers' protein demand. This study pairs matching methods with discrete choice experiments to estimate the impacts of physical exercise on willingness-to-pay for protein while reducing the confounding influences of other consumer characteristics. Aerobic and strength-based exercise, and fitness-driven protein consumption, increase willingness-to-pay for retail protein by up to $1.91 per pound for ribeye steak and foodservice protein by up to $2.47 for a ribeye steak meal. These results indicate that the physically active population is a reliable consumer base that bolsters U.S. domestic protein purchases during periods of price increases.

Keywords: choice model, physical exercise, protein, willingness-to-pay

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1 Introduction

Various government, private, and academic sources suggest that physical exercise is an increasingly common leisure time activity among U.S. residents. From the U.S. Bureau of Labor Statistics, 21.1 percent of citizens aged 15 years and over participated in sports, exercise, or recreation in 2023—an increase by 2.5 percentage points over 2013 levels (U.S. Bureau of Labor Statistics, 2024). On average, these participants spent nearly 1.5 hours per day in those activities. This growth in exercise prevalence is also observed by firms within the fitness industry. In its 2023 Form 10-K to the U.S. Securities and Exchange Commission, Planet Fitness—a major national gym chain—reported operating 2,575 stores and having 18.7 million members nationwide, reflecting compound annual growth rates of 6.5 and 6.8 percent, respectively, from 2019 (Planet Fitness, 2024). Further assessing these trends using data from the National Health and Nutrition Examination Survey (NHANES), Bina and Tonsor (2024b) find that the average time spent in physical exercise among U.S. adults increased from 21 minutes per day in 2007-2008 to nearly 24 minutes per day in 2017-2018, with relatively larger increases observed for younger individuals.

Importantly, trends in exercise and fitness have spillover effects on the U.S. food industry and, specifically, on the consumption of protein. Wilson and Wilson (2006) provide an overview of sports nutrition literature on protein requirements for resistance-trained athletes (i.e., athletes who lift weights/strength train) and the efficacy of various protein sources in stimulating muscle growth. They note that a number of sources recommend protein intakes of between 1.2 and 2.2 grams per kilogram of bodyweight per day for athletes. This is substantially higher than the 0.80 grams per kilogram of bodyweight per day recommended for the average adult (National Academies of Sciences, Engineering, and Medicine, 2006). Further, Bina and Tonsor (2024b) directly quantify the association of physical exercise with protein consumption among U.S. adults, noting that exercise is positively associated with the consumption of total protein, poultry, seafood, eggs, and dairy.

Though the role of protein consumption in physical exercise pursuits is largely understood, what is less certain are the impacts on consumer purchasing behavior in the U.S. protein industry. To my knowledge, Bina et al. (2024) is the first of a very small collection of economic studies to focus on the topic. The authors assess the impact of exercise-related news media on U.S. demand for meat and find little evidence that beef, pork, and chicken demand is sensitive to media information on protein and exercise. However, that effort reflects a nationally-aggregated demand assessment that does not consider consumers' actual exercise behavior or demand at the product level. Later work defines "trainees" as those who intentionally consume protein to aid in strength training or other fitness-related goals, concluding that those individuals are less own-price sensitive than non-trainees in their demand for various retail protein products (Bina & Tonsor, 2024a). However, that work i) does not consider consumer decisions made in a foodservice setting, which reflects 58 percent of U.S. food spending in 2023 (U.S. Department of Agriculture Economic Research Service, 2025b); ii) does not consider heterogeneity in methods of exercise; and iii) does not consider that underlying consumer characteristics other than exercise-related factors may drive demand for protein.

Related to the latter point, efforts to understand decisions made in the U.S. meat and livestock supply chain and, specifically, how those decisions vary across individuals have not typically considered potential confounding influences of the individuals' characteristics. This is not particularly surprising since the characteristics of decision makers evaluated in these efforts are usually exogenous (i.e., randomly assigned) and researchers' objectives are to illustrate variation across groups, rather than to estimate effects. For instance, Tonsor and Marsh (2007) and Lusk and Tonsor (2016) evaluate differences in demand for meat by consumers' nationalities and incomes, respectively, using split-sample demand estimation. Other researchers assess variation in meat purchasing and production technology adoption across city of purchase and age by interacting those characteristics of decision makers with other variables of key interest [e.g., alternative-specific constants in a logit model] (Klain et al., 2014; Olynk et al., 2012). However, I will show that these standard heterogeneity assessments are not appropriate when we are interested in individuals' "selection into treatment" (i.e., physical exercise) and corresponding demand behavior, as a host of other characteristics simultaneously influence that selection and protein-related decision making.

This study expands on a relatively small body of economic literature, shedding further light on the implications of physical exercise for consumer purchasing behavior and in the context of U.S. protein demand. Specifically, my objective is to quantify the impacts of physical exercise on consumers' willingness-to-pay (WTP) for protein products, considering heterogeneity in location of purchase and method of exercise, and accounting for confounding influences of other consumer characteristics. This objective directly addresses the limitations of prior research and provides a series of contributions to consumer behavior and food demand literature, and to industry practitioners.

First, animals and animal products—characterized by greater protein content relative to other commodities—accounted for $250 billion in cash receipts in 2023 (U.S. Department of Agriculture Economic Research Service, 2025a), reflecting a sector of U.S. agriculture that is economically important. Further, retail prices of beef, pork, and chicken products have consistently increased since around 2021 (Federal Reserve Bank of St. Louis, 2025c, 2025b, 2025a), but U.S.

meat purchases remain at record levels (Shike, 2025). Little is known about what is causing this phenomenon. Considering these observations, this research improves our understanding of which consumers are most likely to stay in the market for protein as prices increase and how industry can leverage demand heterogeneity and high-margin product offerings to offset potential reductions in quantities purchased. Related work suggests that intentional, fitness-driven consumers of protein may boost aggregate protein purchases and strengthen economic outcomes for the meat and livestock sector (Bina & Tonsor, 2024a). However, that work makes a strong assumption that protein demand is not driven by other underlying consumer characteristics. If that assumption is incorrect, the effectiveness of health- and fitness-related marketing campaigns or other initiatives aimed at bolstering domestic protein demand may be limited.

In that context, this work additionally contributes to traditional structural demand modeling by showing how heterogeneity assessments can be improved through the use of causal inference methods. To explain variation in demand, it is common practice to i) interact subgroup indicators with other variables of key interest (Kilders et al., 2024; Klain et al., 2014; Lusk, 2017) or ii) estimate demand models separately between subgroups (Lusk & Tonsor, 2016; Tonsor & Marsh, 2007; Tonsor & Shupp, 2011; Yang et al., 2020). These strategies, while important and useful, do not consider that consumer characteristics other than that of primary interest may drive demand (Vass et al., 2022). When the objective is to estimate the effect of a treatment, conclusions derived using these strategies may not accurately portray the true effects of the treatment if it is not randomly assigned. Thus, any associated marketing or policy prescriptions are likely ill-informed.

Last, demand transformations are typically caused by factors that are exogenous to the consumer including, firm-level product design decisions, advertising, and extension of product lines (Johnson & Myatt, 2006). These transformations can reflect a pure shift, a pure rotation, or both a shift and rotation of the demand curve. In this study, physical exercise serves as an endogenous shock (i.e., self-selected treatment) to consumers' demand for protein that may shift the demand schedule. This has obvious implications for the economic welfare of individuals who participate in physical exercise and also has indirect impacts on non-exercising individuals who experience adjustments in aggregate protein prices as markets respond to changes in physical exercise prevalence. This assessment of endogenous demand shifts provides a framework for future research that likewise seeks to estimate the economic impacts of consumers' diet- and health-related decision making.

The remainder of this study is as follows. First, I overview my conceptual framework, data, and empirical strategy. I then provide and discuss key results of my analysis. I conclude with brief comments on the direction of future research.

2 Materials and Methods

Changes in consumers' WTP for protein products due to physical exercise habits reflect an endogenous shift in valuations of the products. Standard structural demand modeling is not sufficient to estimate the demand-shifting impacts of physical exercise on protein demand schedules in the presence of confounding factors. This section overviews my method of identifying these impacts.

2.1 Conceptual Model

Following the random utility framework of McFadden (1973), I first suppose that an individual with characteristics k is faced with a variety of alternatives, having characteristics x, and has a utility function for each alternative that can be written as:

(1) $$U = V(k, x) + \varepsilon(x)$$

where V is the nonstochastic, or observable, portion of utility and ε reflects the idiosyncrasies of the individuals' tastes for the alternative.

Now recall the aforementioned relationship between physical exercise and protein consumption. If two individuals exist who differ *only* in their physical exercise behavior—letting $T = 1$ denote the individual who participates in physical exercise and $T = 0$ denote the individual who does not—and they are both faced with a variety of protein-dense food alternatives, it stands to reason that:

(2) $$V(\bar{k}, x | T = 1) \neq V(\bar{k}, x | T = 0)$$

where $\bar{k}$ is all consumer characteristics except for T, which are identical between the two individuals. That is, the two individuals may not obtain the same utility from protein products *ceteris paribus*.

Equation (2) reflects my assumption that the parameters in V are different between those who participate in physical exercise and those who do not. As an example, an individual who exercises may have a preference for protein over other foods if they perceive protein consumption as aiding them toward their muscle-building or performance goals. These effects of physical exercise on preferences may also vary across protein sources that are heterogeneous in characteristics (i.e., calorie content, fat content, convenience, etc.) and may not align with exercisers' perceived dietary needs. Additionally, those who exercise may be financially invested in their fitness goals (e.g., they purchase gym memberships, exercise equipment, dietary supplements, etc.) such that they have lower price sensitivity than other individuals when purchasing protein. In all, preferences and price sensitivity may be influenced by individuals' physical exercise behavior, which then impacts the utility obtained from purchasing protein and any associated economic measures of interest.

2.2 Data

Publicly available survey data supporting this study is obtained from the Meat Demand Monitor (MDM). The MDM is a long-running project funded by the U.S. Beef and Pork Checkoff programs that is intended to capture preferences and purchase behavior in the domestic meat industry, with separate consideration of retail and foodservice markets (Tonsor, 2020). As part of the MDM project, an online, national survey is distributed each month to a subset of the population that is designed to be representative in terms of age, sex, race, income, educational attainment, and region of residence. Roughly 3,000 usable responses are obtained each month with the data having a pooled cross-sectional structure (i.e., a different sample of the population is surveyed each month).

In addition to key sociodemographic information, the MDM includes two components that, combined, are necessary to fulfill the stated objective. These components are i) retail- and foodservice-framed discrete choice experiments (DCE) capturing stated preferences for protein-dense food products and ii) questions capturing respondents' physical exercise behavior. Regarding the former, MDM respondents are randomly assigned to a DCE that is based in either a grocery retail or restaurant setting [one half of respondents are assigned to each] (Tonsor, 2020). In each DCE, eight protein products are presented, along with a ninth "opt out" option. Prices are the only attributes that are displayed, with these having three levels for each product. Products and price levels for both DCEs are depicted in Table 1, while Appendix Figures A1 and A2 depict example choice tasks.

Table 1. Retail and Foodservice DCE Products 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

Both DCEs are characterized by a main effects orthogonal fractional factorial design with a D-efficiency of 95.3 and 27 unique choice tasks (Tonsor, 2020). The choice tasks are blocked into three sets of nine such that each MDM participant, after being assigned to either the retail- or foodservice-framed DCE, are further assigned to one set of nine choice tasks. The nine choice tasks are then randomly presented to participants to mitigate the potential impacts of respondent fatigue. This design is akin to Lusk (2017) and the Food Demand Survey.

Regarding the second key component of the MDM, respondents are asked a sequence of exercise-related questions. The first is "*Thinking about your typical 7-day week, combined how much moderately-intense (e.g., brisk walking) and vigorously-intense (e.g. running or jogging) aerobic activity (exercise and/or work) do you get?* (Tonsor, 2024)." The second is then "*Thinking about your typical 7-day week, how much muscle-strengthening activity (exercise and/or work) do you get?*" For each, respondents report their weekly activity level in interval form from "less than 30 minutes per week" to "over 240 minutes per week." Last, respondents are asked "*Do you intentionally eat protein to aid in meeting strength-training or other fitness-related goals?*" This final question and broader survey data are utilized in related work estimating protein demand elasticities among health- and fitness-focused consumers (Bina & Tonsor, 2024a). Importantly, the choice experiments precede all exercise-related questions, mitigating concerns of possible framing effects and resulting bias in the reporting of protein choices.

This study uses MDM data from November 2022 through December 2024. Prior to my analyses, MDM respondents are omitted who i) are under the age of 18, ii) are not the primary grocery shopper in their household, iii) do not successfully pass two embedded attentiveness checks, or iv) do not provide complete information on key sociodemographic characteristics, exercise behavior, and DCE choices. This leaves 72,761 usable responses. Table 2 depicts descriptive statistics of the sample, distinguishing between exercise behavior. Importantly, 71 percent of respondents report spending at least 30 minutes per week (m/wk) in aerobic exercise, 53 percent report spending at least 30 m/wk in strength-based exercise, and 32 percent report intentionally consuming protein to meet some fitness-related goal.

Table 2. Descriptive Statistics of the Sample by Exercise Behavior

	Relative Frequency						
		30+ m/wk Aerobic Exercise		30+ m/wk Strength Exercise		Intentional Consumer	
Variable	Full[a]	Yes	No	Yes	No	Yes	No
30+ m/wk aerobic exercise	0.71	1.00	0.00	0.94	0.45	0.86	0.64
30+ m/wk strength exercise	0.53	0.70	0.11	1.00	0.00	0.78	0.41
Intentional consumer	0.32	0.39	0.15	0.47	0.15	1.00	0.00
Sex							
Female	0.53	0.49	0.62	0.46	0.61	0.45	0.57
Male	0.47	0.51	0.38	0.54	0.39	0.55	0.43
Age							
18 to 24 years	0.05	0.06	0.03	0.07	0.02	0.09	0.03
25 to 34 years	0.12	0.14	0.09	0.16	0.08	0.19	0.09
35 to 44 years	0.18	0.20	0.15	0.23	0.14	0.26	0.15
45 to 54 years	0.16	0.16	0.16	0.17	0.16	0.17	0.16
55 to 64 years	0.24	0.22	0.28	0.19	0.29	0.17	0.27
65 years and over	0.24	0.22	0.29	0.18	0.31	0.13	0.30
Annual household income							

	Relative Frequency						
		30+ m/wk Aerobic Exercise		30+ m/wk Strength Exercise		Intentional Consumer	
Variable	Full[a]	Yes	No	Yes	No	Yes	No
Less than $20,000	0.15	0.11	0.23	0.11	0.19	0.13	0.16
$20,000 to $39,999	0.22	0.20	0.26	0.20	0.24	0.20	0.23
$40,000 to $59,999	0.21	0.21	0.21	0.21	0.22	0.21	0.22
$60,000 to $79,999	0.17	0.18	0.14	0.17	0.16	0.16	0.17
$80,000 to $99,999	0.08	0.09	0.06	0.09	0.07	0.08	0.08
$100,000 to $119,999	0.05	0.06	0.03	0.06	0.04	0.06	0.05
$120,000 to $139,999	0.03	0.04	0.02	0.04	0.03	0.04	0.03
$140,000 to $159,999	0.04	0.05	0.01	0.05	0.02	0.06	0.03
$160,000 and over	0.05	0.06	0.02	0.06	0.03	0.06	0.04
Educational attainment							
High school degree or less	0.27	0.24	0.34	0.24	0.30	0.25	0.28
Some college	0.42	0.41	0.45	0.40	0.44	0.39	0.43
4-year degree or higher	0.31	0.36	0.21	0.36	0.26	0.36	0.29
Race							
White	0.73	0.72	0.74	0.70	0.77	0.65	0.76
Black	0.15	0.15	0.15	0.17	0.13	0.20	0.12
Other	0.12	0.13	0.11	0.14	0.11	0.15	0.11
Census region							
Midwest	0.21	0.20	0.23	0.20	0.23	0.19	0.22
Northeast	0.18	0.18	0.17	0.18	0.18	0.18	0.18
South	0.38	0.38	0.39	0.38	0.39	0.39	0.38
West	0.23	0.24	0.20	0.24	0.21	0.25	0.22
Household size							
1 person	0.27	0.25	0.30	0.24	0.29	0.24	0.28
2 people	0.38	0.37	0.39	0.34	0.42	0.30	0.42
3 people	0.16	0.17	0.15	0.18	0.14	0.20	0.15
4 people	0.12	0.13	0.09	0.15	0.09	0.18	0.09
5 people or more	0.07	0.07	0.07	0.08	0.06	0.09	0.06
Diet							
Regularly consumes meat	0.76	0.74	0.81	0.71	0.82	0.67	0.80
Abstains from meat	0.07	0.08	0.04	0.10	0.04	0.13	0.04
Flexitarian/other	0.17	0.18	0.15	0.19	0.15	0.20	0.16
Body mass index							
Underweight (lower than 18.5 kg/m^2)	0.03	0.04	0.03	0.04	0.03	0.05	0.03
Normal weight (18.5 to 24.9 kg/m^2)	0.37	0.40	0.29	0.43	0.30	0.42	0.35
Overweight (25 to 29.9 kg/m^2)	0.33	0.34	0.28	0.33	0.32	0.33	0.32
Obese (30 kg/m^2 or greater)	0.27	0.22	0.40	0.20	0.35	0.20	0.30
Quarter							
1	0.21	0.21	0.22	0.21	0.22	0.21	0.22

	Relative Frequency						
		30+ m/wk Aerobic Exercise		30+ m/wk Strength Exercise		Intentional Consumer	
Variable	Full[a]	Yes	No	Yes	No	Yes	No
2	0.23	0.24	0.23	0.24	0.23	0.24	0.23
3	0.23	0.24	0.22	0.24	0.23	0.24	0.23
4	0.32	0.32	0.33	0.32	0.32	0.31	0.32
Number of observations	72,761	51,763	20,998	38,621	34,140	23,253	49,508

Note: [a]Columns are the full usable sample, those who spend at least 30 m/wk in aerobic exercise, those who do not spend at least 30 min/wk in aerobic exercise, those who spend at least 30 m/wk in strength-based exercise, those who do not spend at least 30 min/wk in strength-based exercise, those who intentionally consume protein to meet a fitness-related goal, and those who do not intentionally consume protein to meet a fitness-related goal.

Notable differences are observed in individuals' exercise behavior. Among those who spend at least 30 m/wk in strength-based exercise, 54 percent are male and 46 percent are female. This difference by sex is similar for the group that intentionally consumes protein for fitness-related goals. Additionally, individuals under the age of 45 more frequently exercise and intentionally consume protein than not. For example, among individuals who spend at least 30 m/wk in aerobic exercise, 40 percent are between the ages of 18 and 44. This is compared to individuals who do not participate in at least 30 m/wk of aerobic exercise, of which 27 percent are between the ages of 18 and 44. Discrepancies in income are also observed with annual household incomes of at least $80,000 consistently reported at a higher frequency among the exercising and intentional protein consumption groups relative to the other groups. For brevity, further differences in exercise behavior are observed across educational attainment, race, region of residence, household size, diets, and (expectedly) body mass index (BMI). As a final note, Bina and Tonsor (2024b) find that in 2017-2018 males, younger individuals, college graduates, and higher earners spent more time per day in physical exercise. That effort uses NHANES data and illustrates correlations that are broadly consistent with those depicted in Table 2.

2.3 Reducing Confounding Influences

From Table 2 descriptive statistics, a host of consumer characteristics are correlated with aerobic exercise, strength-based exercise, and intentional (fitness-driven) consumption of protein. Prior work notes that these sociodemographic factors are likewise correlated with meat consumption (Daniel et al., 2011; Wang et al., 2010; Zeng et al., 2019). Thus, these consumer characteristics likely confound the relationship between physical exercise behavior and preferences for protein-dense foods. This is problematic in the sense that industry efforts to market to health- and fitness-conscious consumers or, at the least, understand the consumer segment may be implicitly tailored to certain sociodemographic groups rather than to true exercise behavior. Any costs of production (e.g., package labels) and marketing intended to capture revenue from physically-active consumers may not be necessary if demand heterogeneity is driven by other underlying consumer characteristics.

To minimize the confounding influences of age, sex, income, and other factors on the relationship between physical exercise behavior and protein demand, I implement a series of matching procedures prior to outcome estimation (i.e., logit choice modeling). In each procedure, I consider three self-selected (i.e., not randomly assigned) treatments. These are i) spending at least 30 m/wk in aerobic exercise, ii) spending at least 30 m/wk in strength-based exercise, and iii) intentionally consuming protein to meet some fitness-related goal. I use age, sex, annual household income, educational attainment, race, region of residence, household size, and diet as matching variables as they exhibit at least slight correlation with exercise behavior and have been noted in prior work as being correlated with meat consumption. Though seasonality appears to be unrelated to physical exercise, I follow related work that accounts for seasonality in meat demand (Brester & Schroeder, 1995; Coffey et al., 2011; Piggott & Marsh, 2004) by including when participants completed the survey (i.e., quarter dummy variables) in each matching procedure. As additional justification, variables that are unrelated to the treatment but related to the outcome (i.e., preferences for protein-dense foods), such as seasonality, should be included in treatment modeling to i) remove bias due to chance associations between those variables and the treatment and ii) to decrease the variance of the estimated treatment effect (Brookhart et al., 2006). In contrast, I omit respondents' BMI from the matching procedures because it is necessarily impacted by the treatments and will create selection bias comparable in size to bias from classical confounding if used (Greenland, 2003; Stuart, 2010).

As a final note on variable selection, the matching procedures using "intentional protein consumption" as the treatment indicator further stratify by binary aerobic and strength-based exercise variables because these variables likely influence individuals' proclivity to consume protein to meet fitness-related goals. However, binary aerobic (strength-based) exercise variables are not included in the matching procedures using strength-based (aerobic) exercise as the treatment indicator because they are likely influenced by the treatment, yielding selection bias if included as stratification variables (Greenland, 2003; Stuart, 2010).

The first matching procedure I consider is coarsened exact matching (CEM). Exact matching is the "gold standard" among matching techniques, replicating a randomized experiment where treated and control groups are randomly different on all covariates (Stuart, 2010; Vass et al., 2022). In exact matching, treated and control units are placed into stratums such that all units in a stratum are perfectly identical across all characteristics. Thus, characteristics are perfectly balanced both within a stratum and on average between treated and control subgroups. No assumptions on functional form are needed to completely eliminate confounding due to measured covariates. The coarsened version of exact matching that I implement simply entails matching on aggregated characteristics [e.g., categorical income rather than continuous] (Iacus et al., 2011). This procedure limits sample losses experienced when units cannot be matched, though at the expense of introducing some imbalance of characteristics within a stratum (Vass et al., 2022), and has been implemented in prior food-related consumer studies (Beatty & Tuttle, 2015).

To test the sensitivity of my findings, I also consider generalized full matching [GFM] (Sävje et al., 2021). This procedure retains all observations and begins with a first-stage logistic regression to derive the probabilities of treatment given a set of predictors (i.e., the matching variables I discuss above). These probabilities are used as a distance measure in the second-stage matching process. In full matching, "optimal" matched sets are created such that i) each set contains at least one treated and one control individual and ii) the average distance between treated and control units is minimized within each set (Hansen, 2004; Sävje et al., 2021; Stuart, 2010). The GFM method is a generalization of traditional full matching, which computes quickly even in large samples and produces near optimal matched sets (Sävje et al., 2021).

After CEM- and GFM-based stratum assignment, stratum propensity scores (SP) are calculated as the proportion of individuals in each stratum that are treated. Each participant in a stratum is then given the same SP. To estimate the average treatment effects on the treated (ATT), treated individuals are assigned a weight of one and control individuals are assigned a weight of SP/(1-SP) to ensure that the weighted average of characteristics are balanced between treated and control subgroups (Austin & Stuart, 2015; Stuart, 2010; Vass et al., 2022).

A total of 12 matching procedures are conducted across the two DCEs (i.e., retail and foodservice), three treatments (i.e., aerobic exercise, strength-based exercise, and intentional protein consumption), and two matching methods (i.e., CEM and GFM). This allows for a robust demand heterogeneity assessment that considers the location of protein purchase, the method of exercise, and confounding influences of other consumer characteristics. Appendix Figure A3 provides a summary of all matching procedures while Appendix Figures A4 through A9 depict the absolute standardized mean differences in measured covariates between treated and control subgroups using the GFM method (the CEM method is omitted as covariates are perfectly balanced between subgroups by design). Matching procedures are conducted using the MatchIt package (Ho et al., 2024) in R version 4.4.1.

2.4 Empirical Model

Consumer preferences are estimated via the multinomial logit (MNL) model. I again suppose that consumer i obtains from alternative j the utility $U_{ij} = V_{ij} + \varepsilon_{ij}$. The observable portion of utility takes the form:

$$V_{ij} = \theta_{ij} + \gamma_i p_j \quad (3)$$

where θ_{ij} is an alternative-specific constant 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. Train (2009) notes that the ratios of coefficients in most discrete choice models have an economic meaning. Using my proposed utility specification, the ratio $-{}^{\theta_{ij}}/_{\gamma_i}$ represents individual i's WTP for alternative j over the opt out option.

Price effects are restricted to being linear and identical across alternatives because flexible price response (e.g., adding quadratic terms) can yield undesirable predictions (Lusk & Tonsor, 2016). This is especially true when leveraging the three-price level design of the MDM DCEs. Additionally, I restrict preference and price parameters to be non-random. Well-documented limitations of the MNL model include i) parameters that are constant across individuals and ii) substitution patterns that are identical across alternatives (Train, 2009). The random parameters logit (RPL) model has been designed to address both of these limitations. However, Bina and Tonsor (2024a) have already addressed the relationship between exercise-driven protein consumption and protein demand elasticities in related work, finding that the differences in substitution patterns between behavioral groups are small in magnitude. Additionally, heterogeneity in preferences and price responsiveness can be assessed by interacting observed consumer characteristics with the alternative-specific constants and the price term and without the added complexity and computational expense introduced through RPL designs. Thus, equation (3) allows for the estimation of doubly robust treatment effects (which I discuss shortly), fulfilling the stated objective of this study in a pragmatic manner.

Following my assumption that those who exercise have different preference and price parameters, θ_{ij} and γ_i are allowed to vary across individuals such as in Lusk (2017). I let $\theta_{ij} = \delta_j + \sum_{k=1}^{K} \delta_{jk} z_{ik} + \pi_j Treatment_i$, where z_{ik} is the vector of survey participant characteristics that is used in the matching procedures and influence choice through the parameters δ_{jk}; and $Treatment_i$ is a treatment indicator that influences choice through the parameters π_j, allowing for the impacts of physical exercise behavior on utility to vary across protein sources. Further, I allow price responsiveness to vary across physical exercise behavior by letting $\gamma_i = \alpha + \omega Treatment_i$. It should be noted that price responsiveness can also be allowed to vary by survey participant characteristics other than physical exercise behavior. However, that level of flexibility yields marginal utility of a price change (rather than disutility) and nonsensical WTP estimates for numerous participants.

As an additional sensitivity assessment, I also estimate the effects of physical exercise on WTP for protein when i) restricting the treatment (i.e., physical exercise, intentional protein consumption) impacts on the alternative-specific constants to equal zero (i.e., $\pi_j = 0\ \forall_j$) and ii) restricting the treatment impacts on price responsiveness to equal zero (i.e., $\omega = 0$). These sensitivity assessments are conducted using CEM-derived choice data, with the results indicating how robust the WTP effects are to my assumption that those who exercise have different preferences and sensitivity to price.

2.5 Outcome and Effect Estimation

The outcome models described by equation (3) are estimated via maximum likelihood and separately using retail and foodservice choice data; using aerobic exercise, strength-based exercise, and intentional (fitness-driven) protein consumption treatments; and using the full sample, CEM, and GFM. Thus, the primary results of this study reflect the estimation of 18 choice models using the Apollo package (Hess & Palma, 2019) in R version 4.4.1. The matching weights obtained from the aforementioned matching procedures are incorporated into estimation of the respective outcome models. The outcome models using the full retail- and foodservice-framed DCE choice data are unweighted and reflect traditional heterogeneity assessments that do not consider confounding influences of other consumer characteristics.

After estimation of the weighted outcome models (i.e., those using CEM- and GFM-derived samples), I follow prior developments in causal inference to estimate doubly robust treatment effects (Chatton & Rohrer, 2024; Funk et al., 2011; Snowden et al., 2011; Vansteelandt & Keiding, 2011). This procedure reduces the confounding influences of other consumer characteristics on the relationship between physical exercise behavior and protein demand. The multi-step doubly robust standardization begins with (after estimating the weighted outcome models) i) predicting θ_{ij} and γ_i among the treated assuming that $Treatment_i = 1$ and ii) predicting θ_{ij} and γ_i among the treated assuming that $Treatment_i = 0$. In the second step, I calculate the mean WTP for each alternative across all treated individuals, and separately for each counterfactual exposure regimen. Last, the ATT estimates are obtained by calculating the difference in the mean WTP estimates between the counterfactuals.

These ATT estimates are unbiased if either the outcome model described by equation (3) is correctly specified or the matching procedure sufficiently reduces imbalance in covariates between those who exercise and those who do not (Chatton & Rohrer, 2024; Funk et al., 2011). Regarding the latter, the CEM method eliminates much of the confounding due to imbalance in measured covariates, though it must be considered that some variation may be present between individuals within a stratum either due to the coarsening of measured covariates or the presence of unmeasured confounders. In all, my use of covariate balancing techniques prior to choice modeling is not intended to estimate true "causal" effects of physical exercise on WTP for protein. Rather, it demonstrates how demand heterogeneity assessments can be improved by minimizing confounding influences of other factors when the effect of a specific, self-selected subgroup indicator (e.g., physical exercise) is the primary interest.

There is debate among researchers whether uncertainty in the matching procedure needs to be considered when estimating the variance of treatment effects (Stuart, 2010). Further, bootstrap confidence intervals prescribed by Funk et al. (2011) and Snowden et al. (2011) are not practical in my application to discrete choice modeling, requiring many estimations of equation (3) across all sets of choice data. Thus, I do not consider uncertainty in the matching procedures, but rather construct Krinsky and Robb (1986) confidence intervals to account for uncertainty in outcome estimation.

3 Results and Discussion

Appendix Tables A1 and A2 provide parameter estimates obtained from the 18 choice models. These models include between 258 and 274 parameters. For the purposes of readability, I report only the price effects, interactions with the treatment indicator, and model fit measures.

Mean WTP estimates and differences in mean WTP between treated and control groups are the primary interest in this study. Table 3 depicts the mean WTP of those who exercise or intentionally consume protein for fitness goals (i.e., the treated) and those who do not using the full, unmatched sample. These reflect standard demand estimation results that do not consider confounding characteristics of other consumer traits. Also depicted are the effects of treatment on WTP that are obtained by the doubly robust standardization procedure using CEM and GFM, which illustrate how demand heterogeneity conclusions are impacted by confounding characteristics of consumers.

Table 3. Physical Exercise Effects on WTP for Retail Protein ($/lb)

				Doubly Robust ATT	
Product	Treated[a]	Untreated	Difference	CEM	GFM
		30+ Min/Week Aerobic Exercise[b]			
Ribeye steak	16.88	15.00	1.88	0.14*	0.97*
Ground beef	8.53	6.79	1.74	0.42*	1.19*
Pork chop	7.24	5.53	1.71	0.46*	1.27*
Bacon	5.91	4.76	1.16	0.29*	0.94*
Chicken breast	8.47	6.34	2.12	0.67*	1.55*
Plant-based patty	7.69	5.84	1.85	0.97*	1.93*
Shrimp	9.71	8.27	1.43	0.46*	1.13*
Beans and rice	3.56	1.88	1.68	0.65*	1.40*
		30+ Min/Week Strength Exercise			
Ribeye steak	17.99	14.90	3.09	0.55*	1.78*
Ground beef	9.58	6.66	2.92	0.74*	1.96*
Pork chop	8.14	5.51	2.63	0.74*	2.00*
Bacon	6.58	4.71	1.87	0.49*	1.32*
Chicken breast	9.39	6.46	2.93	0.92*	2.07*
Plant-based patty	8.12	6.33	1.79	0.60*	1.20*
Shrimp	10.18	8.52	1.66	0.43*	1.23*
Beans and rice	4.08	2.15	1.93	0.70*	1.31*

Product	Treated[a]	Untreated	Difference	Doubly Robust ATT	
				CEM	GFM
		Intentional Consumer			
Ribeye steak	20.63	15.09	5.54	1.91*	3.49*
Ground beef	12.02	6.87	5.15	1.31*	3.06*
Pork chop	10.15	5.75	4.40	1.15*	2.77*
Bacon	8.18	4.86	3.32	0.92*	2.13*
Chicken breast	11.62	6.73	4.89	1.23*	3.12*
Plant-based patty	9.09	6.62	2.47	0.82*	1.18*
Shrimp	11.49	8.69	2.80	0.78*	2.20*
Beans and rice	5.53	2.35	3.19	1.02*	1.86*

Note: [a]Columns are mean WTP across treated individuals in the full sample, mean WTP across untreated individuals in the full sample, the difference in mean WTP between treated and untreated individuals in the full sample, the treatment effect using coarsened exact matching (CEM), and the treatment effect using generalized full matching (GFM). [b]Treatments are spending at least 30 m/wk in aerobic exercise, spending at least 30 m/wk in strength-based exercise, and intentionally consuming protein to meet a fitness-related goal. Asterisks (*) denote statistically significant treatment effects using 95 percent Krinsky and Robb (1986) confidence intervals.

It is immediately obvious that individuals who exercise or who intentionally consume protein to meet fitness-related goals are willing to pay more for all evaluated retail protein sources. Differences in mean WTP between subgroups range from $1.16 per pound for bacon (aerobic exercise treatment) to $5.54 per pound for ribeye steak (intentional consumption treatment). These differences are, with the exception of plant-based patty, smallest when separating subgroups by aerobic exercise activity and largest when separating by intentional protein consumption. These results align with my expectations as aerobic exercise is not generally intended to result in muscle growth (requiring protein) and intentionally consuming protein to meet fitness-related goals is a distinct indicator of commitment to those goals and, more broadly, nutrition. Further, higher mean WTP for protein among those who exercise indicates that, *ceteris paribus*, these individuals may

i) purchase relatively higher volumes of protein products in a retail setting than those who do not exercise or ii) purchase at a similar volume but have relatively higher expenditures as they shift to products with higher quality or value added (e.g., "high in protein" labels, convenient protein snacks, etc.).

Discrepancies between the standard heterogeneity assessment and causal inference approaches are more interesting. For example, those who participate in aerobic exercise are willing to pay \$1.88 more per pound for ribeye steak than those who do not, on average. However, when I implement covariate balancing methods—considering that sex, age, income, and other factors influence both the proclivity to exercise and preference for protein goods—the effect of the aerobic exercise treatment declines to between \$0.14 (CEM) and \$0.97 (GFM) per pound. This is consistent across products, treatments, and matching methods (with the exception of plant-based patty, aerobic exercise, and GFM). These results illustrate that other consumer traits may underpin heterogeneity in food demand and, thus, bias estimates of the consumer characteristic of interest, as evident when comparing simple associations to CEM- and GFM-derived effects of treatment on WTP. This is problematic in that food marketing or healthy-eating campaigns may not have the intended result if focused on a specific consumer type. As a simplistic example, a retailer may believe that those who participate in physical exercise have higher WTP for lean protein sources (i.e., chicken breast) and, correspondingly, market those products with a "low in calorie" or physical activity calorie equivalent label. In reality, factors such as income (if correlated with both physical exercise and preferences for chicken breast) may drive the higher WTP and the new labels introduce an unnecessary cost of production.

That said, balancing covariates prior to demand estimation still results in increases in WTP (i.e., rightward shift effects on protein demand) ranging from \$0.14 per pound for ribeye steak (aerobic exercise treatment) to \$1.91 per pound also for ribeye steak (intentional consumption treatment) using CEM. Further, these impacts of physical exercise reflect sizable premiums over the mean WTP of those who do not exercise. For instance, participating in strength-based exercise yields higher WTP for chicken breast of \$0.92 per pound, which is a roughly 14 percent increase over the mean WTP reported among those who are not involved in strength-based exercise (\$6.46 per pound). These results suggest that i) there is potential for food manufacturers and retailers to capture meaningfully higher WTP among the physically active population through targeted product development and marketing and ii) these fitness-conscious individuals exit the market for protein later than other consumers in instances of increasing prices. Importantly, positive shift effects on protein demand are observed across each treatment group. Thus, firm-level decisions and aggregate market participation depend on a multitude of physical exercise methods.

Further, market trends such as recently experienced cattle inventory contractions (U.S. Department of Agriculture Economic Research Service, 2023)—which, all else equal, yield higher beef prices—and observed price increases across other protein sources (Federal Reserve Bank of St. Louis, 2025a, 2025b) may cause the physically active population to represent a progressively larger share of the market for protein as other consumers alter their purchasing habits. Additionally, higher WTP for protein among the physically active may serve to offset recent reductions (or stagnation) in per capita red meat and poultry consumption (U.S. Department of Agriculture Economic Research Service, 2024). Put another way, behavioral determinants of protein demand such as physical exercise may bolster domestic livestock and meat industries in periods of distress. This is consistent with Lusk and Tonsor (2016) remarks that higher income households, if less price sensitive than lower income households, may compose a larger share of total purchases as meat prices increase. However, upstream players in the livestock and meat supply chain should recognize that, while those who exercise may be “reliable consumers” and bolster demand in periods of industry distress, price-induced changes in the composition of the market (in terms of which consumers are participating) require flexibility in marketing and product offerings in order to meet the changing needs of consumers. Such flexibility in firm- and industry-level decision making should consider consumers’ wide variety of methods of physical exercise, as suggested by positive and meaningful effects on WTP for protein observed across every treatment group.

Similar results are observed in a foodservice setting. Table 4 depicts mean WTP for foodservice protein among those who exercise (i.e., the treated) and those who do not using the full, unmatched sample. Also depicted are the CEM- and GFM-derived differences in WTP that account for confounding characteristics of consumers. Again, those who participate in physical exercise or otherwise intentionally consume protein to meet fitness-related goals are willing to pay more for all evaluated protein goods, and by a magnitude of up to $8.56 for a meal including ribeye steak as the entrée (intentional consumption treatment). Like in the retail assessment, this association of WTP with physical exercise is smallest (largest) in magnitude for aerobic exercise (intentional, fitness-driven protein consumption), with the exception of plant-based patty. Higher WTP among those who exercise in a foodservice setting are less likely to result in higher volumes purchased (relative to those who do not exercise), as meals in many dine-out settings have a standardized quantity of protein. More likely, higher WTP for foodservice protein found in this study may materialize as physically active consumers purchasing higher-quality protein items or purchasing protein in higher-quality food outlets, increasing their aggregate expenditures on protein.

Table 4. Physical Exercise Effects on WTP for Foodservice Protein ($/lb)

				Doubly Robust ATT	
Product	Treated[a]	Untreated	Difference	CEM	GFM
		30+ Min/Week Aerobic Exercise[b]			
Ribeye steak	26.55	23.85	2.70	0.20	1.35*
Hamburger	19.73	17.05	2.68	0.47*	1.53*
Pork chop	16.21	13.00	3.22	0.94*	2.45*
Baby back ribs	18.90	16.68	2.22	0.34*	1.50*
Chicken breast	18.78	15.39	3.38	1.26*	2.63*
Plant-based patty	12.51	8.36	4.15	2.36*	3.40*
Shrimp	18.39	16.10	2.29	0.46*	1.62*
Salmon	19.96	16.04	3.91	1.78*	2.68*
		30+ Min/Week Strength Exercise			
Ribeye steak	28.33	23.57	4.76	1.37*	3.25*
Hamburger	21.43	16.80	4.63	1.27*	3.18*
Pork chop	17.46	13.36	4.11	1.51*	3.32*
Baby back ribs	20.02	16.74	3.28	1.11*	2.60*
Chicken breast	19.99	15.87	4.12	1.56*	3.31*
Plant-based patty	13.20	9.71	3.49	1.81*	2.31*
Shrimp	19.46	16.22	3.24	1.28*	2.77*
Salmon	20.99	16.91	4.07	2.17*	3.24*
		Intentional Consumer			
Ribeye steak	32.47	23.92	8.56	2.47*	6.06*
Hamburger	25.47	17.16	8.31	1.96*	5.17*
Pork chop	20.29	13.88	6.42	1.11*	4.31*
Baby back ribs	22.62	17.10	5.53	1.11*	3.93*
Chicken breast	23.10	16.32	6.78	2.11*	5.06*
Plant-based patty	14.33	10.49	3.84	1.01*	1.68*
Shrimp	21.86	16.60	5.26	1.34*	3.86*
Salmon	23.90	17.39	6.52	2.20*	4.93*

Note: [a]Columns are mean WTP across treated individuals in the full sample, mean WTP across untreated individuals in the full sample, the difference in mean WTP between treated and untreated individuals in the full sample, the treatment effect using coarsened exact matching (CEM), and the treatment effect using generalized full matching (GFM). [b]Treatments are spending at least 30 m/wk in aerobic exercise, spending at least 30 m/wk in strength-based exercise, and intentionally consuming protein to meet a fitness-related goal. Asterisks (*) denote statistically significant treatment effects using 95 percent Krinsky and Robb (1986) confidence intervals.

The effect estimates using CEM and GFM methods are again consistently smaller in magnitude than the associations of WTP with physical exercise. However, these demand-shifting effects are always positive and generally statistically significant at the five percent level (with the exception of ribeye steak, aerobic exercise treatment, CEM). As an example, those who participate in strength-based exercise are willing to pay $4.63 more for a hamburger meal than those who do not, on average. However, the impact of strength-based exercise participation falls to $1.27 and $3.18 for CEM and GFM methods, respectively. That said, these effects still reflect notable increases in WTP. The $1.27 increase in WTP for a hamburger meal in foodservice is a roughly 7.6 percent increase over the mean WTP of individuals who do not participate in strength-based exercise ($16.80).

Like in the retail setting, the magnitude of effects in foodservice suggests that substantial price increases in protein-based menu items could be experienced before fitness-focused consumers elect not to purchase. Additionally, decisions made on restaurant location (i.e., in proximity to a gym), theme, and menu offerings may need to seriously consider broad trends in consumers' exercise behavior in order for foodservice outlets to capture additional revenue. I leave marketing, pricing, and other retail and foodservice strategies to industry decision makers but, given my findings, emphasize that the economic outcomes observed by U.S. livestock and meat producers are in part driven by nontraditional sources of demand heterogeneity (i.e., physical exercise habits).

As a final note on the implications of my results, the rightward-shift effects of physical exercise and intentional, fitness-driven protein consumption in both retail and foodservice settings additionally reflects a *rotation* effect on aggregate protein demand. That is, physical exercise yields a uniform increase in the valuation of protein among individuals who participate in those activities.

However, this increases the overall dispersion of preferences for protein as individuals who begin to exercise move into the upper end of the distribution of valuation. As discussed by Johnson and Myatt (2006), this increase in dispersion reflects a clockwise rotation of the aggregate inverse demand curve for protein and lessens aggregate own-price price sensitivity (i.e., aggregate protein demand becomes more inelastic). Thus, the increasing prevalence of physical exercise among U.S. citizens may explain industry observations that consumers are purchasing meat products at record levels despite being in a high-price environment (Shike, 2025).

3.1 Sensitivity and Limitations

The CEM-derived differences in WTP estimates are generally robust to my specification of θ_{ij} and γ_i. That is, omitting the interactions of the treatment indicator with the alternative-specific constants or price term yields similar conclusions regarding consumer preferences. Appendix Tables A3 and A4 depict these differences. Physical exercise effects on WTP for protein are still positive across all products, outlets, and treatments. The magnitudes of effects are generally lower than the primary results when the alternative-specific constant interactions are omitted, but similar when the price term interaction is omitted. Further, omitting the intentional consumption treatment interaction with the price term in foodservice results in some effects not being statistically significant at the five percent level (i.e., hamburger, baby back ribs, and shrimp). However, all other sensitivity assessment results are aligned with my primary findings in terms of direction and statistical significance.

Though the primary results reported in this study are robust to matching method and utility specification, several limitations should be discussed. First, and most important, my identification strategy relies on the selection on observables assumption. That is, after having controlled for observed sociodemographic characteristics, the decision to participate in physical exercise is as good as randomly assigned. However, a limitation of matching techniques exists in that unobserved variables may determine both physical exercise habits and WTP for protein, confounding the effect estimates. When selection on unobservables is a concern, instrumental variable (IV) approaches are often utilized instead to derive causal effects; however, I am unable to identify variables in the MDM survey that satisfy both the relevance and exclusion criteria for IV estimation. Thus, the effects I present should not be interpreted as truly causal.

Second, MDM-based choice data reflects stated preferences and, thus, is subject to hypothetical bias in reported WTP. Various *ex post* approaches have been developed to reduce the effects of hypothetical bias in stated preference studies, including data screening, related market calibration, and uncertainty recoding (Loomis, 2014). I rely on the data screening method by omitting MDM participants from analysis if they are not their household's primary grocery shopper or if they fail one of two attentiveness checks. Further, since my research objective is to estimate the impacts of physical exercise on WTP for protein products, hypothetical bias would have to exist *disproportionately* between treated (i.e., those who exercise) and control groups to be a major concern. I have no reason to believe that this is the case, especially since treated and control groups are balanced on all observable sociodemographic characteristics.

4 Conclusions

This study is motivated by substantial prices increases recently experienced across a variety of protein sources, a new body of economic literature focused on exercise- and fitness-related protein demand, and concerns that erroneous conclusions are drawn when evaluating endogenous demand transformations. I estimate the effects of physical exercise on consumers' WTP for retail and foodservice protein products by balancing exercising and non-exercising subgroups on measured covariates and then utilizing the matched samples in multinomial logit-based choice modeling. My findings indicate that those who participate in aerobic or strength-based exercise, or otherwise intentionally consume protein to meet fitness-related goals, are uniformly willing to pay more for protein-dense food items in retail and foodservice outlets. The effects of physical exercise on WTP are sizable, ranging from $0.29 per pound for bacon (aerobic exercise, retail setting) to $2.47 per ribeye steak meal (intentional protein consumption, foodservice setting) after controlling for observed confounders.

Moving forward, future researchers should consider that the effects of physical exercise pursuits may carry over to industries other than meat and livestock. My results related to plant-based patties and beans and rice suggest as much. Fruits, vegetables, dairy, and dietary supplements (e.g., plant- or dairy-based protein powders) may be impacted similarly by societal trends in health and fitness. Future researchers should address how consumers change their consumption and purchasing patterns for those food groups and how the economic outcomes of the respective industries are impacted. Tangentially related, such future research efforts should also address how overall diet composition and quality changes as consumers begin to participate in physical exercise. Physical exercise and any corresponding dietary changes may have joint downstream impacts on medical expenses, health insurance enrollment, or any other market related to the physical health of consumers.

Additionally, various other health-related demand transformations are impacting the food system and their economic impacts are not well understood. For instance, “food is medicine” interventions have arisen as a method to combat diet-related chronic disease by providing patients with medically tailored meals and groceries, and produce prescriptions (Downer et al., 2020). Such interventions typically call for increased consumption of food products such as fruit and vegetables. More recently, glucagon-like peptide-1 (GLP-1) receptor agonists have changed how many consumers purchase and consume food (Dilley et al., 2025; Roe, 2024). Notably, these weight loss medications are highly correlated with factors such as sex and income. Thus, consumers who self-select into GLP-1 treatment are already likely to exhibit fundamentally different food demand schedules, necessitating methods of causal inference—such as those that appear in this study—to accurately identify how the medications affect food demand.

My hope is that this study provides a framework and inspiration for other researchers to tackle those emerging issues related to health- and fitness-trends and food purchasing behavior.

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Appendix

The following text precedes the presented retail-framed choice tasks. "*Imagine you are at the grocery store buying the ingredients to prepare a meal for you or your household. Each product would be boneless and uncooked for you to prepare at home as desired. For each of the following 9 questions, please indicate which you would most likely buy. The only difference across these 9 questions is the price ($/lb) of each option.*"

Figure A1. Retail DCE Example Choice Task

The protein contents of these retail products per 100 grams are as follows:

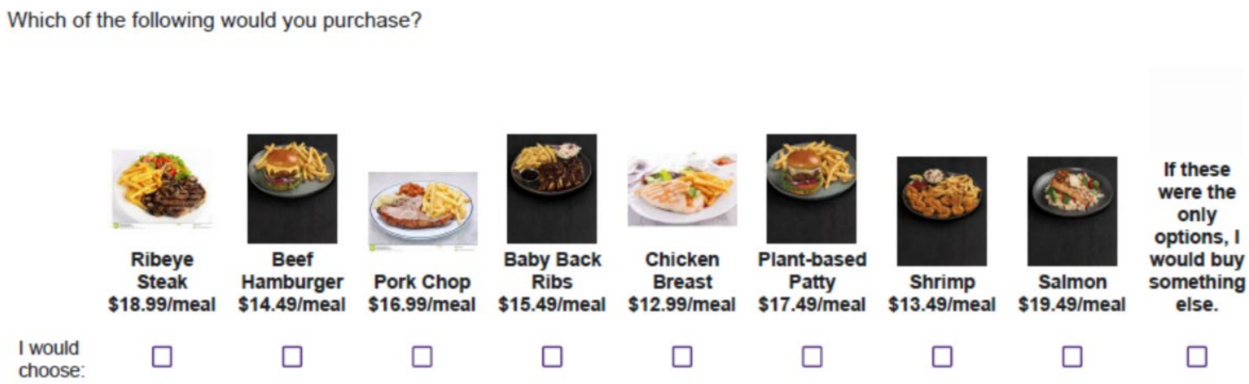
Product	NBD Number	Protein Content (per 100 g)
Ribeye steak (boneless, choice, grilled)	23267	24.2 g
Ground beef (85% lean, crumbles, pan-browned)	23570	27.7 g
Pork chop (boneless, broiled)	10068	27.6 g
Bacon (pan fried)	10862	33.9 g
Chicken breast (roasted)	5064	31.0 g
Plant-based patty (Beyond Burger)	-	17.7 g
Shrimp (cooked)	15271	24.0 g
Beans and rice (white)	-	6.5 g

Note: The FDC ID for plant-based patty is 2367272. The FDC ID for beans and rice is 2708990.

U.S. Department of Agriculture Agricultural Research Service. (2025). FoodData Central. USDA Agricultural Research Service. https://fdc.nal.usda.gov/

The following text precedes the presented foodservice-framed choice tasks. "*Imagine you are at your local restaurant for dinner. For each of the following 9 questions, please indicate which main entrée you would most likely select for your meal. Each product would be the dinner meal's main entree, would be prepared as you desire, and served with two side dishes of your choosing. The only difference across these 9 questions is the meal price associated with each main entrée option.*"

Figure A2. Foodservice DCE Example Choice Task



The protein contents of these foodservice products per 100 grams are as follows:

Product	NBD Number	Protein Content (per 100 g)
Ribeye steak (boneless, choice, grilled)	23267	24.2 g
Beef hamburger (85% lean, pan-broiled)	23569	24.6 g
Pork chop (boneless, broiled)	10068	27.6 g
Baby back ribs (boneless, braised)	10195	26.3 g
Chicken breast (roasted)	5064	31.0 g
Plant-based patty (Beyond Burger)	-	17.7 g
Shrimp (cooked)	15271	24.0 g
Salmon (smoked)	15077	18.3 g

Note: These protein contents reflect the entrée and do not consider any side dishes. The FDC ID for plant-based patty is 2367272.

U.S. Department of Agriculture Agricultural Research Service. (2025). FoodData Central. USDA Agricultural Research Service. https://fdc.nal.usda.gov/

Figure A3. Overview of Full and Matched Samples

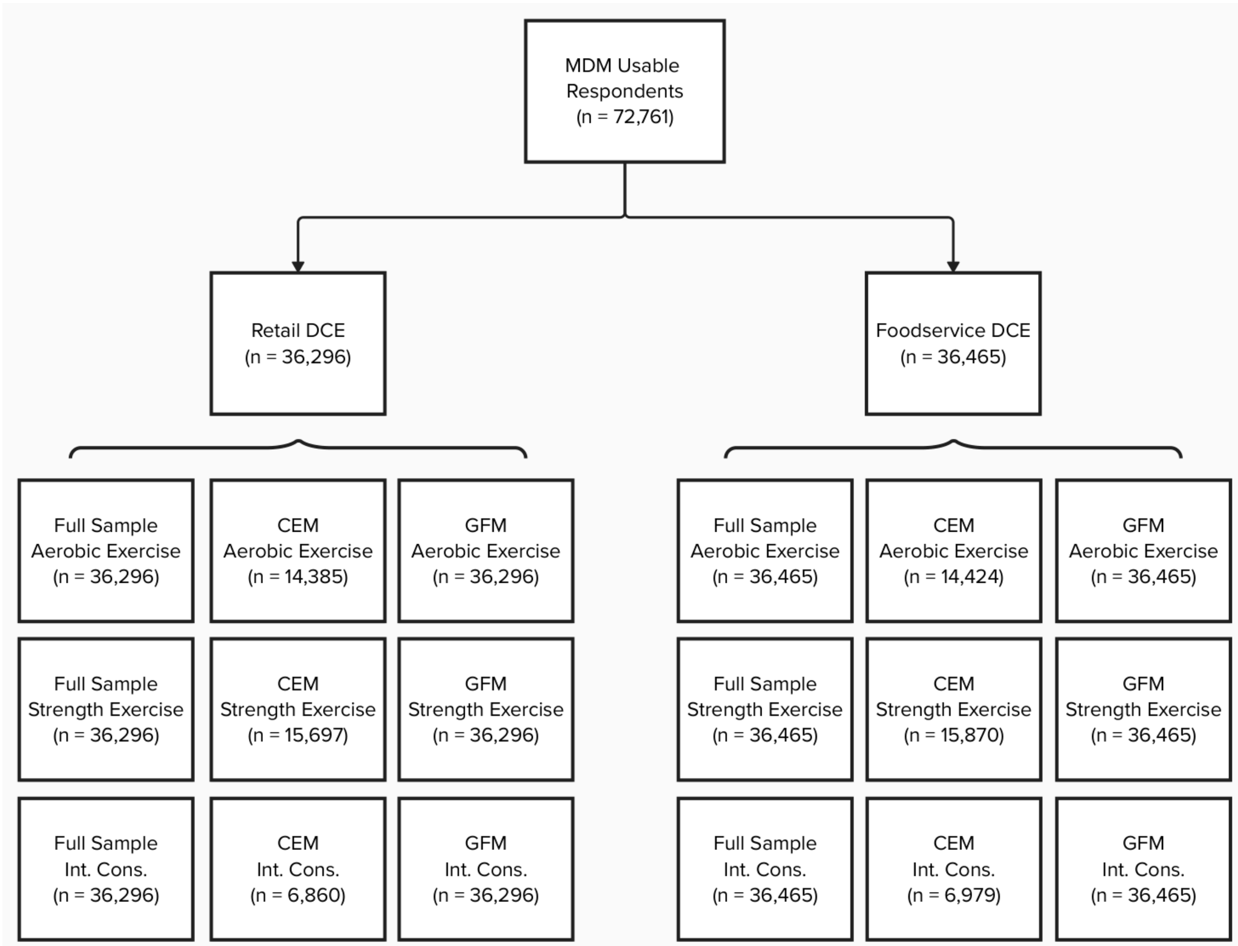


Figure A4. GFM Covariate Balance—Retail DCE, Aerobic Exercise Treatment

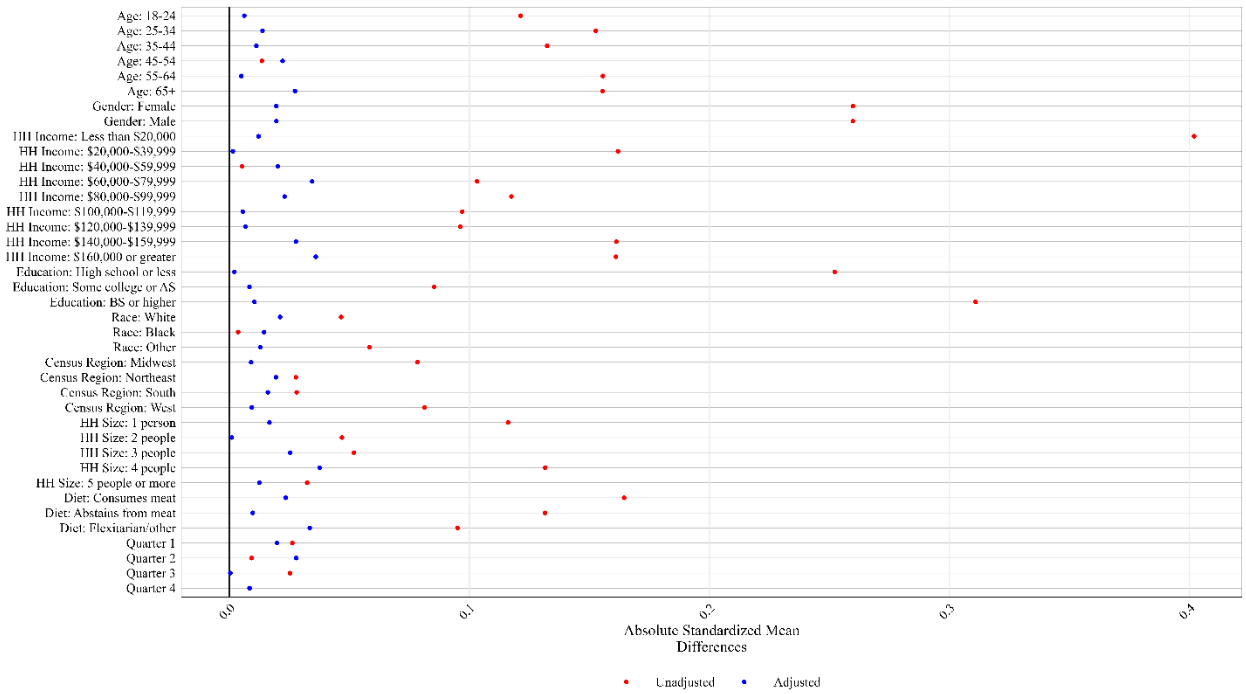


Figure A5. GFM Covariate Balance—Retail DCE, Strength-Based Exercise Treatment

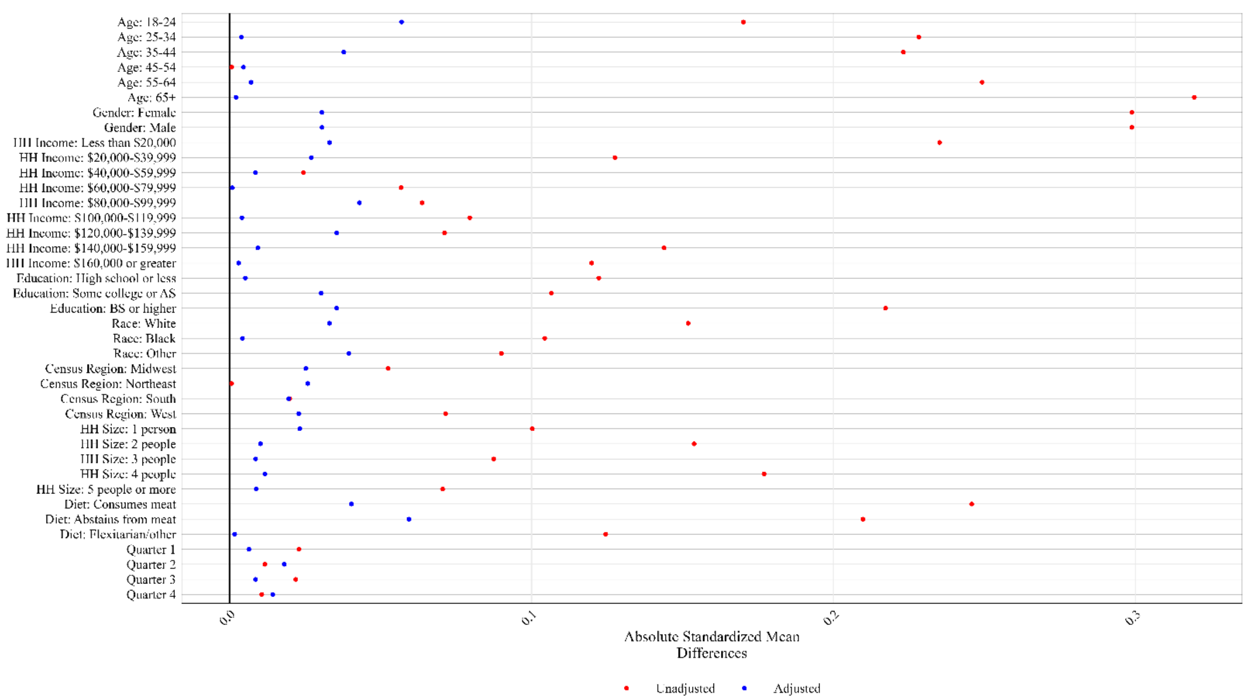


Figure A6. GFM Covariate Balance—Retail DCE, Intentional Consumption Treatment

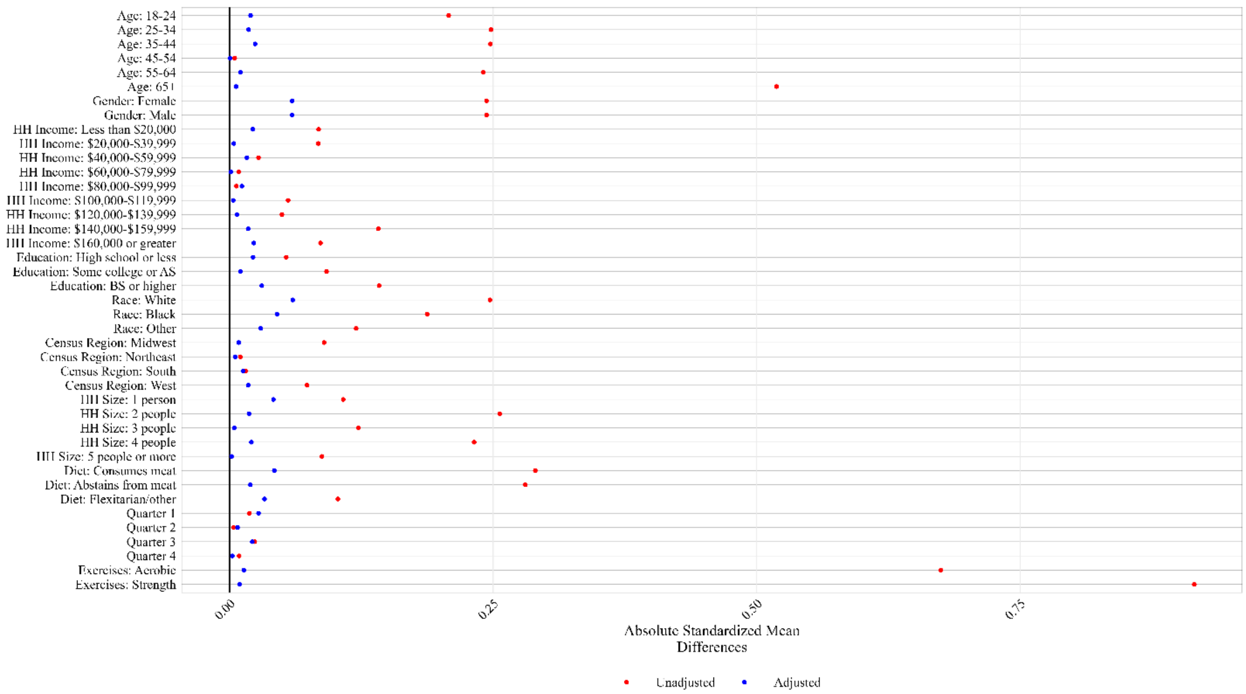


Figure A7. GFM Covariate Balance—Foodservice DCE, Aerobic Exercise Treatment

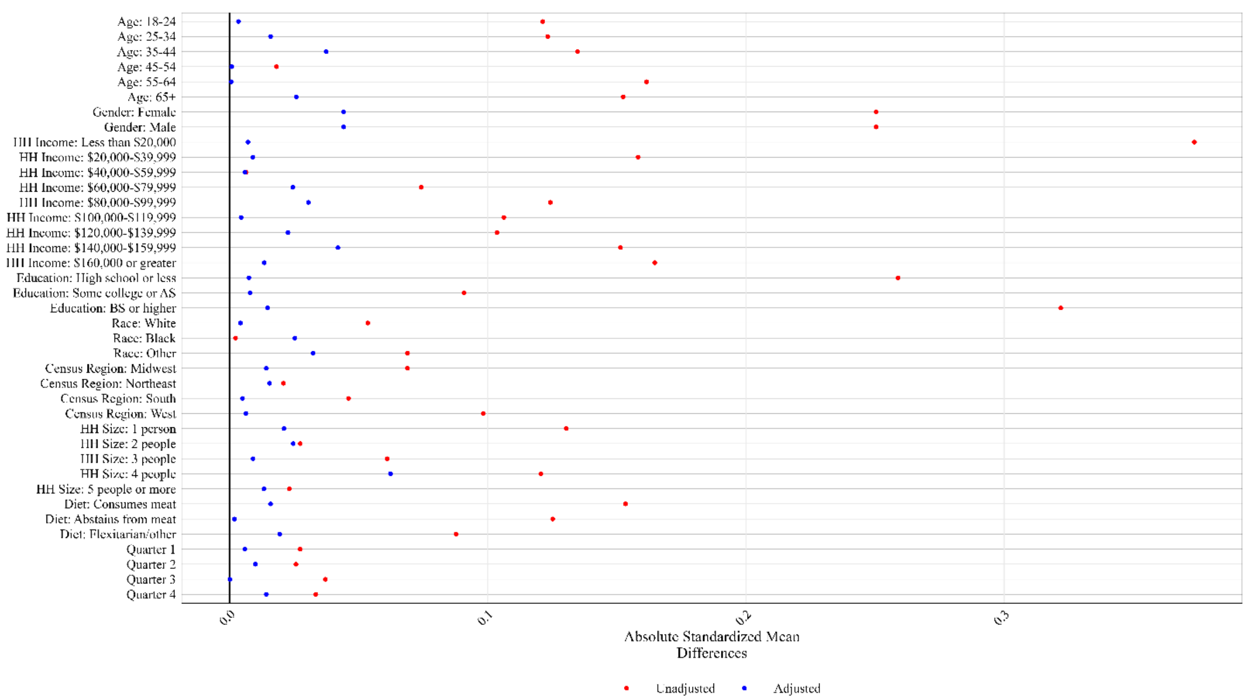


Figure A8. GFM Covariate Balance—Foodservice DCE, Strength-Based Exercise Treatment

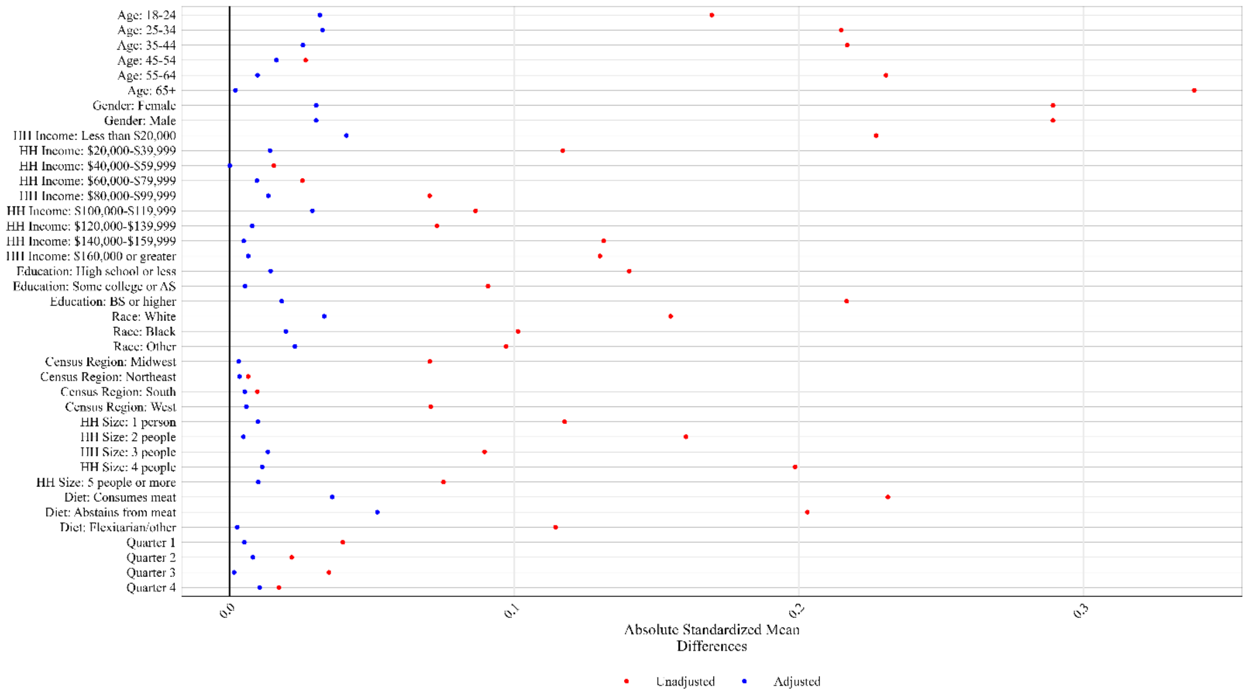


Figure A9. GFM Covariate Balance—Foodservice DCE, Intentional Consumption Treatment

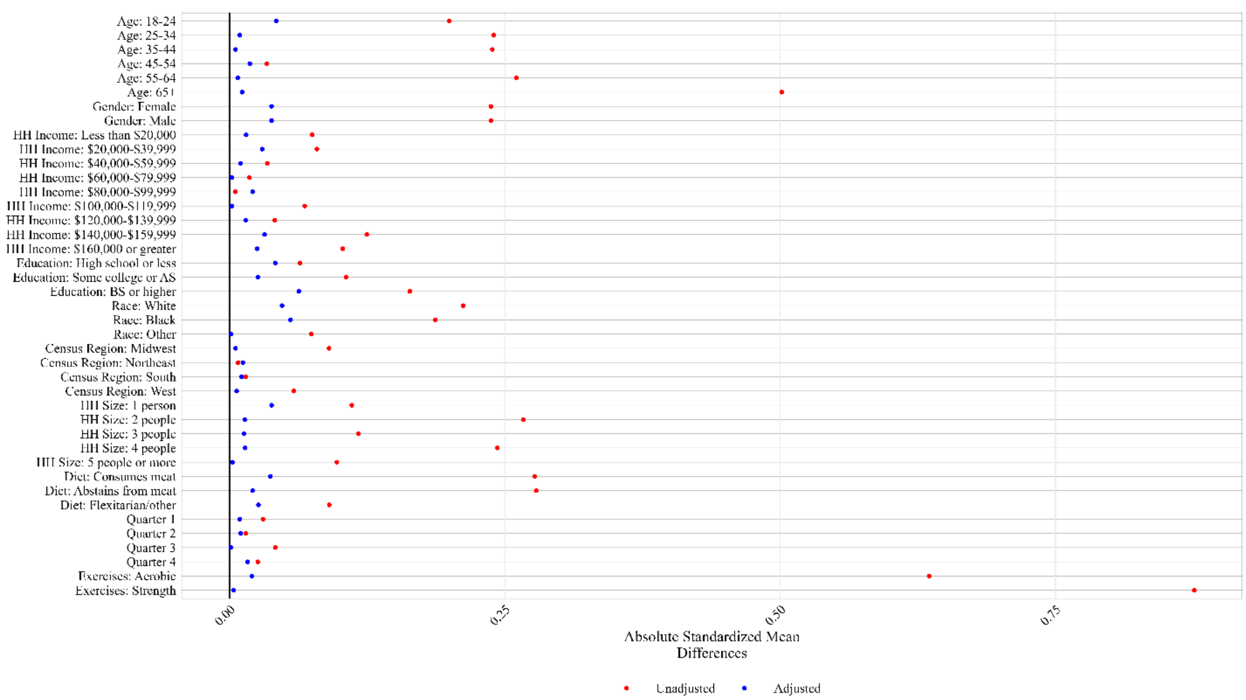


Table A1. Retail MNL Parameter Estimates

Variable	30+ Min/Week Aerobic Exercise[a] Full[b]	CEM	GFM	30+ Min/Week Strength Exercise Full	CEM	GFM	Intentional Consumer Full	CEM	GFM
Linear price effect	-0.44*	-0.50*	-0.38*	-0.46*	-0.48*	-0.36*	-0.44*	-0.40*	-0.30*
Linear price effect x Treatment	0.11*	0.03*	0.05*	0.17*	0.05*	0.08*	0.22*	0.07*	0.07*
Alternative-specific constants									
Ribeye steak x Treatment	-1.40*	-0.31*	-0.46*	-2.24*	-0.59*	-0.72*	-2.65*	-0.47*	-0.49*
Ground beef x Treatment	-0.24*	0.04	0.04	-0.46*	-0.05	-0.02	-0.52*	-0.12	0.01
Pork chop x Treatment	-0.16*	0.08	0.13*	-0.37*	0.01	0.10*	-0.49*	-0.10	0.06
Bacon x Treatment	-0.26*	0.02	0.07	-0.48*	-0.05	-0.02	-0.59*	-0.09	0.02
Chicken breast x Treatment	-0.06	0.16*	0.17*	-0.34*	0.04	0.04	-0.44*	-0.14	0.06
Plant-based patty x Treatment	-0.41*	0.34*	0.35*	-1.11*	-0.06	-0.18	-1.69*	-0.20	-0.34*
Shrimp x Treatment	-0.68*	0.01	-0.04	-1.30*	-0.29*	-0.33*	-1.64*	-0.40*	-0.20*
Beans and rice x Treatment	0.24*	0.27*	0.36*	0.00	0.19*	0.16*	-0.11*	0.13	0.13*
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.	.	.	.	.	.	.	.	.	.
# of individuals	36,296	14,385	36,296	36,296	15,697	36,290	36,296	6,860	36,291
# of choices	326,664	129,465	326,664	326,664	141,273	326,610	326,664	61,740	326,619
Log-likelihood	-564,526	-201,514	-571,249	-562,497	-225,320	-581,263	-560,256	-104,358	-597,279
AIC	1,129,569	403,543	1,143,015	1,125,510	451,157	1,163,041	1,121,059	209,265	1,195,105
BIC	1,132,328	406,064	1,145,774	1,128,270	453,700	1,165,801	1,123,990	211,739	1,198,036

Note: [a]Treatments are spending at least 30 m/wk in aerobic exercise, spending at least 30 m/wk in strength-based exercise, and intentionally consuming protein to meet a fitness-related goal. [b]Choice data is Full = the full, unmatched sample; CEM = the coarsened exact matched sample; and GFM = the generalized full matched sample. Asterisks (*) denote statistical significance at the five percent level using robust standard errors.

The number of individuals included in models using GFM-derived choice data do not always exactly match the number of individuals included in models using the full sample. A small number of untreated individuals are substantially upweighted using the GFM procedure, which causes the respective MNL models to fail to converge. To bypass this issue, I omit untreated individuals with GFM weights greater than 20.0 from outcome estimation (re-normalizing the weights of all other untreated individuals back to 1.0).

Table A2. Foodservice MNL Parameter Estimates

	30+ Min/Week Aerobic Exercise[a]			30+ Min/Week Strength Exercise			Intentional Consumer		
Variable	Full[b]	CEM	GFM	Full	CEM	GFM	Full	CEM	GFM
Linear price effect	-0.24*	-0.27*	-0.21*	-0.26*	-0.27*	-0.22*	-0.25*	-0.26*	-0.19*
Linear price effect x Treatment	0.03*	-0.01	0.01	0.08*	0.02*	0.04*	0.11*	0.05*	0.05*
Alternative-specific constants									
Ribeye steak x Treatment	-0.48*	0.18	0.10	-1.21*	-0.25*	-0.34*	-1.71*	-0.78*	-0.36*
Ground beef x Treatment	-0.15*	0.22*	0.19*	-0.65*	-0.10	-0.10	-0.95*	-0.54*	-0.20*
Pork chop x Treatment	-0.08	0.33*	0.41*	-0.63*	0.03	0.08	-1.07*	-0.59*	-0.12
Bacon x Treatment	-0.25*	0.18	0.19	-0.83*	-0.15	-0.17*	-1.24*	-0.73*	-0.30*
Chicken breast x Treatment	0.07	0.43*	0.43*	-0.53*	-0.01	-0.02	-0.92*	-0.49*	-0.12
Plant-based patty x Treatment	0.26*	0.68*	0.64*	-0.51*	0.24*	0.01	-1.25*	-0.36*	-0.38*
Shrimp x Treatment	-0.15*	0.21*	0.21*	-0.69*	-0.09	-0.12	-1.12*	-0.65*	-0.28*
Beans and rice x Treatment	0.03	0.57*	0.43*	-0.72*	0.11	-0.07	-1.17*	-0.52*	-0.18*
.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.
# of individuals	36,465	14,424	36,464	36,465	15,870	36,464	36,465	6,979	36,459
# of choices	328,185	129,816	328,176	328,185	142,830	328,176	328,185	62,811	328,131
Log-likelihood	-627,283	-240,939	-629,760	-626,813	-266,286	-632,290	-625,076	-118,902	-636,685
AIC	1,255,082	482,395	1,260,036	1,254,143	533,089	1,265,096	1,250,700	238,351	1,273,917
BIC	1,257,842	484,916	1,262,797	1,256,904	535,635	1,267,857	1,253,632	240,830	1,276,850

Note: [a]Treatments are spending at least 30 m/wk in aerobic exercise, spending at least 30 m/wk in strength-based exercise, and intentionally consuming protein to meet a fitness-related goal. [b]Choice data is Full = the full, unmatched sample; CEM = the coarsened exact matched sample; and GFM = the generalized full matched sample. Asterisks (*) denote statistical significance at the five percent level using robust standard errors.

Table A3. CEM Effect Sensitivity to Utility Specification—Retail

	30+ Min/Week Aerobic Exercise[a]			30+ Min/Week Strength Exercise			Intentional Consumer		
Product	Primary[b]	No Asc	No Px	Primary	No Asc	No Px	Primary	No Asc	No Px
Ribeye steak	0.14*	0.17*	0.15*	0.55*	0.61*	0.55*	1.91*	1.89*	1.67*
Ground beef	0.42*	0.07*	0.28*	0.74*	0.28*	0.36*	1.31*	0.96*	0.42*
Pork chop	0.46*	0.06*	0.36*	0.74*	0.24*	0.47*	1.15*	0.84*	0.49*
Bacon	0.29*	0.05*	0.25*	0.49*	0.20*	0.38*	0.92*	0.69*	0.57*
Chicken breast	0.67*	0.07*	0.52*	0.92*	0.28*	0.51*	1.23*	0.95*	0.29*
PB patty	0.97*	0.06*	1.21*	0.60*	0.24*	1.11*	0.82*	0.81*	1.42*
Shrimp	0.46*	0.10*	0.51*	0.43*	0.35*	0.52*	0.78*	1.11*	0.76*
Beans and rice	0.65*	0.02*	0.63*	0.70*	0.09*	0.61*	1.02*	0.38*	0.71*

Note: [a]Treatments are spending at least 30 m/wk in aerobic exercise, spending at least 30 m/wk in strength-based exercise, and intentionally consuming protein to meet a fitness-related goal. [b]Primary = primary effect estimates obtained using coarsened exact matching (CEM); No Asc = effect estimates obtained using CEM and setting $\pi_j = 0\ \forall_j$ in the alternative-specific constants; No Px = effect estimates obtained using CEM and setting $\omega = 0$ in the price term. Asterisks (*) denote statistically significant treatment effects using 95 percent Krinsky and Robb (1986) confidence intervals.

Table A4. CEM Effect Sensitivity to Utility Specification—Foodservice

	30+ Min/Week Aerobic Exercise[a]			30+ Min/Week Strength Exercise			Intentional Consumer		
Product	Primary[b]	No Asc	No Px	Primary	No Asc	No Px	Primary	No Asc	No Px
Ribeye steak	0.20	0.40*	0.27*	1.37*	1.62*	1.01*	2.47*	2.57*	1.23*
Hamburger	0.47*	0.28*	0.57*	1.27*	1.15*	0.72*	1.96*	1.88*	0.25
Pork chop	0.94*	0.24*	0.90*	1.51*	0.97*	1.63*	1.11*	1.63*	1.01*
Baby back ribs	0.34*	0.29*	0.39*	1.11*	1.16*	0.84*	1.11*	1.90*	0.11
Chicken breast	1.26*	0.27*	1.33*	1.56*	1.12*	1.13*	2.11*	1.85*	0.67*
PB patty	2.36*	0.14*	2.24*	1.81*	0.63*	2.22*	1.01*	1.13*	1.54*
Shrimp	0.46*	0.28*	0.53*	1.28*	1.12*	0.87*	1.34*	1.84*	0.02
Salmon	1.78*	0.29*	1.80*	2.17*	1.20*	1.97*	2.20*	1.96*	1.32*

Note: [a]Treatments are spending at least 30 m/wk in aerobic exercise, spending at least 30 m/wk in strength-based exercise, and intentionally consuming protein to meet a fitness-related goal. [b]Primary = primary effect estimates obtained using coarsened exact matching (CEM); No Asc = effect estimates obtained using CEM and setting $\pi_j = 0\ \forall_j$ in the alternative-specific constants; No Px = effect estimates obtained using CEM and setting $\omega = 0$ in the price term. Asterisks (*) denote statistically significant treatment effects using 95 percent Krinsky and Robb (1986) confidence intervals.