Arizona State University

GLP-1 Use and Protein Demand

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Summary

- Glucagon-like peptide-1 (GLP-1) receptor agonists altering appetites…demand behavior???
- **Objective**: quantify GLP-1 protein demand transformations
- **Methods**: matching & DCE/OECE with structural demand modeling
- **Results**:
  - Rightward demand shifts across most evaluated proteins…up to 38% increases in WTP
  - Clockwise rotation for some proteins…up to 0.22 increases in own-price elasticities

Researchers

& affiliations

- **Justin D. Bina**
- Assistant Professor of Agribusiness
- Morrison School of Agribusiness at ASU

- **Glynn T. Tonsor**
- Professor of Agricultural Economics and MDM administrator
- Department of Agricultural Economics at KSU

- **Timothy J. Richards**
- Professor and Morrison Endowed Chair of Agribusiness
- Morrison School of Agribusiness at ASU

Background

GLP-1 Drugs in the U.S. Food System

Motivating the research

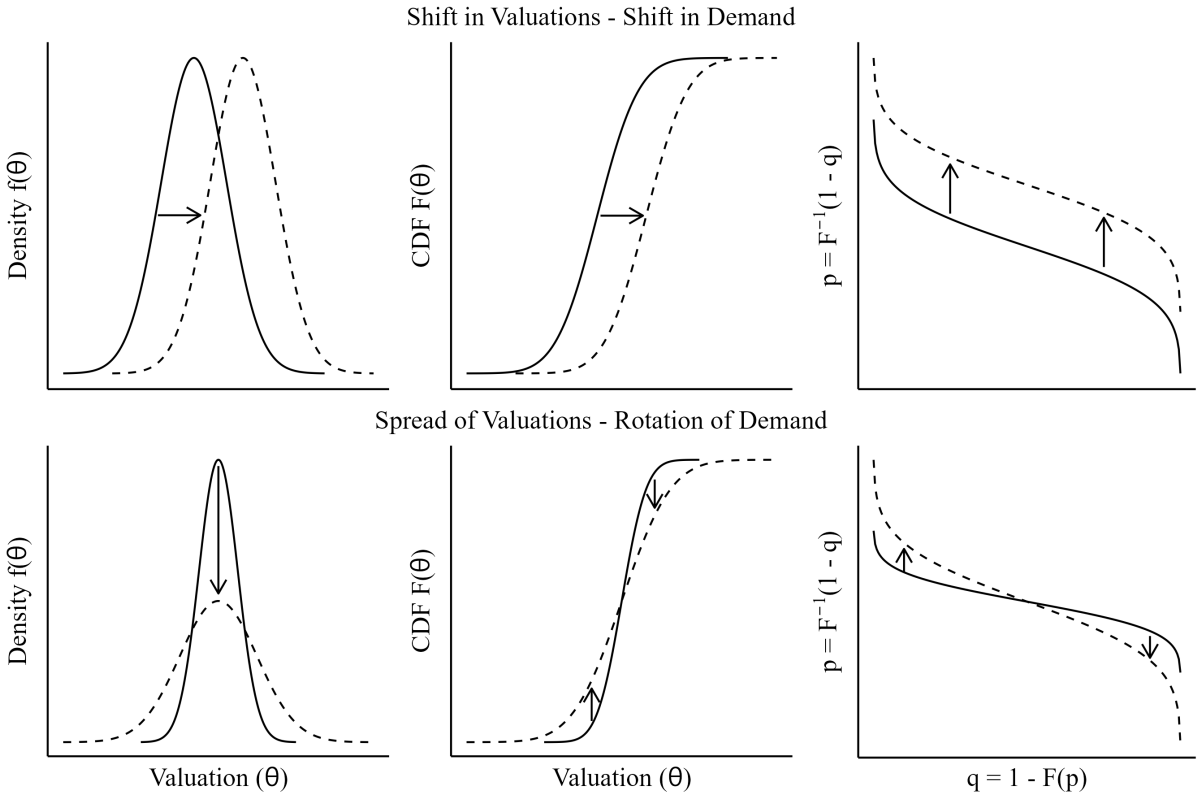
- **Use & Adoption**
- Type 2 diabetes
- Appetite suppression
- Rapid growth…8.3% July 2024[1], 12.4% October 2025[2]

- **Protein Importance**
- Lean proteins, ⇧ red meats[3] ⇩
- Benefits of protein during weight loss[4-6]
- Economic importance[7-8]

- **Early Observations**
- Shifts toward protein[9]
- Industry supply response[10-13]
- Mixed empirical findings[1,14-15]

- **Implications**
- Labeling and product (re)formulation
- Menu design
- Endogeneity of health and food systems…gov't action
- Sustainability

Framework – Johnson & Myatt (2006)



Data

Meat Demand Monitor

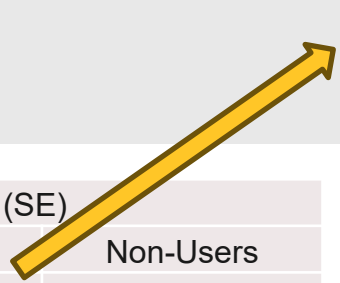
Survey data

- Collaboration b/w K-State Research & Extension, U.S. Beef and Pork Checkoffs
- Monthly, online survey of U.S. adults
  - Pooled, cross-sectional
  - ~3,000 usable respondents monthly
  - Tracks domestic retail and foodservice meat demand
- Sociodemographic info, GLP-1 use (since July 2024), and choice experiments

Funded by the Beef Checkoff

Select Summary Statistics

July 2024 – June 2025



	Relative Frequency (SE)		
	Full Sample	GLP-1 Users	Non-Users
Variable	n = 36,406	n = 4,347	n = 32,059
Sex			
Female	0.515 (0.003)	**0.449 (0.008)**	0.524 (0.003)
Male	0.484 (0.003)	**0.548 (0.008)**	0.475 (0.003)
Did not report	0.001 (0.000)	**0.003 (0.001)**	0.001 (0.000)
Age			
18 to 24 years	0.046 (0.001)	**0.082 (0.004)**	0.041 (0.001)
25 to 34 years	0.127 (0.002)	**0.178 (0.006)**	0.120 (0.002)
35 to 44 years	0.182 (0.002)	**0.250 (0.007)**	0.173 (0.002)
45 to 54 years	0.171 (0.002)	0.166 (0.006)	0.171 (0.002)
55 to 64 years	0.244 (0.002)	**0.202 (0.006)**	0.250 (0.002)
65 years and over	0.231 (0.002)	**0.121 (0.005)**	0.246 (0.002)
Did not report	-	-	-

Select Summary Statistics

July 2024 – June 2025

11.9%

Variable	Relative Frequency (SE)		
	Full Sample	GLP-1 Users	Non-Users
	n = 36,406	n = 4,347	n = 32,059
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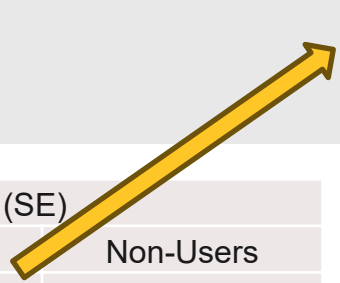

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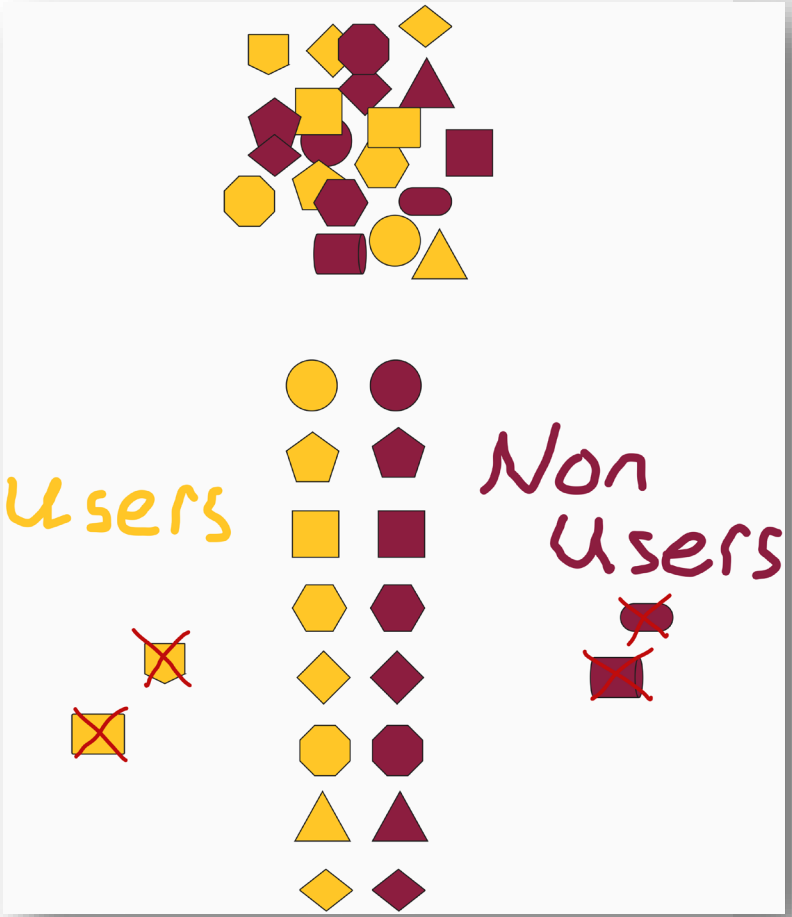
Select Summary Statistics cont.

July 2024 – June 2025

	Relative Frequency (SE)		
	Full Sample	GLP-1 Users	Non-Users
Variable	n = 36,406	n = 4,347	n = 32,059
Annual household income			
Less than $20,000	0.134 (0.002)	**0.107 (0.005)**	0.137 (0.002)
$20,000 to $39,999	0.212 (0.002)	**0.176 (0.006)**	0.216 (0.002)
$40,000 to $59,999	0.205 (0.002)	**0.177 (0.006)**	0.209 (0.002)
$60,000 to $79,999	0.171 (0.002)	**0.147 (0.005)**	0.174 (0.002)
$80,000 to $99,999	0.087 (0.001)	0.090 (0.004)	0.087 (0.002)
$100,000 to $119,999	0.056 (0.001)	**0.093 (0.004)**	0.050 (0.001)
$120,000 to $139,999	0.040 (0.001)	**0.050 (0.003)**	0.039 (0.001)
$140,000 to $159,999	0.041 (0.001)	**0.081 (0.004)**	0.036 (0.001)
$160,000 and over	0.052 (0.001)	**0.075 (0.004)**	0.048 (0.001)
Did not report	0.003 (0.000)	0.003 (0.001)	0.003 (0.000)



Addressing selection into treatment

Coarsened Exact Matching

- Consumer traits correlated w/ GLP-1 use also correlated w/ meat consumption
- Selection on observables and CEM[17]
  - Sex, age, income, education, race, region, household size, diet, quarter
- Matches samples, weights used in structural demand modeling

Study 1 – Demand Shifts

Discrete Choice Experiments

Retail & foodservice

	 Ribeye Steak $19.49/lb	 Ground Beef $6.99/lb	 Pork Chop $7.49/lb	 Bacon $5.49/lb	 Chicken Breast $1.49/lb	 Plant-Based Patty $14.49/lb	 Shrimp $10.99/lb	 Beans and Rice $2.99/lb	If these were the only options, I would buy something else.
I would choose:	☐	☐	☐	☐	☐	☐	☐	☐	☐

	 Ribeye Steak $18.99/meal	 Beef Hamburger $14.49/meal	 Pork Chop $16.99/meal	 Baby Back Ribs $15.49/meal	 Chicken Breast $12.99/meal	 Plant-based Patty $17.49/meal	 Shrimp $13.49/meal	 Salmon $19.49/meal	If these were the only options, I would buy something else.
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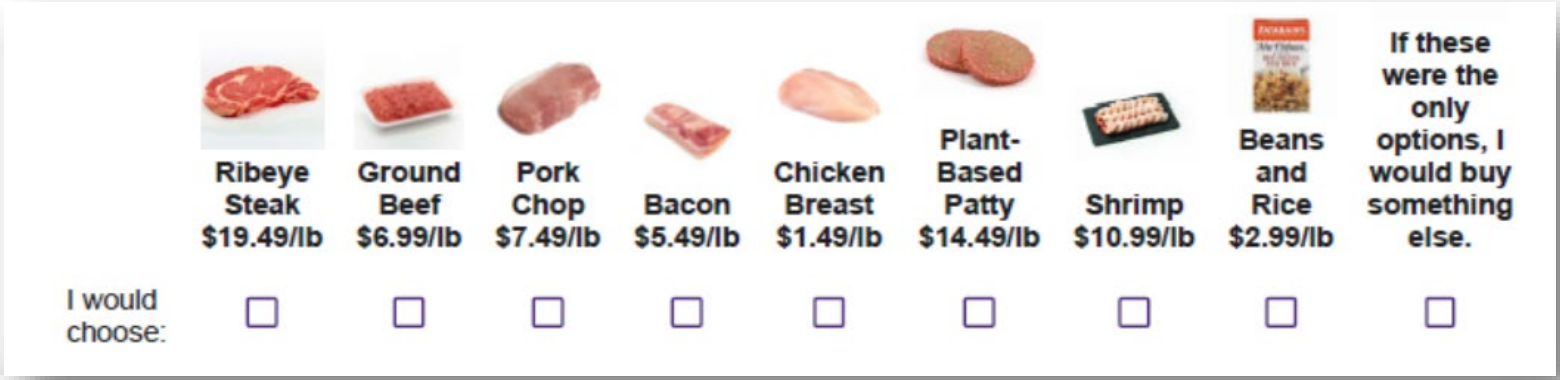
Discrete Choice Experiments

Retail & foodservice

8 alternatives, 1 opt out
3 price levels



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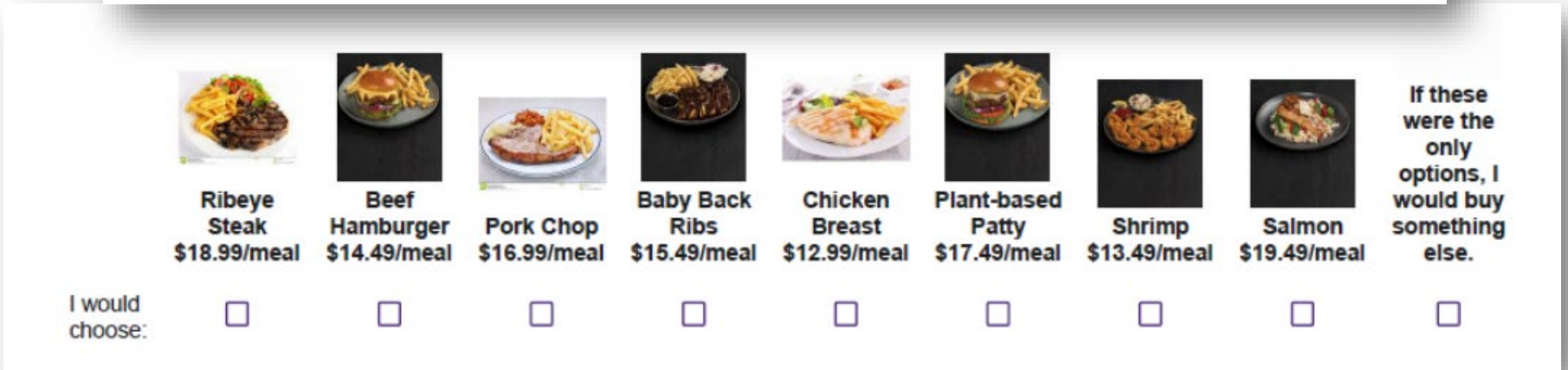

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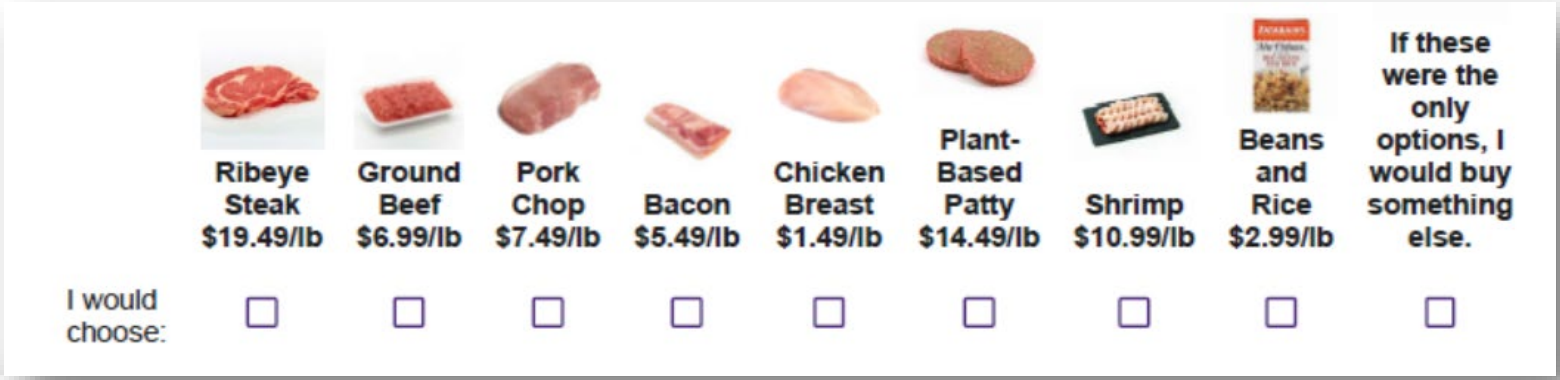
Discrete Choice Experiments

Retail & foodservice

Random assignment



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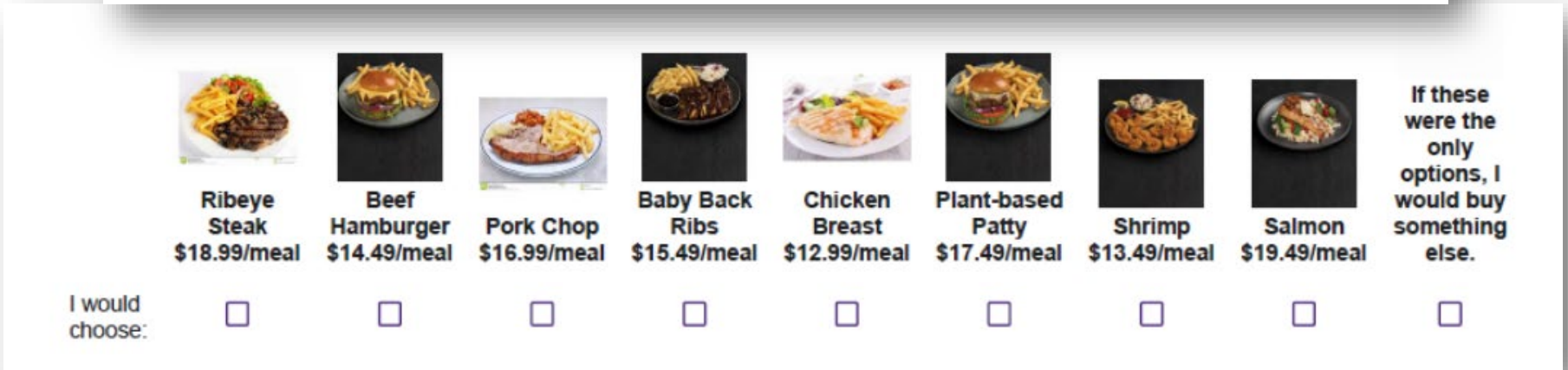

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Outcome & Effect Estimation

- Random utility framework[18]
- $V_{ij} = \theta_{ij} + \gamma_i p_j$
  - $\theta_{ij} = \delta_j + \sum_{k=1}^{K} \delta_{jk} z_{ik} + \pi_j GLP_i$
  - $\gamma_i = \alpha + \omega GLP_i$
- Estimate retail and foodservice MNL models w/ matched data and weights

*RPL also considered, findings robust

- Doubly robust standardization[19]
- Estimate θ_{ij} and γ_i among treated under both treatment regimes
  - And derive individual-specific WTP as $-{}^{\theta_{ij}}/_{\gamma_i}$
- Take difference in average WTP under both treatment regimes for ATT

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  - And derive individual-specific WTP as $-{}^{\theta_{ij}}/_{\gamma_i}$
- Take difference in average WTP under both treatment regimes for ATT

Study 1 Results

Retail

Full (unmatched) sample estimation…difference in mean WTP b/w groups

Retail WTP ($/lb)				
Product	Users	Non-Users	Difference	ATT
Ribeye steak	22.99	16.00	6.99	2.30*
Ground beef	14.76	7.64	7.12	1.69*
Pork chop	12.67	6.34	6.33	1.19*
Bacon	10.20	5.40	4.80	1.30*
Chicken breast	12.80	7.56	5.24	1.52*
Plant-based patty	9.42	6.96	2.46	1.55*
Shrimp	12.64	9.22	3.42	1.06*
Beans and rice	5.38	2.87	2.51	0.14

Study 1 Results

Retail

9.6% (shrimp) to 38.1% (chicken breast) increases in WTP over midpoint retail DCE prices

Retail WTP ($/lb)				
Product	Users	Non-Users	Difference	ATT
Ribeye steak	22.99	16.00	6.99	2.30*
Ground beef	14.76	7.64	7.12	1.69*
Pork chop	12.67	6.34	6.33	1.19*
Bacon	10.20	5.40	4.80	1.30*
Chicken breast	12.80	7.56	5.24	1.52*
Plant-based patty	9.42	6.96	2.46	1.55*
Shrimp	12.64	9.22	3.42	1.06*
Beans and rice	5.38	2.87	2.51	0.14

Study 1 Results

Retail

18.0% (bacon) to 36.1% (chicken breast) increases over August 2025 BLS prices

Retail WTP ($/lb)				
Product	Users	Non-Users	Difference	ATT
Ribeye steak	22.99	16.00	6.99	2.30*
Ground beef	14.76	7.64	7.12	1.69*
Pork chop	12.67	6.34	6.33	1.19*
Bacon	10.20	5.40	4.80	1.30*
Chicken breast	12.80	7.56	5.24	1.52*
Plant-based patty	9.42	6.96	2.46	1.55*
Shrimp	12.64	9.22	3.42	1.06*
Beans and rice	5.38	2.87	2.51	0.14

Study 1 Results

Foodservice

8.4% (salmon) to 31.1% (hamburger) increases in WTP over midpoint foodservice DCE prices

Foodservice WTP ($/meal)				
Product	Users	Non-Users	Difference	ATT
Ribeye steak	37.84	25.19	12.66	3.87*
Hamburger	31.31	18.41	12.89	3.73*
Pork chop	24.55	15.11	9.43	2.34*
Baby back ribs	26.20	17.82	8.38	3.07*
Chicken breast	25.30	17.41	7.90	3.22*
Plant-based patty	12.33	10.86	1.47	-0.23
Shrimp	25.02	17.18	7.84	3.20*
Salmon	25.04	18.64	6.40	1.42*

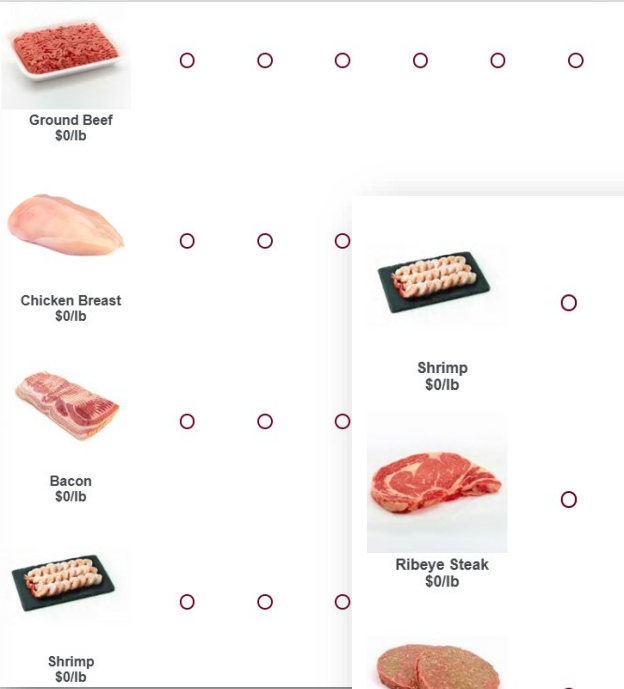
Study 2 – Demand Rotations

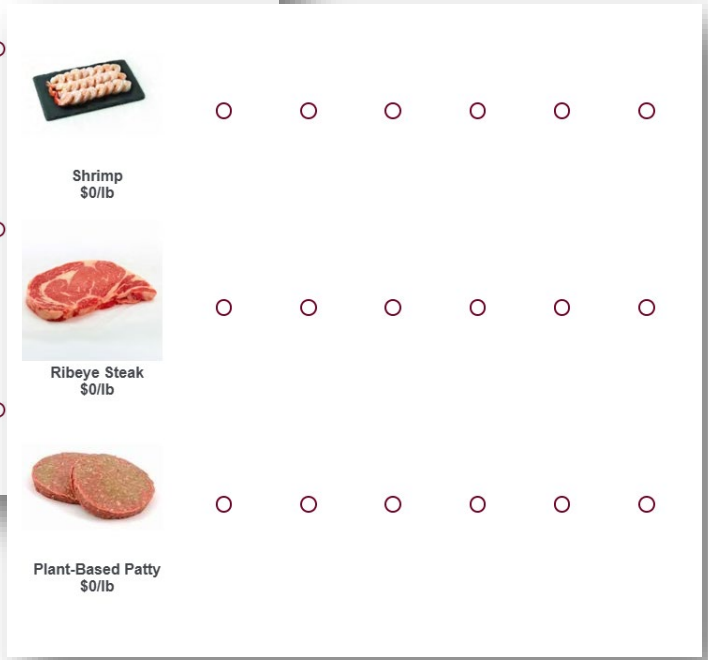
Open-Ended Choice Experiment

Retail

How many of the following retail products would you purchase given these asking prices?

	Zero (None)	One, 1-lb package	Two, 1-lb packages	Three, 1-lb packages	Four, 1-lb packages	Five or More, 1-lb packages
 Beans and Rice $0/package	○	○	○	○	○	○
 Pork Chop $0/lb	○	○	○	○	○	○
 Ground Beef $0/lb	○	○	○	○	○	○





Open-Ended Choice Experiment

Retail

Multi-product, multi-quantity

How many of the following retail products would you purchase given these asking prices?

	Zero (None)	One, 1-lb package	Two, 1-lb packages	Three, 1-lb packages	Four, 1-lb packages	Five or More, 1-lb packages
 Beans and Rice $0/package	○	○	○	○	○	○
 Pork Chop $0/lb	○	○	○	○	○	○
 Ground Beef $0/lb	○	○	○	○	○	○

 Ground Beef $0/lb	○	○	○	○	○	○
 Chicken Breast $0/lb	○	○	○			
 Bacon $0/lb	○	○	○			
 Shrimp $0/lb	○	○	○			

 Shrimp $0/lb	○	○	○	○	○	○
 Ribeye Steak $0/lb	○	○	○	○	○	○
 Plant-Based Patty $0/lb	○	○	○	○	○	○

Open-Ended Choice Experiment

Retail

Prices randomly generated, exogenous

How many of the following retail products would you purchase given these asking prices?

	Zero (None)	One, 1-lb package	Two, 1-lb packages	Three, 1-lb packages	Four, 1-lb packages	Five or More, 1-lb packages
 Beans and Rice $0/package	○	○	○	○	○	○
 Pork Chop $0/lb	○	○	○	○	○	○
 Ground Beef $0/lb	○	○	○	○	○	○
 Ground Beef $0/lb	○	○	○			
 Chicken Breast $0/lb	○	○	○			
 Bacon $0/lb	○	○	○			
 Shrimp $0/lb	○	○	○			
 Shrimp $0/lb	○	○	○	○	○	○
 Ribeye Steak $0/lb	○	○	○	○	○	○
 Plant-Based Patty $0/lb	○	○	○	○	○	○

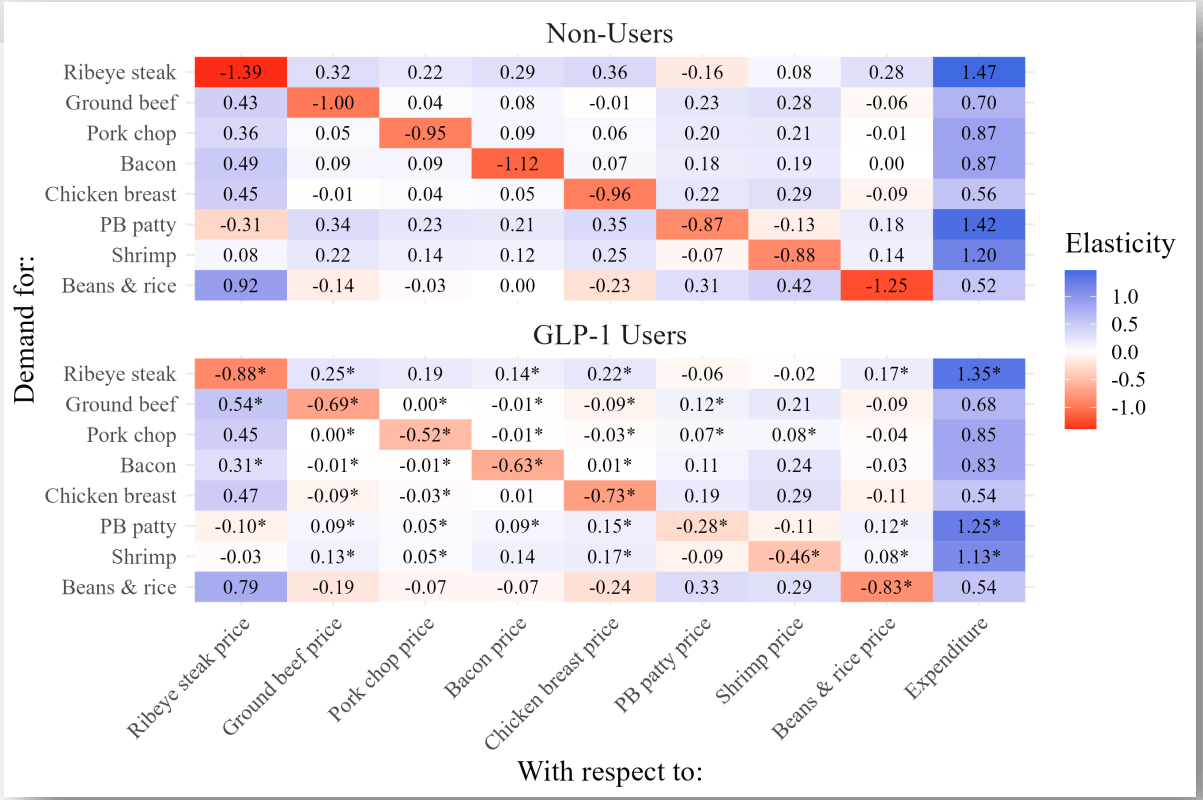
Demand Estimation

- Almost Ideal Demand System[20]
- $w_j = \bar{\alpha}_j + \sum_{l=1}^{8} \gamma_{jl} \ln(p_l) + \beta_j \ln(X/P)$
  - $\ln(P) = \alpha_0 + \sum_{j=1}^{8} \bar{\alpha}_j \ln(p_j) + \frac{1}{2} \sum_{j=1}^{8} \sum_{l=1}^{8} \gamma_{jl} \ln(p_j) \ln(p_l)$
  - $\bar{\alpha}_j = \alpha_j + \sum_{k=1}^{K} \delta_{jk} z_k$
- Weak separability of 8 OECE goods
- Homogeneity, adding up, symmetry imposed

- Split-sample estimation using matched sample & weights
- Expectation Maximization algorithm used to adjust for censored expenditures[21]
- Bootstrap resampling and Poe, Giraud, and Loomis (2005)[22] complete combinatorials for differences in elasticities b/w groups

Study 2 Results

Unmatched sample "associations"



Study 2 Results

GLP-1 effects

Difference = user *less* non-user elasticity

Quantity of:	With respect to:	Unmatched Sample	CEM Sample
Ribeye steak	Expenditure	-0.13*	-0.08
Ground beef		-0.02	0.01
Pork chop		-0.02	-0.02
Bacon		-0.04	-0.07
Chicken breast		-0.02	0.00
Plant-based patty		-0.17*	-0.11
Shrimp		-0.08*	-0.09
Beans & rice		0.01	-0.15
Ribeye steak	Own price	0.51*	-0.20
Ground beef		0.31*	**0.19***
Pork chop		0.43*	**0.22***
Bacon		0.49*	0.29
Chicken breast		0.23*	**0.22***
Plant-based patty		0.59*	0.28
Shrimp		0.42*	0.41
Beans & rice		0.41*	0.08

Study 2 Results

GLP-1 effects

Difference = user *less* non-user elasticity

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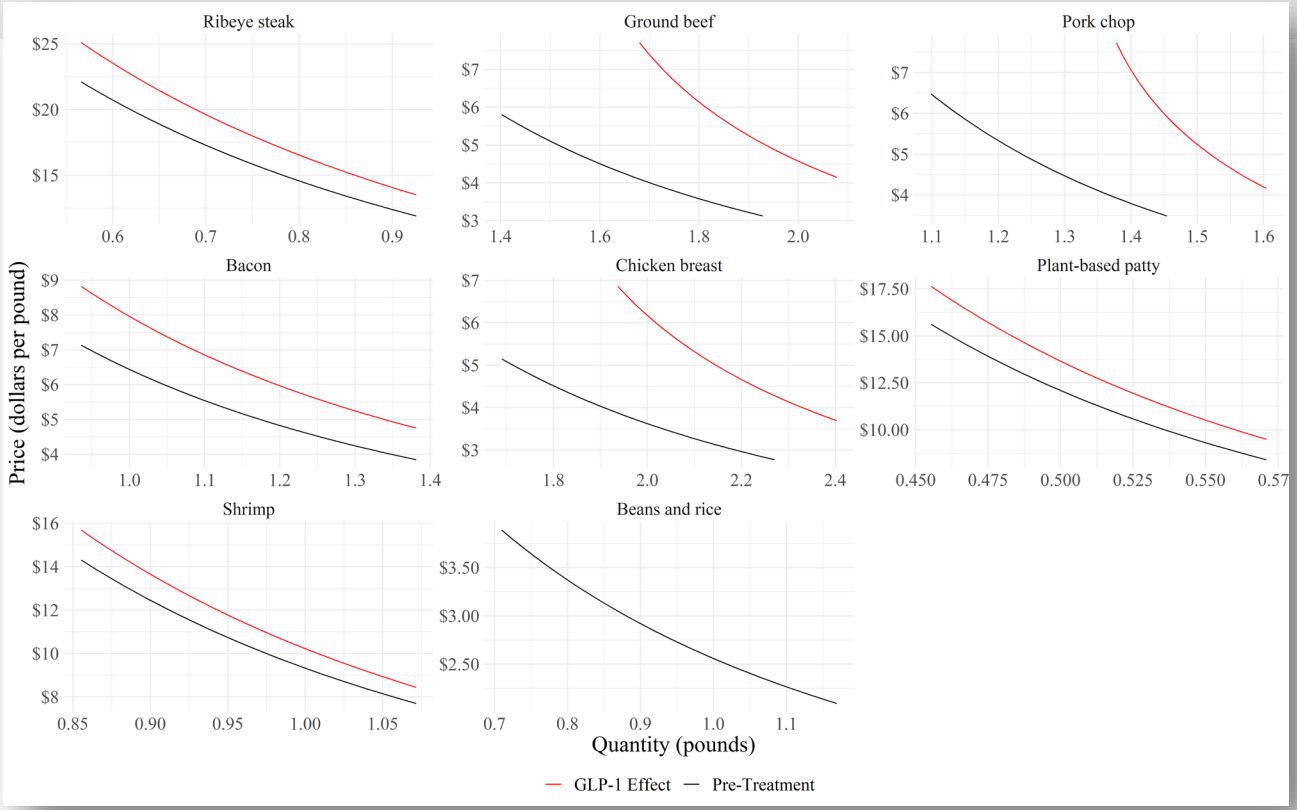
Pork chop		-0.02	-0.02
Bacon		-0.04	-0.07
Chicken breast		-0.02	0.00
Plant-based patty		-0.17*	-0.11
Shrimp		-0.08*	-0.09
Beans & rice		0.01	-0.15
Ribeye steak	Own price	0.51*	-0.20
Ground beef		0.31*	**0.19***
Pork chop		0.43*	**0.22***
Bacon		0.49*	0.29
Chicken breast		0.23*	**0.22***
Plant-based patty		0.59*	0.28
Shrimp		0.42*	0.41
Beans & rice		0.41*	0.08

Who Cares?

Illustration of Demand Transformations

Our findings in a nutshell



Purely illustrative!

"GLP-1 premium"

Some evidence of reduced price sensitivity

Implications
& recommendations

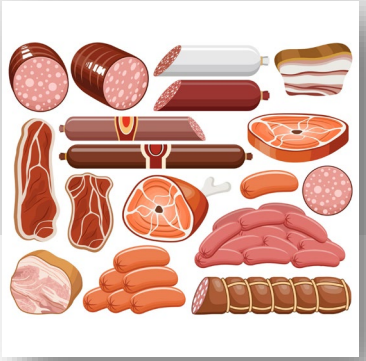
- **Market participation**
- Distribution of preferences…lower *aggregate* price sensitivity[16]
- Market composition in contraction phase of cattle cycle

- **Industry response**
- "GLP-1 premium" is opportunity to offset volume reductions
- Labeling/product (re)formulation
- Menu design

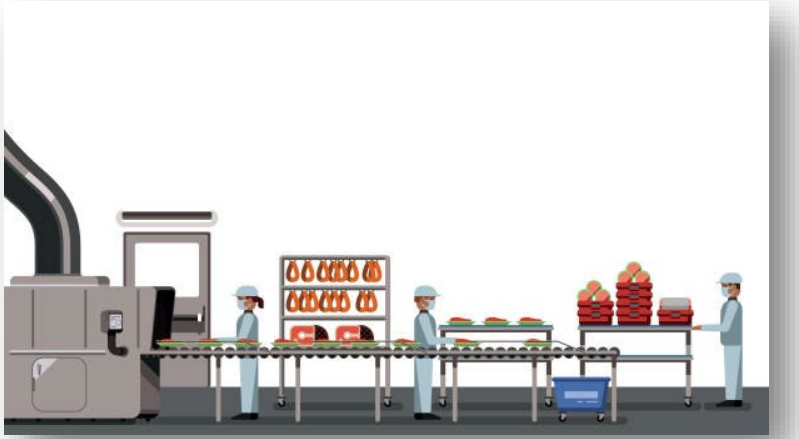
- **Policy**
- Externalities to food system
  - Lower income access to protein
  - Industrial policy?
- Data
- Interagency collaboration
- Sustainability

Future Research

What we have in store



- Expanded demand assessment using revealed preference data
- Equilibrium industry response in price and attribute (protein content) space
- Demand-side sustainability assessment



Questions?

GLP-1 Use and Protein Demand

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