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Essays on the Economics of Animal Welfare

By

Trevor Kent Woolley

A dissertation submitted in partial satisfaction of the
requirements for the degree of

Doctor of Philosophy

in

Agricultural and Resource Economics

in the

Graduate Division

of the

University of California, Berkeley

Committee in charge:

Professor James Sallee, Chair

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Spring 2026

Essays on the Economics of Animal Welfare

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Abstract

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Doctor of Philosophy in Agricultural and Resource Economics

University of California, Berkeley

Professor James Saltee, Chair

Farm animal welfare is an increasingly prominent policy priority across the world, yet the market and political forces shaping it remain poorly understood. This dissertation draws on large administrative datasets and large-scale text analyses to study the supply of, demand for, and public valuation of farm animal welfare improvements in the United States.

The first chapter establishes the empirical footing for the central argument of the dissertation. I develop a structural framework to identify public-good preferences from referendum data, applying it to California’s Proposition 12 (2018)—a ballot initiative mandating cage-free housing for laying hens, approved by 63% of voters despite raising egg prices. The key insight is that market purchases and referendum votes identify different equilibrium objects: markets reveal Nash-equilibrium private (use) valuation, while referenda reveal Lindahl-equilibrium total valuation, and the gap is non-use value. Combining NielsenIQ retail scanner data with precinct-level vote shares and a supply-side instrument for local cage-free prices, I find that over 85% of voters’ total willingness to pay—roughly \$17 of \$20 per capita per year—reflects public-good (non-use) benefits that private markets structurally underprovide. The framework generalizes to any referendum in which the voter’s cost is a commodity price change rather than a tax.

The second chapter, coauthored with Sharon Pailler, Jon McFadden, Sharon Raszap Skorbianski, Zach Raff, and Kevin Kuruc, identifies supply-side incentives and disincentives for adopting animal welfare-improving farming practices in the United States. We conduct a scoping review of nearly 25,000 publications from EconLit, CAB Abstracts, and Web of Science, we apply Latent Dirichlet Allocation and iterative manual review to identify 74 papers meeting our eligibility criteria. Across five practice categories—indoor environment, outdoor access, enrichment, confinement, and bodily mutilation—and four species—dairy cows, layer hens, broilers, and hogs—we find that operating costs are a near-universal disincentive to the adoption of welfare-improving practices. Conversely, improved indoor environment and enrichment practices show promising benefits for animal health and productivity, suggesting interventions that need not substantially harm farm profitability. The literature is sparse, particularly for broilers and hogs and for mutilation practices, pointing to important research gaps for evidence-based policy design.

The third chapter, coauthored with Carl Meyer and Zach Freitas-Groff, documents trends in the consumption of animal products in the U.S. using a panel of 40,000–60,000 U.S. households from 2004 to 2020 linked to ingredient-level product data classified via a machine-learning-based method. Despite stable or rising aggregate meat consumption, the share of households purchasing no meat in a given month rises from approximately 5.0% to 6.2% by end-2019, and the share purchasing no animal products rises from 0.5% to 1.3%. These trends partially reverse in 2020 as the pandemic shifts food consumption back toward food at home. The patterns predate the introduction of modern plant-based meat alternatives, whose limited market share is insufficient to explain the broader changes. Demographic heterogeneity and declining food-at-home purchase volume both appear to be important contributors. The findings reconcile persistently high aggregate meat consumption with the increasing visibility of meat avoidance.

Taken together, these three chapters map the economic landscape of farm animal welfare from farm gate to ballot box. The analysis uncovers social preferences that are obscured by coordination failures and identifies critical barriers that hinder the realization of full economic efficiency. Correcting for this gap is essential for designing policy that aligns with social values.

For Cora, who made all of this possible — and for our sons, who joined us along the way.

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²Researcher’s own analyses calculated (or derived) based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researcher(s) and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

Chapter 1

Voting Against Your Grocery Bill: Revealed Public-Good Preferences from Referendum Data

1.1 Introduction

When voters approve a regulation that raises the price of a good they regularly buy, they are revealing something their shopping behavior cannot: how much they value a public benefit that private markets structurally underprovide. Market purchases identify what consumers are willing to pay for a good unilaterally, taking others' choices as given. Referendum votes identify what they are willing to pay for a collective outcome that no individual can achieve alone. The wedge between the two is non-use value—willingness to pay for a public good—and it is, in principle, exactly identified by combining market and voting data. This chapter develops that identification strategy and applies it to recover the distribution of public-good preferences across a large voter population.

The empirical setting is California's Proposition 12, a 2018 ballot initiative mandating cage-free housing for all laying hens whose eggs are sold in the state. The setting is particularly well suited to the identification strategy but the question is general. A large literature in political economy, from Fiorina (1981) to Ansolabehere et al. (2014), asks whether voters respond to their personal economic costs or to broader societal conditions—the pocketbook-versus-sociotropic debate. The evidence generally favors the sociotropic account. The framework here offers a structural reinterpretation: when a policy generates genuine public-good benefits, pocketbook costs and public-good preferences are positively correlated across voters, so OLS conflates the two and attenuates the estimated cost sensitivity toward zero. This suggests that in referendum settings over public goods, apparent sociotropic patterns may partly reflect omitted public-good preferences rather than genuine indifference to personal costs.

The puzzle that motivates the application is the “vote-buy gap” phenomenon. Proposition 12 passed with 63 percent of the vote despite the fact that 70 percent of eggs sold in California at the time came from caged hens—meaning the overwhelming majority of Yes voters chose to raise the price of something they regularly buy. Cage-free eggs were already

on the shelf, at a premium of roughly \$1 per dozen. Only 25 percent of consumers were buying them. Whatever the remaining 75 percent valued in Prop 12 was not something they were willing to pay for unilaterally.¹ The wedge between what Californians voted for and what they bought is a public-good problem, and measuring it is the central task of this chapter.

The key insight is that market purchases and referendum votes identify different equilibrium objects. When a consumer decides whether to pay the cage-free premium, she takes everyone else’s purchasing decisions as given. Her willingness to pay reflects only her private return to cage-free eggs—taste, perceived quality, whatever moral satisfaction she derives from her own choice—because that is all she can influence. When the same consumer votes on Prop 12, she is choosing whether to impose cage-free production on the entire market. Her vote reflects her valuation of that collective outcome, which includes the animal-welfare improvement she could never achieve through her own purchases alone. The difference between these two objects is non-use value, and I show it is identified exactly as the residual between what voting reveals and what markets reveal, without any restriction on how preferences over consumption and animal welfare interact.²

I implement this in two stages. In the first, I estimate consumers’ marginal willingness to pay for cage-free eggs at the ZIP code level using NielsenIQ retail scanner data covering California in 2018. A logit demand model with housing-tier product classifications, ZIP-level demographic interactions, and supply-side price instruments yields a median MWTP of \$0.11 per dozen, far below the average cage-free markup of \$1.06, confirming that most consumers preferred conventional eggs at prevailing prices. In the second stage, I construct for each of 19,061 California precincts a “non-use price”: the expected annual consumer-surplus loss that Prop 12 would impose on a conventional-egg consumer in that precinct, net of the private value she places on cage-free eggs. I estimate a fractional logit of precinct-level vote shares on this non-use price, controlling for demographics, political orientation, and county fixed effects, and instrument using a supply-side shifter that moves local prices through chain-level assortment decisions rather than local demand. While the naive coefficient on the non-use price is indistinguishable from zero—consistent with the omitted-variable interpretation above—the instrumented coefficient is -0.063 ($SE = 0.010$), implying that voters facing exogenously higher non-use prices were less likely to vote in favor of Prop 12.

The structural voting model recovers the full distribution of willingness to pay across California voters. Non-use value dominates: the median voter’s total WTP for Prop 12 is approximately \$20 per year, of which \$17 reflects willingness to pay for the collective animal-welfare improvement and only \$2.60 reflects private consumption benefits (for conventional consumer-voters). The full-population net-WTP distribution, constructed as a mixture of logistics across precincts, predicts that 64 percent of Californians had net-positive valuations for the policy, closely matching the actual Yes vote of 63 percent.³

Three features of the setting make this identification strategy feasible. First, the voter’s

¹Of the 75% of egg consumers not purchasing cage-free eggs, 5 percentage points of consumers were consuming eggs with other premium welfare labels such as “pasture-raised” and “cage-free”.

²See Appendix A.2.

³Since the model was estimated entirely on within-sample variation in consumer costs and demographics; matching the aggregate vote share is an out-of-sample validation.

“policy price” arrives as a grocery price change rather than a tax. In prior applications of referendum-based WTP estimation (Deacon and Shapiro, 1975; Burkhardt and Chan, 2017; Anderson et al., 2023), the voter’s cost is a tax liability imputed from fiscal formulas, and the private benefit of whatever the tax funds is unobserved, so total WTP can be estimated but not decomposed. When the cost is a price, the private benefit is separately identified in retail market data and the decomposition goes through exactly. Second, a price-based cost variable is endogenous in a tractable, instrumentable way. Chan (2025) identifies both the generated-regressor problem and the instrumentation problem as unresolved in the referendum WTP literature; this chapter resolves both. Third, the logistic structure of the voting model implies that within-precinct heterogeneity in WTP follows a logistic distribution, so aggregating across precincts yields a mixture-of-logistics population CDF.

California consumers’ relatively low pre-policy market share of cage-free eggs was not a measure of how much they valued animal welfare but of how much they valued it when acting alone. The referendum revealed that collective demand was far larger. Bursztyn et al. (2023) call this a collective trap: individually rational behavior produces a market outcome that most participants would prefer to change but cannot change unilaterally. This chapter provides what is, to my knowledge, the first quasi-experimental revealed-preference estimate of how large that gap is. In the case of Prop 12, non-use benefits account for 85 percent of voters’ total WTP, implying that the 25 percent private market share captures only a small fraction of the social value voters placed on cage-free production.

The chapter proceeds as follows. Section 1.2 reviews related literature. Section 1.3 develops the structural model. Section 1.4 describes the data. Section 1.5 presents results. Section 1.6 concludes.

1.2 Related Literature

The chapter connects three strands of the political economy and public finance literatures: (i) voter demand and the pocketbook-versus-sociotropic debate, (ii) referendum-based public-good valuation, and (iii) the political economy of consumer price regulation. It also builds on a non-market valuation literature that motivates the use/non-use decomposition and provides methodological precedents in stated-preference settings.

1.2.1 Voter Demand and the Pocketbook-Sociotropic Debate

A central question in the political economy of voting is whether electoral behavior responds to voters’ personal economic interests or to broader societal conditions. The classical pocketbook voting hypothesis—that voters support candidates and policies that improve their own economic situation—has found modest empirical support in standard reduced-form settings. Fiorina (1981) and Kinder and Kiewiet (1979) conclude that aggregate economic conditions drive electoral outcomes more strongly than personal circumstances, a finding echoed in later experimental and registry-based work (Ansolabehere et al., 2014). The prevailing interpretation is that voters are sociotropic: they vote on behalf of the collective rather than the pocketbook.

This chapter argues that the dichotomy is incomplete for a class of policy referenda. When the policy generates public-good benefits, the standard prediction is that pocketbook cost sensitivity will be attenuated under OLS, because unobserved public-good preferences are positively correlated with willingness to absorb the cost. This is not evidence against pocketbook sensitivity but of omitted-variable bias from unobserved public-good valuation.

The closest empirical antecedents in this tradition are Mian et al. (2010), who show that congressional representatives whose constituents face larger mortgage-default losses are more likely to support the Foreclosure Prevention Act, and Kahn and Matsusaka (1997), who provide foundational evidence that support for California environmental ballot initiatives rises with income. In related work, Hazlett and Mildenberger (2020) and Boomhower (2024) show that voters exposed to costly environmental shocks increase support for environmental regulation, while Bombardini et al. (2025) document that both local climate exposure and employment in green industries shift partisan voting margins on climate policy.

1.2.2 Referendum-Based WTP Estimation

The idea that referendum outcomes can reveal public WTP originates with Deacon and Shapiro (1975), who showed that a voter’s support for a ballot measure can be modeled as a binary choice in which perceived benefits are weighed against personal costs. This logic parallels the dichotomous-choice contingent valuation framework of Hanemann (1984) and Cameron and James (1987), but with the critical advantage that the choice is consequential rather than hypothetical.⁴

Empirical applications of referendum-based WTP estimation have been relatively few. Vossler et al. (2003) pioneered the approach using two Corvallis, Oregon referenda. Schl  pfer et al. (2004) applied the method to a Swiss landscape-preservation referendum. Burkhardt and Chan (2017) examined multiple California ballot propositions and recovered per-capita WTP estimates ranging from \$3 for children’s hospitals to \$94 for transportation infrastructure. Anderson et al. (2023) estimated WTP for carbon pricing using precinct-level votes on two Washington State initiatives.

In every prior application, the voter’s cost is a *tax*. My setting differs in three ways that address what Chan (2025) identifies as the two open methodological challenges in this literature. First, the policy cost is a commodity price change rather than a fiscal imposition. This makes the private-benefit channel directly observable in retail market data, enabling the exact use/non-use decomposition that is the chapter’s main contribution. Second, it makes the cost variable endogenous in a tractable, instrumentable way via supply-side price variation. Third, it plausibly improves cost salience: voters observe grocery prices directly and repeatedly (Jensen and Grunert, 2014), whereas calculating one’s own tax burden from aggregate fiscal projections is notoriously difficult (Lang et al., 2025).

The use/non-use distinction has been central to non-market valuation since Krutilla (1967) introduced the concept of existence value. In the canonical framework, use value is

⁴Referenda have also been used to elicit WTP in the experimental contingent valuation literature (Bishop and Heberlein, 1979; Hanemann, 1984; Carson and Groves, 2007; Czajkowski et al., 2024). I restrict the discussion here to natural experiments using real ballot outcomes.

the utility derived from personal consumption, while non-use value encompasses existence value, bequest value, altruism, and public-good motivations (Samuelson, 1954; Andreoni, 1989, 1990). Contingent valuation was developed in part to capture non-use values invisible to revealed-preference market data (Hanemann, 1984; Carson and Groves, 2007).⁵ Prior work has either estimated total WTP from referenda without separating components (Burkhardt and Chan, 2017; Anderson et al., 2023) or relied on stated-preference methods to separate them (McClelland et al., 1992; Nilgen, 2024). This chapter provides the first revealed-preference decomposition.

1.2.3 Political Economy of Consumer Price Regulation

A growing literature in political economy studies how voters respond to regulations that change the prices of widely purchased goods. Anderson et al. (2023) and Bombardini et al. (2025) document pocketbook resistance to carbon pricing: energy cost exposure reduces support for environmental regulation in both referendum and electoral settings.

The agricultural product-regulation literature is the closest substantive precedent. Bovay and Sumner (2019) and Oh et al. (2025) study precinct-level Prop 12 vote shares and find that demographic and political variables explain substantial variation, but neither chapter instruments for the price signal or recovers the structural WTP distribution. Lusk and Norwood (2011) and Sumner (2010) provide detailed cost-side analyses of egg market mandates but leave the benefit side unmonetized. The present chapter fills that gap.

The vote-buy gap—the divergence between collective demand revealed by referenda and private demand revealed by markets—is a recurrent observation in this literature but has not been structurally explained. The gap is predicted by models of markets with social externalities and coordination failures (Bursztyrn et al., 2023; Andreoni et al., 2017): when individual consumption has public-good components, the Nash equilibrium outcome generically underprovides the public good relative to the Lindahl optimum, and voting can resolve this through collective commitment.

1.3 Model

This section develops a structural model in which each voter’s decision on Proposition 12 depends on a comparison between the policy’s expected private cost and its non-use value. Section 1.3.1 sets up the consumer-voter’s problem and the use/non-use decomposition. Section 1.3.2 derives the non-use price for conventional consumers. Section 1.3.3 aggregates to precinct-level vote shares; Section 1.3.4 recovers WTP from the estimated model; and Section 1.3.5 extends the distribution to the individual level. Section 1.3.6 states the demand model used for private MWTP.

⁵Classic examples include Loomis et al. (1996) for northern-spotted-owl habitat, Duffield and Loomis (1998) for wolf reintroduction in Yellowstone, and Álvarez-Farizo and Hanley (2002) for landscape preservation.

1.3.1 Consumer-Voter Problem

Consumer-voter i has quasi-linear utility

$$U_i = V_i(q_i^{free}, q_i^{conv}, A) + w_i, \quad (1.1)$$

where q_i^{free} and q_i^{conv} are own consumption of cage-free and conventional eggs, w_i is numeraire (income net of egg expenditure), and A is the aggregate animal-welfare state. Quasi-linearity ensures that willingness to pay is well-defined without income effects, which is appropriate given that egg expenditure is a small share of household budgets.⁶

The function V_i is unrestricted: it may be non-separable in (q, A) , so the consumer may derive utility from the perceived impact of her own consumption on animal welfare. The animal-welfare state A depends on the consumption choices of all consumers: $A = A(q_i^{free}, \mathbf{q}_{-i})$, where $\mathbf{q}_{-i}$ denotes the consumption of everyone other than i .

Let subscript 0 denote the no-policy state and subscript 1 the with-policy state. The voter supports Proposition 12 if the policy raises her expected utility:

$$\text{Vote Yes}_i = \mathbf{1} \left[V_i(q_{1i}^{free}, 0, A_1) - V_i(q_{0i}^{free}, q_{0i}^{conv}, A_0) > 0 \right]. \quad (1.2)$$

Decomposition into use and non-use value

I define total WTP for the policy as the compensating variation from State 0 to State 1:

$$\text{WTP}_i^{\text{total}} = V_i(q_{1i}^{free}, 0, A_1) - V_i(q_{0i}^{free}, q_{0i}^{conv}, A_0). \quad (1.3)$$

I decompose this into two components by inserting and subtracting $V_i(q_{1i}^{free}, 0, A_0)$:

$$\text{WTP}_i^{\text{total}} = \underbrace{V_i(q_{1i}^{free}, 0, A_0) - V_i(q_{0i}^{free}, q_{0i}^{conv}, A_0)}_{\text{WTP}_i^{\text{use}}} + \underbrace{V_i(q_{1i}^{free}, 0, A_1) - V_i(q_{1i}^{free}, 0, A_0)}_{\text{WTP}_i^{\text{non-use}}}. \quad (1.4)$$

Use WTP measures the value of the change in the consumer's own egg-consumption bundle, holding animal welfare fixed at its pre-policy level A_0 . $\text{WTP}_i^{\text{non-use}}$ measures the value of the change in the animal-welfare state from A_0 to A_1 , evaluated at the with-policy consumption bundle.

Proposition 1 (Exact decomposition of WTP). *For any utility function $V_i(q^{free}, q^{conv}, A)$ —including non-separable specifications—the decomposition*

$$\underbrace{\text{WTP}_i^{\text{total}}}_{\text{revealed in Lindahl (vote)}} = \underbrace{\text{WTP}_i^{\text{use}}}_{\text{revealed in Nash (market)}} + \text{WTP}_i^{\text{non-use}}$$

⁶Annual per-capita egg expenditure in California in 2018 was approximately \$75–\$100, or less than 0.2% of median household income.

is exact (not an approximation), provided WTP_i^{use} is defined as the compensating variation for the consumption-bundle change at the pre-policy animal-welfare state A_0 , which is the object identified from market behavior in Nash equilibrium.

The proof is in Appendix A.2. The economic content is that this cancellation reflects a structural property of the identification strategy: the decomposition partitions the total utility change along the boundary between what the consumer can achieve through private market behavior (Nash equilibrium) and what requires collective action (Lindahl equilibrium).

1.3.2 The Non-use Price

Consumer-voter types

Three types of consumer-voters face different policy costs:

1. **Cage-free (and premium) consumer-voters** already purchase cage-free or higher-welfare eggs, comprising approximately 30% of the California egg market in 2018. For these voters, $MWTP_i^{free} \geq P^{free} - P^{conv}$, so the policy does not raise their effective price. Their non-use price is weakly negative, and they support Prop 12 on consumption grounds alone.
2. **Conventional consumer-voters** purchase only conventional eggs, comprising approximately 70% of the market. For these voters, $MWTP_i^{free} < P^{free} - P^{conv}$ by revealed preference, so the policy raises their quality-adjusted price and reduces their egg consumption. Their non-use price is strictly positive, and a Yes vote implies $WTP_i^{non-use} > 0$.
3. **Non-consumer voters** (approximately 3% of Californians) never purchase eggs. Their non-use price is zero.

Empirical identification focuses on conventional consumer-voters, for whom a Yes vote constitutes a revealed preference for positive non-use value.

Non-use price for conventional consumers

A conventional consumer-voter supports Prop 12 if and only if:

$$WTP_i^{non-use} > \mathbb{E} \left[\int_{P_0^{conv}}^{\tilde{P}_1} q_i(p) dp \right] \equiv NP_i, \quad (1.5)$$

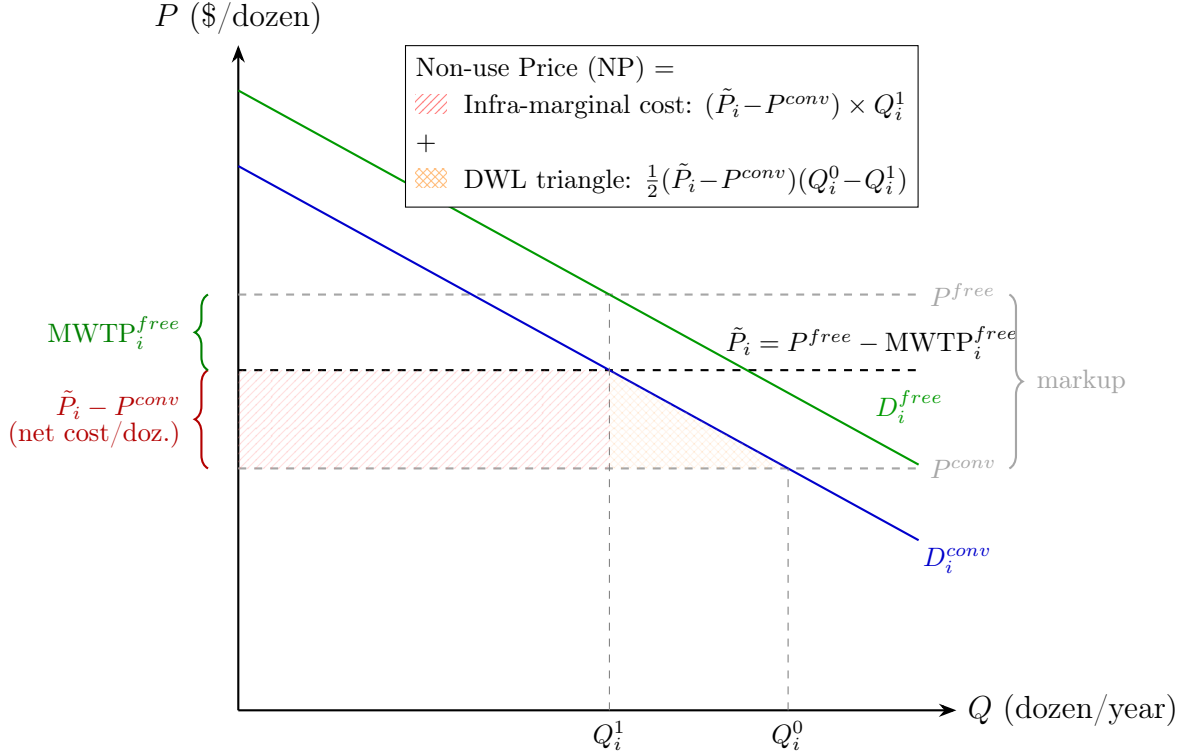
where $\tilde{P}_1 = P_1^{free} - MWTP_i^{free}$ is the quality-adjusted post-policy price and NP_i is the “non-use price”—the expected trapezoidal consumer-surplus loss from the mandate.

Under locally linear demand with own-price elasticity ε , the non-use price is:

$$NP_i = \underbrace{(\tilde{P}_1 - P_0^{conv})}_{\text{net price increase}} \cdot Q_i^1 + \frac{1}{2}(\tilde{P}_1 - P_0^{conv}) \cdot |Q_i^0 - Q_i^1|, \quad (1.6)$$

where Q_i^0 is pre-policy annual egg consumption, $Q_i^1 = Q_i^0(1 + \varepsilon \cdot \Delta P / P^{conv})$ is post-policy consumption, and $\Delta P = \tilde{P}_1 - P_0^{conv}$.

Figure 1.1: Non-use Price for a Conventional Consumer-voter



Note: The figure depicts the consumer-surplus loss (“non-use price”) facing a conventional consumer-voter under Proposition 12. The consumer’s demand for conventional eggs (D_i^{conv} , solid blue) intersects the conventional price P^{conv} at pre-policy quantity Q_i^0 . Her demand for cage-free eggs (D_i^{free} , dashed green) is the same curve shifted vertically by MWTP_i^{free} —her marginal willingness to pay for the cage-free attribute, as revealed in Nash equilibrium. The quality-adjusted post-policy price is $\tilde{P}_i = P^{free} - \text{MWTP}_i^{free}$, which exceeds P^{conv} for all conventional consumers (since $\text{MWTP}_i^{free} < \text{markup}$ by revealed preference). The shaded trapezoid—the infra-marginal rectangle plus the deadweight-loss triangle—is the non-use price NP_i from Equation (1.6). A conventional consumer votes Yes if and only if $\text{WTP}_i^{\text{non-use}} > NP_i$. The “policy price” equals the full change in consumer surplus: non-use price plus $\text{MWTP}_i^{free} \times Q_i^1$.

1.3.3 From Individuals to Precincts

Within each precinct p , voters differ in their non-use WTP. I model this heterogeneity with an additive logistic error:

$$\text{WTP}_{ip}^{\text{non-use}} = \mu_p + \eta_{ip}, \quad \eta_{ip} \stackrel{\text{iid}}{\sim} \text{Logistic}(0, \sigma), \quad (1.7)$$

where μ_p is the precinct-level location parameter (the median voter's non-use WTP) and $\sigma = 1/|\beta_{\text{NP}}|$ is a scale parameter common across precincts.

Writing $\mu_p = -\mathbf{X}'_p \boldsymbol{\gamma} / \beta_{\text{NP}} - \delta_c / \beta_{\text{NP}}$, the model becomes:

$$\tilde{Y}_p = \Lambda(\beta_{\text{NP}} \cdot \text{NP}_p + \mathbf{X}'_p \boldsymbol{\gamma} + \delta_c + u_p), \quad (1.8)$$

where $\Lambda(\cdot)$ is the logistic CDF, $\tilde{Y}_p$ is the conventional-consumer Yes share (adjusted for cage-free market share), and u_p captures precinct-level unobservables. This is the fractional logit estimated by quasi-maximum likelihood (GLM with binomial family and logit link).

The coefficient β_{NP} has a direct structural interpretation: it is the inverse of the within-precinct standard deviation of non-use WTP ($\beta_{\text{NP}} = -1/\sigma$). A larger $|\beta_{\text{NP}}|$ implies less within-precinct heterogeneity and a steeper relationship between the non-use price and the vote share.

1.3.4 WTP Recovery

The logit structure permits closed-form recovery of precinct-level WTP following Hanemann (1984). At the point of indifference, $\Pr(\text{Yes}) = 0.5$, which requires $\beta_{\text{NP}} \cdot \text{NP}_p^* + \mathbf{X}'_p \boldsymbol{\gamma} + \delta_c = 0$, yielding:

$$\widehat{\text{WTP}}_p^{\text{non-use}} = \text{NP}_p^* = -\frac{\mathbf{X}'_p \hat{\boldsymbol{\gamma}} + \hat{\delta}_c}{\hat{\beta}_{\text{NP}}}, \quad (1.9)$$

which is the non-use price the median voter would tolerate purely for animal welfare. The remaining WTP components are:

$$\begin{aligned} \widehat{\text{WTP}}_p^{\text{use}} &= \widehat{\text{MWTP}}_p^{\text{free}} \times Q_p^1 \\ \widehat{\text{WTP}}_p^{\text{total}} &= \widehat{\text{WTP}}_p^{\text{use}} + \widehat{\text{WTP}}_p^{\text{non-use}} \\ \widehat{\text{WTP}}_p^{\text{net}} &= \widehat{\text{WTP}}_p^{\text{total}} - \text{policy_price}_p \end{aligned}$$

where policy_price_p is the full consumer-surplus loss before netting out private valuation. A precinct's median voter has positive net WTP if and only if the model's predicted Yes probability exceeds 0.5.

1.3.5 Individual-Level WTP Distribution

The precinct-level estimates recover the *median* voter’s WTP in each precinct. To construct the full individual-level distribution across California’s adult population, I exploit the logistic structure of within-precinct heterogeneity.

By (1.7), within precinct p , an individual conventional consumer’s net WTP is distributed as:

$$\text{WTP}_{ip}^{\text{net}} \sim \text{Logistic} \left(\widehat{\text{WTP}}_p^{\text{net}}, \frac{1}{|\hat{\beta}_{\text{NP}}|} \right).$$

The population-level CDF of net WTP is therefore a finite mixture of logistics:

$$F(w) = \sum_p \omega_p \cdot \Lambda \left(|\hat{\beta}_{\text{NP}}| \cdot (w - \widehat{\text{WTP}}_p^{\text{net}}) \right), \quad (1.10)$$

where ω_p is precinct p ’s share of the adult population.

For the full-population distribution, I extend the mixture to include non-conventional consumer types. The full-population CDF is:

$$F^{\text{full}}(w) = \frac{1}{N} \sum_p \left[N_p^{\text{conv}} \cdot \Lambda \left(|\hat{\beta}_{\text{NP}}| (w - \mu_p^{\text{net,conv}}) \right) + N_p^{\text{other}} \cdot \Lambda \left(|\hat{\beta}_{\text{NP}}| (w - \mu_p^{\text{non-use}}) \right) \right], \quad (1.11)$$

where N_p^{conv} and N_p^{other} are the conventional and non-conventional adult populations in precinct p .

1.3.6 Private MWTP: Demand Model

The use-value component of WTP requires an estimate of consumers’ marginal willingness to pay for the cage-free attribute. I estimate this from a logit demand model on the product–ZIP–month panel. Consumer i in ZIP z in month t chooses among J_{zt} egg products and an outside option. The indirect utility from product j is:

$$u_{ijzt} = \alpha p_{jzt} + \mathbf{x}_j' \boldsymbol{\beta} + \boldsymbol{\beta}^{d'} (\mathbf{x}_j \times \mathbf{d}_z) + \xi_{jzt} + \epsilon_{ijzt}, \quad (1.12)$$

where p_{jzt} is price per dozen, $\mathbf{x}_j$ is a vector of product characteristics (housing-tier indicators, organic, size indicators), $\mathbf{d}_z$ is a vector of ZIP-level demographics (demeaned log median household income, demeaned mean years of education), ξ_{jzt} is an unobserved product–market quality term, and ϵ_{ijzt} is a Type I extreme value error. The Berry (1994) inversion yields:

$$\ln s_{jzt} - \ln s_{0zt} = \alpha p_{jzt} + \mathbf{x}_j' \boldsymbol{\beta} + \boldsymbol{\beta}^{d'} (\mathbf{x}_j \times \mathbf{d}_z) + \xi_{jzt}. \quad (1.13)$$

The price coefficient α is identified by three instruments: (i) a leave-one-out retailer assortment propensity; (ii) a BLP-style sum of rivals’ large-size indicators; and (iii) the

number of food stores per household.⁷ The ZIP-level MWTP for the cage-free attribute is:

$$\text{MWTP}_z^{\text{free}} = -\frac{\hat{\beta}^{\text{free}} + \hat{\beta}^{\text{free} \times \text{educ}} \cdot \text{educ}_z + \hat{\beta}^{\text{free} \times \text{inc}} \cdot \text{inc}_z}{\hat{\alpha}}, \quad (1.14)$$

which varies across ZIP codes through the demographic interactions.

1.4 Data

The empirical analysis combines three data sources, each available at a different spatial unit: (i) NielsenIQ Retail Measurement Services (RMS) scanner data on egg sales at the store-week-UPC level; (ii) California precinct-level returns for Proposition 12 and demographic variables from the Statewide Database (SWDB); and (iii) American Community Survey (ACS) five-year estimates of household income, education, employment, and population. Linking these sources requires two geographic crosswalks, described in Section 1.4.4. The final analysis sample (Section 1.4.5) consists of 19,061 precincts, each matched to the ZIP codes that overlap its geographic boundaries and to product-level cage-free pricing in those ZIPs during 2018.

1.4.1 Retail scanner data

I use NielsenIQ RMS scanner data for California in 2018, the year of the referendum. The RMS data contain store-UPC-week records of unit sales and weighted-average prices for participating retailers, covering approximately 58% of California grocery and mass-merchandise dollar volume in the relevant categories (NielsenIQ, 2020). I restrict attention to fresh egg products, to food and mass-merchandise channels, and to chicken eggs (dropping duck and quail). Because cage-free labeling is only informative for chicken eggs and because small-volume retailers occasionally report implausibly low prices (e.g., one retailer’s unit prices are uniformly below \$1, suggestive of item-level promotional coding errors), I drop stores from retailers whose within-year price distributions are incompatible with observed wholesale costs.⁸ Prices are converted to a dollar-per-dozen basis using the reported carton size (`size1_amount`).

Product definitions. The RMS Products and Products_Extra files allow me to decode each UPC into structured attributes. I classify each UPC along two dimensions that matter for both demand estimation and the policy: production-system label (regular/conventional, cage-free, free-range, pasture-raised, organic, fertile, and combinations thereof) and carton size (large, extra large, jumbo, mixed, medium, unclassified). Because a UPC-level BLP would produce thousands of products with many zero-share market cells, I collapse UPCs to

⁷The three retained instruments jointly satisfy relevance and overidentification criteria (first-stage $F = 100.3$; Hansen J $p = 0.294$).

⁸In practice, this amounts to dropping one retailer with all reported unit prices below \$1. Retaining or dropping this retailer does not materially affect estimates.

products defined by the Cartesian product of label and size, yielding 29 realized combinations out of 62 possible. This product-level aggregation retains the policy-relevant attribute (cage-free status) while delivering sufficient cross-product variation within each local market to identify demand.⁹

Geographic aggregation to ZIP-months. RMS reports a three-digit ZIP for each store, which is too coarse for matching to precincts. I use a probabilistic store–ZIP crosswalk constructed from the NielsenIQ Homescan consumer panel (Oh et al. (2025)). The crosswalk assigns each RMS store to five-digit ZIP codes based on the geographic distribution of Homescan panelist trips to that store. For each store s and ZIP z , the crosswalk records π_{sz} , the share of trips to store s originating from panelists residing in ZIP z , with $\sum_z \pi_{sz} = 1$. I allocate store-level sales volumes to ZIPs in proportion to π_{sz} , yielding a product–ZIP–week panel. Because the panelist trip counts underlying π_{sz} are annual, the allocation captures structural catchment patterns rather than short-run shopping noise. I then aggregate from weekly to monthly frequency, defining a *market* as a ZIP–month. The final scanner panel is at the product–ZIP–month level.

Market size. Defining shares requires a measure of market size that reflects potential, not realized, egg purchases. Following Berry et al. (1995), I set

$$M_{zt} = H_z \cdot \bar{q} \cdot \rho \cdot \kappa, \quad (1.15)$$

where H_z is the number of households in ZIP z (from ACS), $\bar{q} = 25/12$ dozen per household-month is USDA-reported average egg consumption, $\rho = 0.58$ is NielsenIQ RMS’s coverage share of California retail egg volume, and $\kappa = 0.50$ is the share of UPCs for which I can assign a cage-free/conventional label from Products_Extra. The product $\rho \cdot \kappa$ rescales the USDA quantity benchmark to the subset of transactions observed with usable labeling. This calibration yields a median total inside share of 20.8% and median cage-free share of 5.3%, which are consistent with industry-reported 2018 cage-free penetration of 20-30%. Sensitivity of the demand estimates to the choice of $\bar{q}$, ρ , and κ is examined in Appendix A.7.1; estimates of the marginal willingness to pay for the cage-free attribute are not materially sensitive to these calibration choices within plausible ranges.

Sample restrictions for attribute demand estimation. I impose the following restrictions on the product–ZIP–month panel before estimation: (i) markets with fewer than 500 households are dropped, because small populations yield unstable shares; (ii) markets with zero cage-free sales or zero within-market variation in the cage-free indicator are dropped, because they contribute nothing to identification of the cage-free coefficient; (iii) markets with total inside share above 0.98 are dropped, as these imply an implausibly small outside option; (iv) product–market cells with shares of exactly zero or one are dropped, since

⁹UPC-level demand estimation is infeasible in this setting because the typical ZIP-month contains only a handful of UPCs per producer, inducing selection and mechanical zeros. Product-level aggregation is standard in the egg-demand literature; see Allender and Richards (2010) and Oh et al. (2025).

the log-share transformation is undefined at these endpoints. These restrictions leave 11,936 ZIP-month markets and 120,718 product–ZIP–month observations covering 1,009 unique ZIP codes, from which the mean marginal willingness to pay (MWTP) for the cage-free attribute is estimated at the ZIP level.

Instruments To identify the price coefficient, I construct three instruments that shift prices conditional on product and month fixed effects and unobserved product quality:

1. *Leave-one-out retailer assortment propensity* (IV_{jzt}^{assort}): For each retailer r operating in ZIP z , I compute the leave-one-out share of product j in retailer r ’s total egg volume *in other ZIPs within the same DMA*, and then average across retailers present in ZIP z in month t . If a retailer chain stocks cage-free heavily in its other stores, its presence in a given ZIP shifts local cage-free availability and prices without reflecting that ZIP’s own demand shock. This IV follows the logic of DellaVigna and Gentzkow (2019) and Hitsch et al. (2021) in using retailer-level assortment rules as exogenous supply-side variation.
2. *BLP-style rival large-size sum* ($IV_{jzt}^{\text{BLP-large}}$): For product j in ZIP z and month t , the count of *other* products in the same market that are classified as large-size. This is a standard BLP-style instrument (Berry et al., 1995) that captures competitive pressure from the availability of close substitutes in the size dimension, shifting markups through the competitive environment rather than through demand.
3. *Food stores per household* (IV_z^{stores}): The number of unique RMS-participating food and mass-merchandise stores in ZIP z divided by the number of households. This captures local retail competitiveness, which shifts markups but is arguably orthogonal to idiosyncratic product-level demand shocks conditional on income, population, and product fixed effects.

I also constructed Hausman-style leave-one-out DMA prices, within-county (FIPS) leave-one-out prices, and additional BLP rival-characteristic sums (organic, cage-free, pasture-raised, free-range, number of rivals). These instruments either fail overidentification tests (Hansen J p -values below 0.01) or lack sufficient cross-ZIP variation within product–month cells after absorbing fixed effects; I report estimates using only the three instruments listed above, which jointly satisfy the relevance and overidentification criteria (first-stage $F = 100.3$; Hansen J p -value: 0.294).

1.4.2 Proposition 12 voting data

Precinct-level returns on Proposition 12 come from the California Statewide Database (SWDB), housed at UC Berkeley Law, which compiles official Statement of Vote (SOV) tallies, registration rolls, and ballot-voter counts at the state-registration-precinct (SRPREC) level for every statewide election. I combine three SWDB files for the November 2018 general election: a report of Yes/No counts for each ballot measure and vote counts for every race

on the ballot; a record of voter demographics by party affiliation, race/ethnicity, age, and gender; and a report of registered-voter counts along the same demographic dimensions. The three files merge cleanly on the SRPREC key, yielding 21,353 precincts.^{10 11}

The central dependent variable is the precinct-level Yes share on Proposition 12, defined as $\text{Yes}_p = \text{PR_12_Y}_p / (\text{PR_12_Y}_p + \text{PR_12_N}_p)$. Across the 19,061 precincts that enter the final analysis sample (Section 1.4.5), the mean Yes share is 0.611 with a standard deviation of 0.137 (Table 1.4.5); the fifth and ninety-fifth percentiles are 0.325 and 0.818 respectively. The distribution’s histogram appears in Appendix Figure A.1.

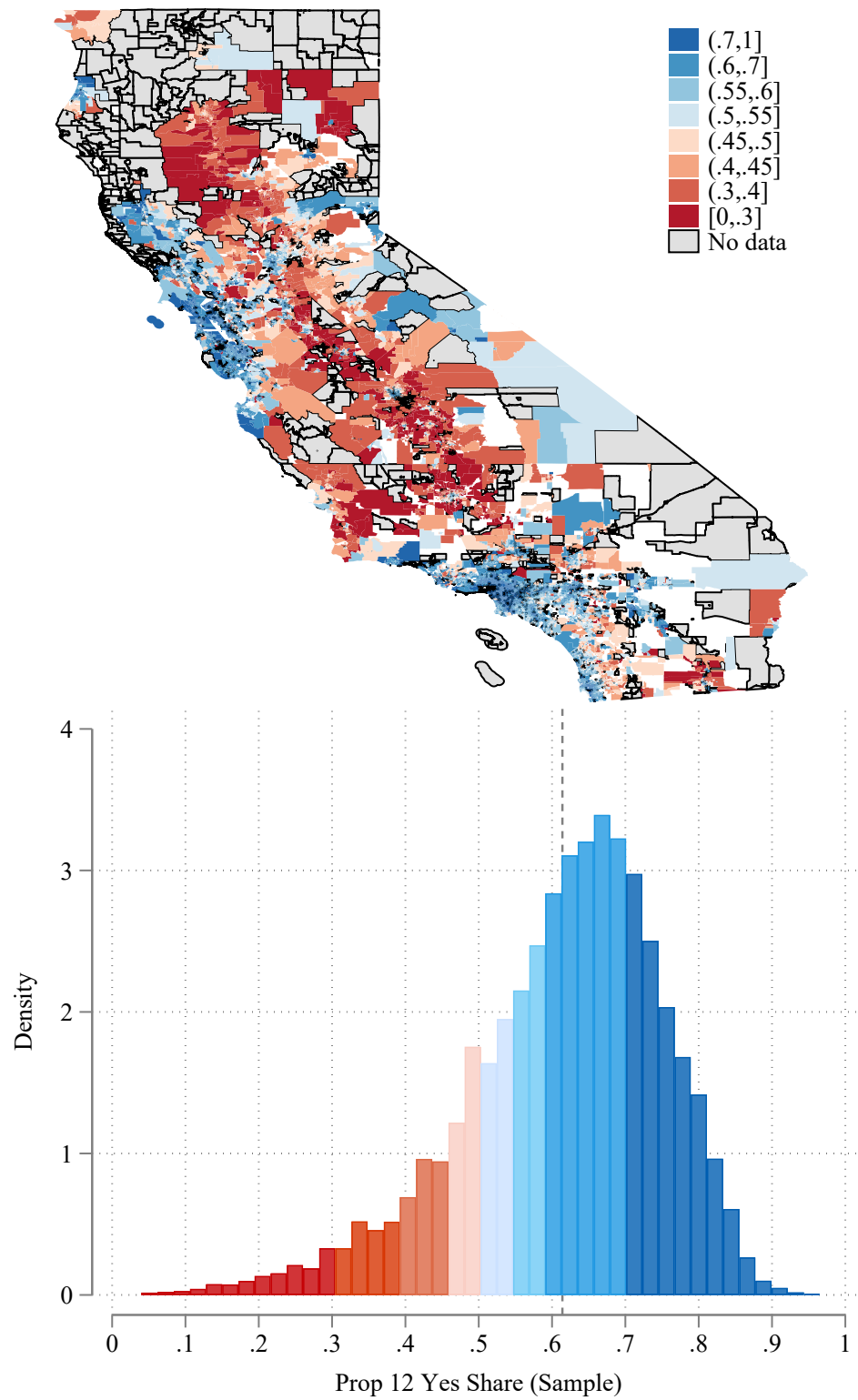
From the voter and registration files I construct two political-orientation variables that subsequent work by Sumner (2010) and Oh et al. (2025) identifies as central predictors of animal-welfare-initiative support: the two-party Democratic share of the concurrent 2018 gubernatorial vote (GOVDEM_SHARE_2P), which proxies for the ideological disposition of precinct voters toward regulation, and the share of right-leaning registered voters (RIGHT_VOTERS: the sum of Republican, American Independent, Libertarian, Natural Law, and Reform registrations divided by total registrations). Racial/ethnic and gender composition from the registration rolls are also observed.

Proposition 12 appeared seventh on a twelve-measure ballot. The share of gubernatorial voters who also voted on Proposition 12 averages 94.9% across precincts, comparable to the 95–96% completion rates for the other salient measures on the same ballot and consistent with near-zero marginal cost of completing the Prop 12 question conditional on ballot participation. This supports Assumption 4 (constituent representation; see Appendix A.11). A small number of precincts (683, or 3.1%) record more Prop 12 votes than gubernatorial votes; these appear to be driven by a subset of voters with idiosyncratically strong views on animal-welfare policy and are examined in Appendix A.4.3.

¹⁰The names of these files in order are `state_g18_sov_data_by_g18_srprec.csv`; `state_g18_voters_by_g18_srprec.csv`; `state_g18_registration_by_g18_srprec.csv`.

¹¹A small number of SRPREC observations appear in only one of the three files; I retain only precincts that merge across all three. The dropped observations are overwhelmingly very small precincts (median registered voters < 20).

Figure 1.2: Prop 12 “Yes” Share per Precinct (Final Sample)



1.4.3 Demographic and economic controls

Precinct-level demographic and economic controls come from ACS five-year estimates centered on 2018. I pull four ACS tables at the census-tract level for all California tracts: S0101 (population by age and sex), S1501 (educational attainment), S1901 (household income distribution, including mean and median), S2405 (industry of employment, used to construct the agricultural workforce share), and B19083 (Gini index of household income inequality). I also pull S0101, S1501, S1901, S2405, and B19083 at the ZIP (ZCTA) level for merging to scanner data. Tract-to-precinct allocation is described in Section 1.4.4.

The control set retained in the main voting specifications (Table 1.4.5) consists of median household income, share of population aged 25 and older with a bachelor’s degree or higher, share of the working-age population employed in agriculture, the Gini coefficient of household income, and population 18 and older within the precinct’s ZIP overlap (used for scaling, as described below). These controls are economically motivated: income proxies for the opportunity cost of the egg price increase; education proxies for awareness of and sensitivity to animal-welfare considerations (Viscusi et al., 2011); agricultural employment captures direct producer-side stakes in the policy; and the Gini index captures within-precinct heterogeneity that may itself shift support (Kahn and Matsusaka, 1997).

1.4.4 Geographic linkage

Two crosswalks are required to bring the scanner, voting, and ACS data into a single analysis file. Both are area-based and are summarized here.

Precinct-to-ZIP crosswalk. I use a precinct-ZIP area crosswalk obtained from Oh et al. (2025), which records for every California precinct p and every ZIP z the fraction of precinct p ’s land area that lies within ZIP z . Of the 21,651 precincts in the crosswalk, 44% lie entirely within a single ZIP, 31% span two ZIPs, and the remaining 25% span three or more (maximum: 16). I allocate ZIP-level cage-free prices and MWTP estimates to precincts using area-weighted averages, and I allocate ZIP-level ACS population quantities (e.g., adults over 18) to precincts using the reciprocal weighting so the contributions sum correctly across precincts sharing a ZIP. Letting α_{pz} denote the area share, the cage-free premium assigned to precinct p is

$$\widehat{\text{markup}}_p = \sum_z \alpha_{pz} \cdot \text{markup}_z, \quad (1.16)$$

and analogously for $\widehat{\text{MWTP}}_p$, $\widehat{\text{price_free}}_p$, and $\widehat{\text{price_caged}}_p$.

Tract-to-precinct crosswalk. For ACS demographic variables (which are released at the tract level), I use the block-to-SRPREC crosswalk for California 2018 from the SWDB, which reports for every census block the number of registered voters it contributes to each SRPREC. Aggregating blocks to tracts yields a tract–precinct linkage with weights ω_{tp} equal to the share of tract t ’s registered voters residing in precinct p . Precinct-level totals (e.g., population counts) are constructed by ω_{tp} -weighting tract totals; precinct-level rates and shares (e.g.,

median income, educational attainment) are constructed by ω_{tp} -weighted averaging. After the merge, 36,392 of 36,432 tract–precinct combinations receive ACS data, with the small residual reflecting tract code revisions between vintages.

The combined crosswalk pipeline produces, for each of the 21,353 precincts, (i) ACS demographic variables, (ii) weighted averages of ZIP-level cage-free and conventional prices and markups, and (iii) weighted averages of the BLP-estimated MWTP for the cage-free attribute across overlapping ZIPs.

1.4.5 Final analysis sample

The analysis sample for the precinct-level vote-share regressions consists of the 19,061 precincts that (i) appear in all three SWDB files, (ii) have nonzero overlap with at least one ZIP for which the logit demand model produces a valid MWTP estimate, and (iii) have non-missing ACS controls.¹²

Table 1.4.5 reports summary statistics for the final sample. Consistent with the statewide vote, 63.2% of voters in the median precinct supported Proposition 12. The mean precinct contains 618 voters, of whom 606 voted in the gubernatorial race and 586 voted on Proposition 12. Precinct-level cage-free and conventional egg prices, constructed as area-weighted averages over overlapping ZIPs, average \$5.02 and \$3.53 per dozen respectively, yielding a mean cage-free markup of \$1.06 per dozen (standard deviation \$0.47) and a mean within-sample cage-free share of 31.7%.¹³ A map of precinct-level Prop 12 Yes shares appears in Appendix Figure A.1; maps of cage-free markups and estimated MWTPs appear in Appendix Figures A.2 and A.3.

1.5 Empirical Analysis

¹²Attrition from 21,353 to 19,061 is driven primarily by (ii): some ZIPs have insufficient product variation or are dropped during BLP estimation (see Section 1.4.1), and precincts whose entire area lies within such ZIPs cannot be assigned an MWTP. The dropped precincts are disproportionately rural, with a mean registered-voter count of 532. Because rural precincts also exhibit lower support for Prop 12 (the agricultural-employment share is negatively correlated with the Yes share), the main estimates should be interpreted as reflecting urban and suburban California, where approximately 94% of the state’s 2018 Prop 12 ballots were cast.

¹³Note that this is higher than the share reported at the zip code level in the market (25%) due to systematic selection of high cage-free-available precincts.

Table 1.1: Precinct-level Summary Statistics

	Mean	SD	Min	Max	N
% Pr12 Yes vote	0.611	0.161	0.00	1.00	19061
Prop 12 Y share (conv. consumers)	0.428	0.225	0.00	1.00	19061
Cage-free price (\$/dozen)	5.021	0.301	2.99	6.94	19061
Conventional price (\$/dozen)	3.529	0.518	1.89	5.32	19061
CF markup, large non-organic (\$/dozen)	1.058	0.389	-3.21	2.59	19061
Med. MWTP CF label	0.106	0.138	-0.45	0.70	19061
Cage-free market share	0.317	0.138	0.02	0.85	19061
Total voters	618.419	434.939	1.00	6624.00	19061
Prop 12 total votes	586.350	412.877	1.00	6127.00	19061
Governor total votes	606.339	427.381	1.00	6505.00	19061
% Vote Dem. Gov.	0.603	0.212	0.00	1.00	19061
% Right-wing voters	0.302	0.187	0.00	1.00	19061
% BA or higher (edu.)	0.015	0.022	0.00	0.56	19061
% Workforce in ag.	0.027	0.063	0.00	0.62	19061
GINI Index	0.424	0.055	0.10	0.67	19061
Med. HH inc. (100K)	0.254	0.246	0.00	2.24	19061
Adult pop. in precinct-ZIP overlap	121116.112	104659.239	6.46	1837273.75	19061
% voters Female	0.492	0.088	0.00	2.00	19061
% voters Hispanic	21.849	20.363	0.00	200.00	19061
% voters Asian	7.645	10.272	0.00	100.00	19061

1.5.1 Private MWTP for Cage-free Eggs

The first stage of the analysis estimates consumers' marginal willingness to pay for the cage-free attribute, $\widehat{MWTP}_z^{free}$, at the ZIP code level. This parameter enters the voting model through the non-use price: it governs how much of the cage-free markup represents a genuine welfare loss to conventional consumers when the policy forces them to switch.

I estimate a logit demand model on the product-ZIP-month panel described in Section 1.4.1. The dependent variable is the Berry (1994) log-share ratio $\ln s_{jzt} - \ln s_{0zt}$, where s_{jzt} is the market share of product j in ZIP z in month t and s_{0zt} is the outside-good share. The model includes product and month fixed effects and controls for ZIP-level median household income and total households. Price is instrumented with the three instruments described in Section 1.3.6: the leave-one-out retailer assortment propensity, the BLP rival large-size sum, and food stores per household. Standard errors are clustered at the ZIP level.

The MWTP for the cage-free attribute is $-\hat{\beta}_{\text{cage-free}}/\hat{\alpha}$, where $\hat{\alpha}$ is the price coefficient and $\hat{\beta}_{\text{cage-free}}$ is the coefficient on the cage-free indicator. The IV estimate yields a median MWTP of \$0.11 per dozen across ZIP codes (mean: \$0.11; standard deviation: \$0.14), which is substantially below the average cage-free markup of \$1.64 per dozen. This is consistent with the fact that only 25% of eggs sold were cage-free in 2018: the vast majority of consumers preferred the conventional option at prevailing prices.¹⁴

¹⁴I attempted a full random-coefficients BLP specification with the price coefficient interacted with ZIP-level income. The random coefficient did not identify—estimates were unstable and the income interaction was not statistically significant—likely because the within-ZIP, within-month variation in the data is insuf-

Table 1.2: Linear IV - Market Share on Attributes

	(1)	(2)	(3)	(4)
	First Stage	Linear IV	First Stage	Linear IV
Cage-free or above	0.0806*** (0.0167)	0.1984*** (0.0430)	0.1094*** (0.0159)	0.2637*** (0.0421)
Free-range or above	0.4505*** (0.0269)	0.5752*** (0.0695)	0.5165*** (0.0262)	0.8009*** (0.0799)
Pasture-raised	1.0243*** (0.0275)	1.4590*** (0.1117)	1.0182*** (0.0256)	1.7095*** (0.1108)
Organic	1.1534*** (0.0234)	1.8358*** (0.1176)	1.1947*** (0.0236)	2.1674*** (0.1278)
Fertile	-0.6474*** (0.0369)	-1.2414*** (0.0886)	-0.9066*** (0.0343)	-2.0604*** (0.0958)
Extra large	-0.2423*** (0.0171)	-0.4037*** (0.0443)	-0.3525*** (0.0164)	-0.5471*** (0.0432)
Jumbo	1.0512*** (0.0530)	1.0665*** (0.1591)	0.8060*** (0.0522)	0.8310*** (0.1444)
Medium	-1.7612*** (0.0363)	-3.4982*** (0.1515)	-1.7287*** (0.0361)	-3.5371*** (0.1500)
Size unlisted	7.9335*** (0.0390)	11.1420*** (0.6319)	7.4275*** (0.0266)	11.7039*** (0.6359)
Housing tier $\times$ ln(income)	-0.1222*** (0.0220)	-0.5841*** (0.0835)	-0.1085*** (0.0188)	-0.5866*** (0.0766)
Housing tier $\times$ education	0.0712*** (0.0164)	0.8495*** (0.0692)	0.0432*** (0.0121)	0.8006*** (0.0635)
Median HH income	0.0000*** (0.0000)	0.0000*** (0.0000)	0.0000*** (0.0000)	0.0000*** (0.0000)
Total households (ZIP)	-0.0000 (0.0000)	-0.0001*** (0.0000)	-0.0000* (0.0000)	-0.0000*** (0.0000)
LOO retailer assortment	-3.2998*** (0.0706)		-2.8782*** (0.0655)	
Rival large-size count (BLP)	-0.0458*** (0.0093)		0.0406*** (0.0066)	
Food stores per HH	-63.9031*** (16.0844)		-22.9377** (9.3099)	
Price (\$/dozen)		-1.6714*** (0.0731)		-1.8695*** (0.0818)
Constant	5.0961*** (0.0668)	2.1626*** (0.3239)	5.0478*** (0.0645)	4.3801*** (0.4552)
Month FE	Y	Y	Y	Y
County FE	N	N	Y	Y
Observations	120718	120718	120718	120718

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

1.5.2 Specification of the Voting Model

Dependent Variable: Conventional Consumer-Voter Yes Share

The theory in Section 1.3 shows that a conventional consumer-voter supports Prop 12 if and only if her non-use WTP exceeds the non-use price. To isolate the voting behavior of conventional consumers, I adjust the raw precinct-level Yes share by removing the contribution of cage-free consumers, who are assumed to support the policy on private-consumption grounds alone:

$$\tilde{Y}_p = \frac{Y_p - \hat{s}_p^{free}}{1 - \hat{s}_p^{free}}, \quad (1.17)$$

where Y_p is the raw Prop 12 Yes share and $\hat{s}_p^{free}$ is the precinct-level cage-free market share (the fraction of eggs sold that are cage-free, area-weighted across overlapping ZIPs). This transformation assumes that cage-free consumers voted Yes at the same rate as their market share implies—a conservative assumption, since some cage-free consumers may have voted No for reasons unrelated to private consumption. The adjusted share $\tilde{Y}_p$ is floored at zero for precincts where $Y_p < \hat{s}_p^{free}$.

The Non-use Price

The key independent variable is the non-use price facing the median conventional consumer-voter in precinct p , which measures the expected annual consumer-surplus loss from the Prop 12 mandate. As derived in Section 1.3, the non-use price under locally linear demand is the trapezoidal area:

$$NP_p = \underbrace{(\text{net_cost}_p)}_{\text{quality-adj. price increase}} \times Q_p^1 + \frac{1}{2}(\text{net_cost}_p) \times |\Delta Q_p|, \quad (1.18)$$

where $\text{net_cost}_p = \text{markup}_p - \widehat{\text{MWTP}}_p^{free}$ is the quality-adjusted price increase (the cage-free markup net of private valuation), $Q_p^1 = Q^0 + \varepsilon \cdot Q^0 \cdot (\text{markup}_p / P_p^{conv})$ is post-policy annual egg consumption, $Q^0 = 25$ dozen per capita per year (USDA average), and ε is the own-price elasticity of egg demand.

I construct two variants of the non-use price that differ in voter expectations about the post-policy price increase:

1. *Local price expectations* (NP_p^{local}): Voters expect to pay the cage-free price they observe at their local grocery store. The proportional price increase is $\text{markup}_p / P_p^{conv}$, which varies across ZIPs. This is the preferred specification: it exploits the full cross-sectional variation in cage-free premia and corresponds to the assumption that voters use locally available price information to form expectations.

ficient to separately identify taste heterogeneity in the price coefficient from the mean effect. I therefore use the linear IV logit as the primary specification, which identifies the mean MWTP and its cross-ZIP variation. The BLP estimates, when they converge, yield similar mean MWTPs and are reported in Appendix Table A.1.

2. *State-level price expectations* (NP_p^{state}): Voters expect a uniform 30% price increase, as stated in the Official Voter Information Guide sent to every registered voter. The proportional increase is fixed at 0.30, and cross-precinct variation in the non-use price arises only through differences in conventional prices and MWTP. This specification provides a robustness check and a lower bound on the identifying variation.

I use the USDA own-price elasticity of egg demand ($\varepsilon = -0.14$) in the main specification and report sensitivity to the lower-bound Smith (2025) estimate ($\varepsilon = -0.05$) in the appendix. With $\varepsilon = -0.14$ and a 30% price increase, annual per-capita consumption falls from 25 to approximately 24 dozen.

Estimating Equation

The precinct-level voting model is:

$$\tilde{Y}_p = \Lambda(\beta_{\text{NP}} \cdot NP_p + \mathbf{X}_p' \boldsymbol{\gamma} + \delta_c + u_p), \quad (1.19)$$

where $\Lambda(\cdot)$ is the logistic CDF, $\mathbf{X}_p$ is a vector of precinct-level controls (Democratic gubernatorial vote share, right-wing registration share, bachelor's degree share, agricultural employment share, Gini index, log median household income, log adult population, share female, share Hispanic, and share Asian), δ_c are county (FIPS) fixed effects, and u_p is the precinct-level error.¹⁵ I estimate this by fractional logit (GLM with binomial family and logit link), weighted by total votes cast (TOTVOTE_p), with standard errors clustered at the county level.

The coefficient of interest is β_{NP} , the marginal effect of the non-use price on the log-odds of the conventional consumer Yes share. The sign should be negative: precincts where Prop 12 imposes higher costs on conventional consumers should exhibit lower support, conditional on demographics and ideology.

Endogeneity and Instrumentation

The non-use price NP_p is potentially endogenous because it is constructed from local egg prices and MWTP, both of which may be correlated with unobserved precinct-level demand shifters (e.g., local tastes for organic food, health consciousness). If such unobservables are positively correlated with both cage-free premia and Prop 12 support, OLS will attenuate $|\hat{\beta}_{\text{NP}}|$ toward zero.

To address this, I use a control-function approach (Petrin and Train, 2010; Wooldridge, 2015): I regress the non-use price on the excluded instrument(s) and all exogenous controls including county fixed effects, save the first-stage residual $\hat{v}_p$, and include it as an additional regressor in the GLM second stage. This is valid for the fractional logit specification because

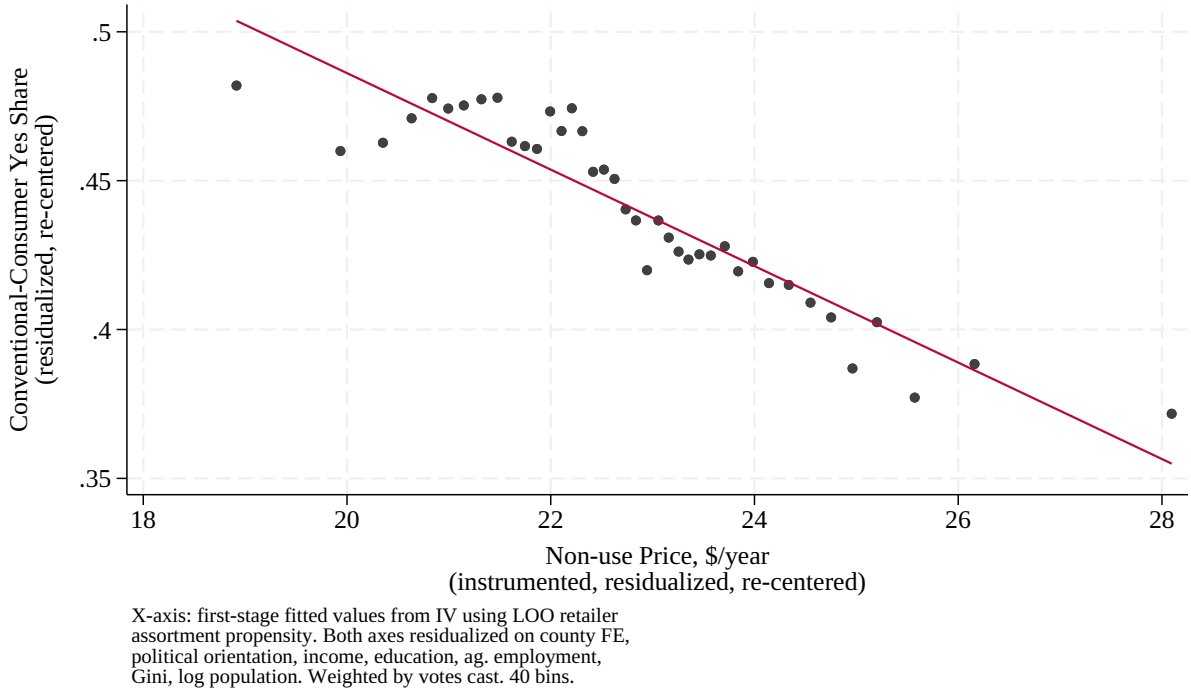
¹⁵Precinct-level demographic controls were intentionally selected as the union of the independent variables used in other articles that regress Prop 12 “Yes” vote share on precinct-level characteristics, namely, Bovay and Sumner (2019) and Oh et al. (2025). This way, the non-use price term only captures variation beyond what has already been identified in the literature.

the control function linearizes the endogeneity correction while preserving the nonlinear link function.¹⁶

For the local-price specification (NP_p^{local}), the excluded instrument is the leave-one-out retailer assortment propensity for cage-free products, $IV_p^{assort,cf}$, which captures chain-level stocking decisions that shift local cage-free availability and prices. The first-stage F -statistic on the excluded instrument is 14.9 ($p < 0.001$). For the state-level specification (NP_p^{state}), the excluded instrument is food stores per household, IV_p^{stores} , which captures local retail competitiveness; the first-stage F -statistic is 9.5.¹⁷

The significance of $\hat{v}_p$ in the second stage serves as a test of endogeneity (Wooldridge, 2015). If $\hat{v}_p$ is insignificant, the naive (non-instrumented) GLM is consistent.

Figure 1.3: Binned Scatter of Residuals



¹⁶Unlike standard 2SLS, which is inconsistent for nonlinear models, the control-function approach remains consistent under the assumption that the endogenous variable is additively separable from the structural error (Wooldridge, 2015). The clustered standard errors from the second stage are conservative (they overstate uncertainty) because they do not account for the generated-regressor nature of $\hat{v}_p$.

¹⁷When both instruments are used jointly, they pass the Hansen J overidentification test for NP_p^{local} ($p = 0.9$) but not for NP_p^{state} , which is why I use a single instrument for each specification in the main results.

1.5.3 Main Results

Table 1.5.3 presents the core result in three columns for the preferred dependent variable ($\tilde{Y}_p$, adjusted by subtracting the cage-free share) and the preferred non-use price (NP_p^{local} , with local price expectations and USDA elasticity).

Column (1) reports the naive fractional logit without instrumentation. The coefficient on the non-use price is -0.0006 ($SE = 0.002$), statistically indistinguishable from zero. This is consistent with the endogeneity concern: unobserved tastes for premium food likely inflate both cage-free premia and Prop 12 support, biasing the coefficient toward zero.

Column (2) reports the control-function GLM. The coefficient on the non-use price is -0.063 ($SE = 0.010$, $p < 0.01$), an order of magnitude larger in absolute value than the naive estimate. The control-function residual $\hat{v}_p$ is highly significant ($t = 6.5$, $p < 0.001$), confirming that the non-use price is endogenous and that the naive estimate is biased. The sign and magnitude accord with theory: a \$1 increase in the annual non-use price facing conventional consumers in a precinct reduces the log-odds of their Yes share by 0.063.

Column (3) reports a linear 2SLS specification as a robustness check. The coefficient is -0.016 ($SE = 0.005$, $p < 0.01$), qualitatively identical in sign and significance. The linear specification is included for transparency; the fractional logit is preferred because it respects the bounded nature of the dependent variable and generates WTP estimates through the Hanemann (1984) formula (Section 1.5.4).

The demographic controls behave as expected across all specifications. The Democratic gubernatorial vote share is strongly positive, consistent with ideological support for regulation. The right-wing registration share is strongly negative. Higher median income reduces support, consistent with the non-use price being a smaller share of income for wealthier households—once ideology and education are controlled for, the residual income effect captures the opportunity cost channel. Agricultural employment share is negative in naive specifications (capturing producer-side opposition) but attenuates toward zero under instrumentation, suggesting that some of its naive effect ran through the price channel. The Gini coefficient is negative and significant in the instrumented specifications, indicating that precincts with greater income inequality are less supportive.

Table 1.3: Predicting Prop 12 Approval

	(1)	(2)	(3)
	Naive GLM	CF-GLM	2SLS Linear
Non-use price (local $\mathbb{E}[P]$)	-0.0001 (0.0020)	-0.0735*** (0.0125)	-0.0162*** (0.0053)
% Dem. governor vote	2.0487*** (0.5205)	0.7838 (0.5411)	0.2274* (0.1343)
% Right-wing registered	-2.2884*** (0.5174)	-3.2275*** (0.5427)	-0.6439*** (0.1566)
% Bachelor's degree+	-0.1718 (0.8185)	-2.9202*** (1.0247)	-0.6354 (0.4253)
% Workforce in agriculture	-0.8273* (0.4820)	-0.0256 (0.5392)	0.0277 (0.1357)
Gini index	-0.0954 (0.2392)	-1.0555*** (0.2983)	-0.2159** (0.1007)
Median HH income (\$100K)	-0.1108* (0.0591)	-0.2323*** (0.0623)	-0.0535** (0.0214)
ln(adult population)	0.0636** (0.0309)	0.1038*** (0.0324)	0.0217*** (0.0083)
% voters Female	0.9512** (0.3894)	0.6309* (0.3792)	0.0953 (0.0914)
% voters Hispanic	-0.0027** (0.0012)	0.0083*** (0.0021)	0.0019*** (0.0006)
% voters Asian	-0.0035*** (0.0013)	-0.0040*** (0.0012)	-0.0010 (0.0007)
Control f residual		0.0775*** (0.0124)	
Constant	-2.0439*** (0.5388)	-0.3548 (0.5426)	0.4048** (0.1864)
Month FE	Y	Y	Y
County FE	Y	Y	Y
Observations	19061.0000	19061.0000	19061.0000

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

1.5.4 Recovering WTP from the Voting Model

Following Hanemann (1984), the logit model identifies the median voter’s WTP from the ratio of the linear index to the price coefficient. Specifically, for each precinct p , the median conventional consumer-voter’s non-use WTP is:

$$\widehat{\text{WTP}}_p^{\text{non-use}} = -\frac{\mathbf{X}'_p \hat{\gamma} + \hat{\delta}_c}{\hat{\beta}_{\text{NP}}} + \text{NP}_p, \quad (1.20)$$

where the numerator is the “structural” linear index (excluding the control-function residual and the policy-price term). The first term, $-(\mathbf{X}'_p \hat{\gamma} + \hat{\delta}_c)/\hat{\beta}_{\text{NP}}$, is the non-use price at which the median voter in precinct p would be exactly indifferent between Yes and No. Adding back the actual non-use price yields the non-use WTP that the median voter would need to hold in order to rationalize the observed vote share.

Use WTP for conventional consumers is the annualized private value of switching to cage-free:

$$\widehat{\text{WTP}}_p^{\text{use}} = \widehat{\text{MWTP}}_p^{\text{free}} \times Q_p^1, \quad (1.21)$$

where Q_p^1 is post-policy annual consumption. Total WTP is the sum of use and non-use, and net WTP is total WTP minus the gross annual cost (i.e., full policy price) of the policy (the full consumer-surplus loss from the price increase, before netting out private valuation):

$$\widehat{\text{WTP}}_p^{\text{net}} = \widehat{\text{WTP}}_p^{\text{total}} - \text{policy_price}_p. \quad (1.22)$$

A precinct’s median voter has positive net WTP if and only if the predicted Yes probability exceeds 0.5, providing an internal consistency check.

WTP Distributions

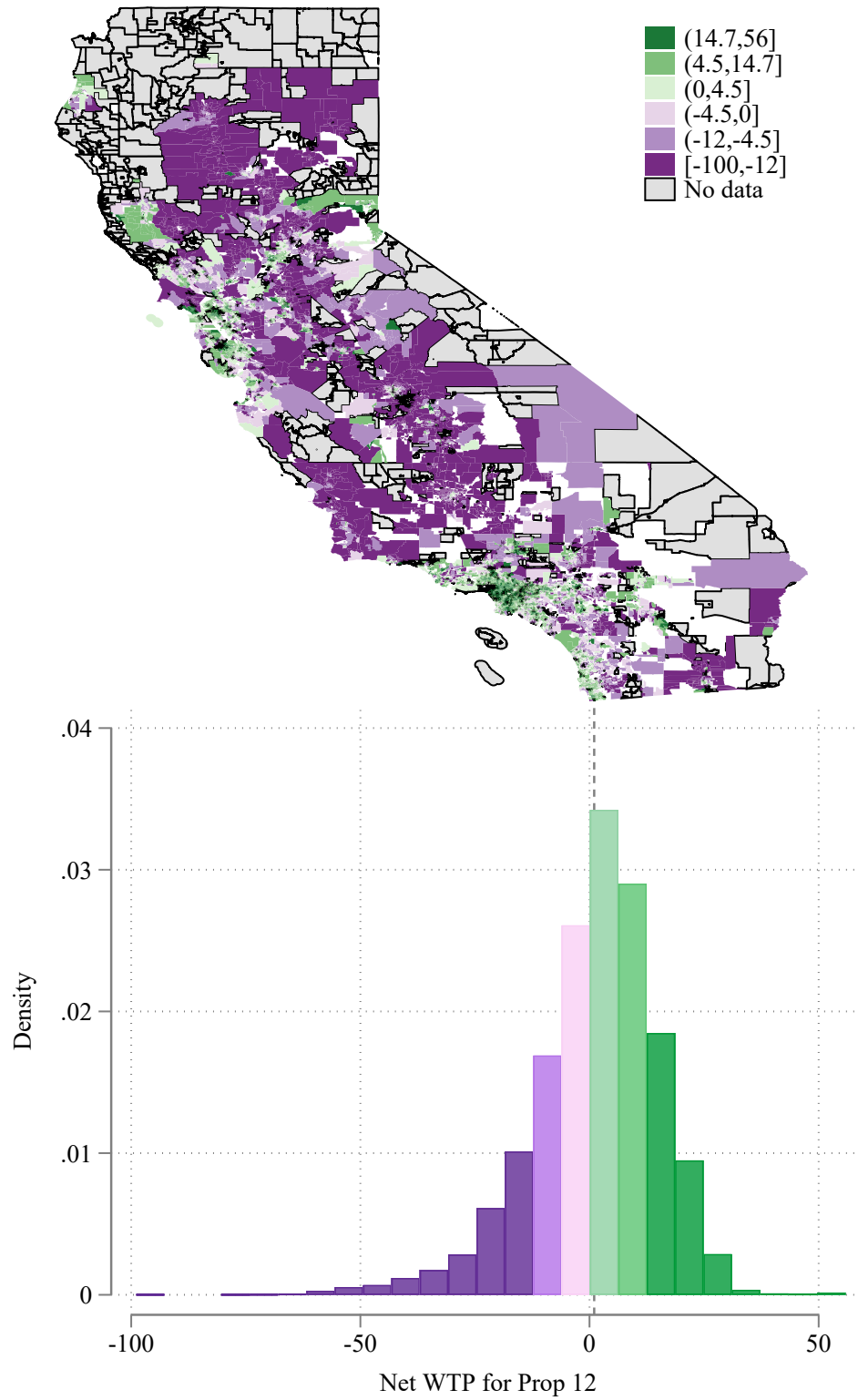
Figure A.5 plots the inverse CDF (“demand curve”) of each WTP component across precinct median voters, weighted by votes cast.

First, the non-use WTP curve (gold dotted) and the total WTP curve (green dash-dot) nearly coincide, visually confirming that non-use value accounts for the overwhelming majority of the policy’s total value to voters. At the median voter across precincts, non-use WTP is approximately \$20 per year; use WTP (gold dashed) is approximately \$2–3 per year. Across the full sample, non-use value constitutes over 90% of total WTP.

Second, the net WTP curve (blue solid) crosses zero at approximately the 37th percentile of median voters, indicating that the median voter in roughly 37% of precincts has net-positive WTP for Prop 12. This is below the 47% conventional-consumer “Yes” share implied by the adjusted dependent variable, because the precinct-level median does not coincide with the population median when precinct sizes vary. When the distribution is re-weighted to the individual level (Figure A.5), the net-WTP zero crossing aligns with approximately 47% of conventional consumer-voters—consistent with the adjusted “Yes” share (47%).

Third, at the extremes: approximately 15% of median voters are willing to pay at least \$30 per year in non-use value, and approximately 5% of the population at the bottom has

Figure 1.4: Net WTP for Prop 12



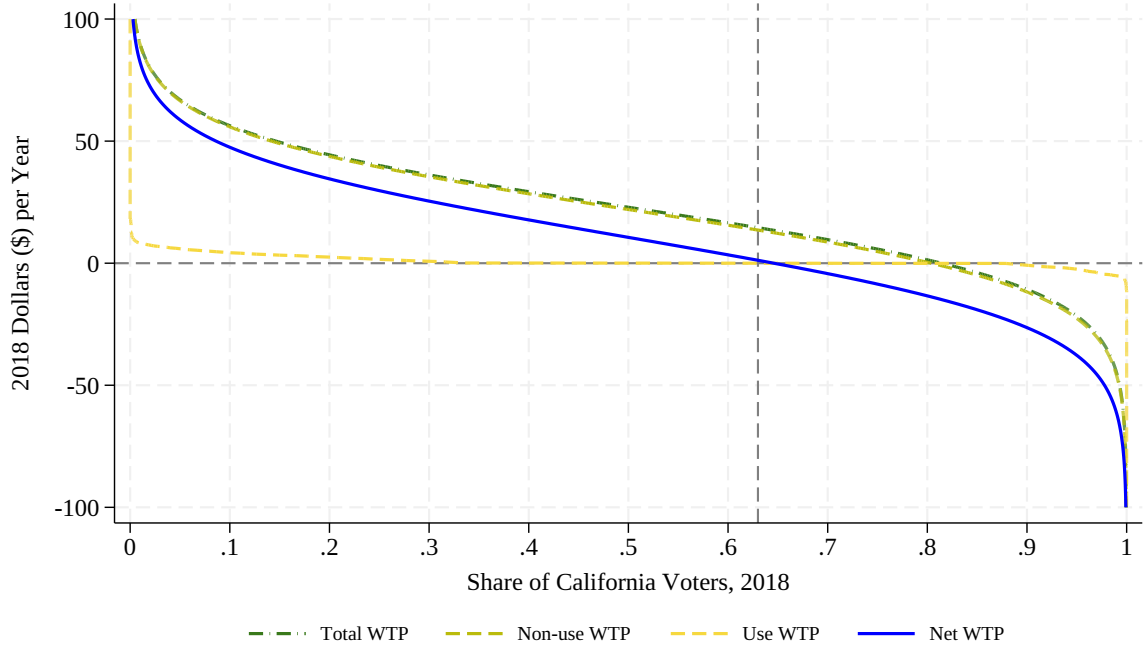
net WTP below $-\$50$ per year (i.e., would require compensation of $\$50$ or more to accept the policy). The distribution is moderately right-skewed in the upper tail and steeply left-skewed in the lower tail, reflecting a small number of precincts with very high policy costs (rural, high-markup ZIPs) and strongly negative net benefits.

Full-Population WTP Distribution

Figure 1.5 extends the WTP distribution to the full adult population by incorporating cage-free consumers, other premium-egg consumers, and non-egg consumers alongside conventional consumers. For non-conventional groups, I assume that (i) their non-use WTP is the same as conventional consumers in their precinct (since non-use preferences are not separately identified from voting data) and (ii) they face zero policy cost (since the mandate does not raise or may lower their effective price). The individual-level distribution is constructed as a mixture of logistic distributions, one per precinct-consumer-type cell, weighted by the population share of each type.

The full-population net-WTP curve crosses zero at approximately the 64th percentile of California’s adult population—close to the actual 63% statewide Yes vote, providing an external validation of the model. The total WTP and non-use WTP curves are nearly indistinguishable across the full population—a visual consequence of use value being small for conventional consumers and zero for everyone else. The average Californian’s total WTP for Prop 12 is approximately $\$18$ – $\$19$ per year, of which only $\$2.60$ is attributable to use value.

Figure 1.5: WTP for Prop 12: All Voters



Note: Individual-level WTP distribution constructed as a mixture of logistic distributions across precincts, weighted by adult population. Incorporates conventional consumers (70% of the market), cage-free consumers (25%), and other premium-egg consumers (5%). The vertical dashed line at 0.63 marks the approximate population share with positive net WTP; the actual statewide Prop 12 Yes vote was 63%. See Section 1.5.4 for construction.

1.5.5 Robustness

I assess sensitivity along three dimensions.

Voter expectations. Table A.7.1 replaces the local-price non-use price with the state-level 30% expectation variant. The coefficient on NP_p^{state} is negative and significant in both the control-function GLM and the linear 2SLS, with magnitudes implying similar WTP levels. Because the state-level specification uses only one instrument (food stores per household, first-stage $F = 9.5$), the local-price specification with its stronger first stage ($F = 14.9$) is preferred.

Own-price elasticity. Replacing the USDA elasticity ($\varepsilon = -0.14$) with the Smith (2025) estimate ($\varepsilon = -0.05$) changes the non-use price by less than 5% because egg demand is inelastic in both cases and the trapezoidal correction is a second-order term. WTP estimates are virtually unchanged.

Functional form. Table 1.5.3 reports a fully linear specification (OLS on the unbounded adjusted share, allowing negative values). The 2SLS linear estimate of β_{NP} is -0.016 ($SE = 0.005$, $p < 0.01$) for the local specification—statistically and economically significant. The linear estimates are qualitatively identical to the fractional logit and confirm that the result is not driven by the logistic functional form.

1.6 Conclusion

Market purchases and referendum votes identify different things. Markets reveal what consumers are willing to pay for a good unilaterally, in Nash equilibrium, taking everyone else’s behavior as given. Referenda reveal what voters are willing to pay for a collective outcome that no individual purchase can achieve. The gap between the two is non-use value—the public-good component of welfare that competitive markets structurally underprovide—and this paper shows it is exactly identified by combining retail scanner data with precinct-level voting data, without stated-preference surveys and without restrictions on how consumption and public-good preferences interact.

Applied to California’s Proposition 12, the framework yields three findings. The gap between private market behavior and collective voting behavior is large: non-use value accounts for over 85 percent of the policy’s total value to voters, with the average Californian’s total WTP of approximately \$20 per year decomposing into \$17 of public-good value and \$2.60 of private consumption benefit. The estimated WTP distribution is internally consistent: the model predicts that 64 percent of the adult population had positive net valuations for the policy, matching the actual 63 percent Yes vote without any calibration to the aggregate outcome. And the vote-buy gap—63 percent voting Yes while only 25 percent of eggs sold were cage-free—is not anomalous but is a structural consequence of public-good underprovision in private markets, resolved through collective choice exactly as the theory predicts.

The attenuation of pocketbook cost sensitivity under OLS, a pattern documented in this setting and in prior referendum studies, has a structural explanation. When a policy generates public-good benefits, voters with stronger preferences for those benefits are also more willing to absorb higher costs, generating positive correlation between the cost variable and unobserved public-good valuation. The result is omitted-variable bias, not evidence that voters are sociotropic. Instrumenting for the local consumer cost with supply-side price variation recovers large and precisely estimated cost sensitivity alongside large public-good valuations. The two are not in tension; they are the use and non-use components of the same underlying preferences.

These findings have direct implications for policy evaluation. Previous benefit-cost analyses of Prop 12 and similar mandates have quantified the cost side in detail while leaving the benefit side unmonetized (Sumner, 2010; Lusk and Norwood, 2011; Oh et al., 2025). The estimates here fill that gap and suggest that consumer-voter benefits alone may be sufficient to justify the policy on welfare grounds, before accounting for any direct welfare gains to the animals. The finding that non-use value dominates also has implications for instrument choice: the large non-use share implies that the efficiency cost of a ban relative to a Pigouvian tax is small, because little consumer surplus on infra-marginal units is forgone when

most of the policy’s value is non-use (Weitzman, 1974; Fullerton and West, 2002). More generally, the ratio of non-use to total WTP estimated here is precisely the parameter that governs the optimal mix of user fees and general taxation for cost recovery of quasi-public goods (Appendix

Four limitations are worth noting. The estimates pertain to consumer welfare only; a complete social welfare analysis would also require accounting for producer adjustment costs, interstate price spillovers, and the welfare of the animals themselves. The framework identifies the magnitude of non-use WTP but is agnostic about its source—altruism, warm glow, coordination failure, or some combination—and distinguishing among these would require complementary experimental evidence. The individual-level WTP distribution relies on the logistic functional form for within-precinct heterogeneity; alternative distributional assumptions would affect the tails but not the central tendency. And the non-use price is constructed under the assumption that voters expected the post-policy egg price to equal the pre-policy cage-free price, though the robustness checks in Section 1.5.5 show that the qualitative findings are stable across alternative expectation schemes.

The identification strategy is portable. Any ballot initiative in which the voter’s cost arrives as a commodity price change, and in which a regulated and an unregulated substitute coexist in observable retail markets, admits the same decomposition. Pesticide-ban referenda could use the organic premium; a plastic-bag ban could use the reusable-bag markup; a fuel-efficiency mandate could use the price gap between efficient and conventional vehicles. In each case, use value is recovered from market data, total value from the vote, and the residual is the public-good component that private markets fail to price. Whether the collective trap documented here for animal welfare—a large gap between what people are willing to pay collectively and what they are willing to pay alone—is a general feature of environmental and social regulation, or specific to settings with strong moral salience, is a question this framework is now equipped to answer.

Chapter 2

A Scoping Review of (Dis-)Incentives for Animal Welfare-Improving Farming Practices

2.1 Introduction

Improving the treatment of animals raised for food is an increasing global priority (Kuruc and McFadden, 2023a; Perino and Schwickert, 2023; Dusel and Wieck, 2023; Bartlett et al., 2024; Espinosa and Treich, 2021; Dawkins, 2023). In the United States, ten states have passed legislation that eliminates the use of highly-confined, enclosed housing systems (i.e., battery cages) in egg production (ASPCA, 2024; Ufer, 2022). The European Union has enacted still more ambitious animal welfare regulations, going as far as appointing a dedicated Animal Welfare Commissioner in 2024 (European Parliament, 2024). As evidenced by the performance of ballot measures—where the public has the opportunity to vote directly on the rule or law under consideration—improvements to the conditions of farmed animals garner widespread support (Mullally and Lusk, 2018a; Hopkins et al., 2022). The coming decades are likely to see more efforts in this direction, especially in countries such as the United States, whose populace demands improved farm animal treatment (Gallup, 2015), and whose researchers have, to date, played a major role in developing methods for monetizing animal welfare to inform policy debates (Budolfson et al., 2023; Blackstone et al., 2024; Budolfson et al., 2024; Kuruc and McFadden, 2023b).

However, implementation of enhanced welfare practices demanded by the U.S. public—typically consumers without substantial knowledge of agricultural production—faces significant challenges (Grethe, 2017). For farmers, improving the welfare of their animals can increase costs, reduce productivity, complicate risk management, and threaten animal health and safety (Nocella et al., 2010; Ortega and Wolf, 2018; Christensen et al., 2019; Niemi, 2020; Bartlett et al., 2024). Indeed, animal welfare regulations would, in general, be unnecessary if what they require were to consistently and predictably improve producers’ profitability (Espinosa, 2024). This logic points to an important consideration and a significant knowledge gap: Better understanding the (dis-)incentives that producers face when considering the adoption of welfare-improving practices is necessary for designing cost-effective animal

welfare policy.

This chapter begins to close this gap by systematically reviewing what is known—and what remains unknown—about producer incentives in these areas of their operations. Summarizing this literature is difficult because it is scant in many areas, and because what has been written spans fields as distinct as animal health and sciences to economics (Norwood and Lusk, 2011). There is little we can do about the dearth of research, but we overcome the latter challenge by conducting a scoping review using machine learning tools that permit searching large academic databases. Specifically, we use tools and techniques that allow us to efficiently search three of the largest repositories of academic papers: EconLit, CAB Abstracts, and Web of Science. The union of these repositories covers an extremely wide range of fields.

Our review searches the scientific literature for evidence regarding the incentives (disincentives) that motivate farmers to adopt (not adopt) animal welfare-improving practices in the United States, where a capital-intensive, land-abundant agricultural system (USDA-ERS, 2024b) produces a major share of global exports of animal-based foods (OECD and FAO, 2024). We focus on five measurable practice categories linked to animal welfare within the livestock sector: 1) the animals’ indoor environment, 2) whether they have outdoor access, 3) their enrichment opportunities, 4) whether and how severely they are confined, and 5) what types of bodily mutilation they undergo. Practices in these categories bear relation to the well-known Five Domains Model for animal welfare assessment (Mellor et al., 2020) and constitute animal welfare issues easily recognizable to the public (e.g., caging layer hens, castrating male piglets without anesthetics). In terms of species, we restrict our focus to dairy cows, layer hens, broilers, and hogs. These are the land animals that give rise to the most widely-produced and consumed animal products in the United States (USDA-ERS, 2024a,c), with the exception of beef cows, which experience arguably higher levels of welfare under conventional practices than the other four animals (Norwood and Lusk, 2011; Fischer, 2024).

The process used to distill this large literature was iterative, leveraging both machine learning and manual researcher review. In particular, we began with large scale keyword searches of multiple academic databases. We then performed successive rounds of Latent Dirichlet Allocation (LDA), a machine learning technique to summarize corpus of texts. Each of these LDA rounds was interspersed by manual research review of a sample of papers, to ensure that each step was working as intended. The final step involved our research team manually reviewing each of the remaining 134 papers deemed within scope.

Our findings are separated into two broad categories: (1) what is *known*, based on this corpus of papers, and (2) what remains *unknown*. Regarding the former, we summarize the number of results and papers pointing towards a specific (dis-)incentive facing producers when choosing to adopt a more humane practice. One novelty of our review is that we search for analyses that ask whether a specific practice (e.g., enrichment) improves or worsens other producer-relevant outcomes (e.g., animal health). This is in contrast to related reviews, which tend to focus their analyses on understanding which farm characteristics predict adoption of certain practices (Pineiro et al., 2020; Li et al., 2023; Prokopy et al., 2019; Pierpaoli et al., 2013). The types of analyses captured in our review more directly speak to the costs and

benefits for producers of adopting certain practices. As a concrete example, we find that improved animal health appears to be a significant incentive for improving the animals' indoor environment. Conversely, increased operation costs are a significant disincentive for nearly all animal welfare improvements.

In terms of what remains unknown, we attempt to summarize absences in this literature. For example, the number of studies our scoping review identified related to broiler welfare issues lagged significantly behind the number of studies focused on layer hen welfare issues. This difference is difficult to rationalize based on human perceptions of the importance of different species—layer hens and broiler chickens are, of course, very similar animals. In terms of (dis-)incentives, we notice a striking absence of papers attempting to understand the cost-structure of these barriers, despite the many findings that operating costs, in general, are a barrier. If these increased operating costs are fixed, rather than variable, this would greatly affect the policy recommendations that follow from merely recognizing “costs” as a barrier. Perhaps the most important lesson of our review is that this literature is sparse, a finding that echoes Carlier and Treich (2020). Given the clear public interest in animal welfare improvements, research to better understand not just the (dis-)incentives of adopting these practices, but the details and structure of these disincentives may be particularly important.

Our findings suggest several policy implications for advancing farm animal welfare while acknowledging producer constraints that we discuss towards the end of the chapter. Practices that improve indoor environments appear particularly promising as policy targets, offering welfare benefits with potential economic advantages through enhanced animal health and productivity. Meanwhile, policies addressing outdoor access or reduced confinement may require more substantial economic incentives to overcome the identified disincentives. We overview potential hybrid policy approaches that combine targeted regulations and economic incentives. We conclude the chapter by outlining specific research priorities that may uncover additional, actionable insights, including better understanding the structure of both markets and producer costs.

The chapter proceeds as follows. Section 2.2 overviews the method of our scoping review, explaining the details of our machine-learning techniques as well as the manual aspects of review. Section 2.3 summarizes the results of our search, in terms of the lessons and omissions arising from our search. Section 2.4 discusses these results, in terms of their strengths and weaknesses, policy relevance. Section 2.5 addresses future research directions that we see as particularly valuable given the current state of the literature. Section 2.6 concludes.

2.2 Methods

This section outlines the methodological approach used in our scoping review. We first describe the PRISMA-ScR framework that guides our review process and explain our research question. We then detail our information sources, search strategy, and study selection criteria, highlighting the novel integration of machine learning techniques with traditional manual review to efficiently analyze a large corpus of literature spanning diverse fields.

Scoping reviews aim to synthesize studies with diverse methodological approaches while identifying key areas for future research. We adhered to the Preferred Reporting Items

for Systematic Reviews and Meta-Analyses extension for scoping reviews (PRISMA-ScR) guidelines. The framework comprises five steps:

1. Research question identification;
2. Relevant study identification;
3. Study selection;
4. Data categorization;
5. Result collation, summarization, and reporting.

The review was guided by the following research question: “What economic and non-economic incentives motivate farmers to adopt animal welfare-improving practices?” To answer this question, the review’s scope was limited to original research that: (1) examines layer, broiler, hog, or dairy cow production; (2) focuses on the United States; and (3) was published between 1991 and 2023. This scoping review had two primary objectives. First, to uncover patterns in the relationships between humane practices and producer outcomes; second, to identify gaps in the academic literature regarding producer incentives for adopting such practices.

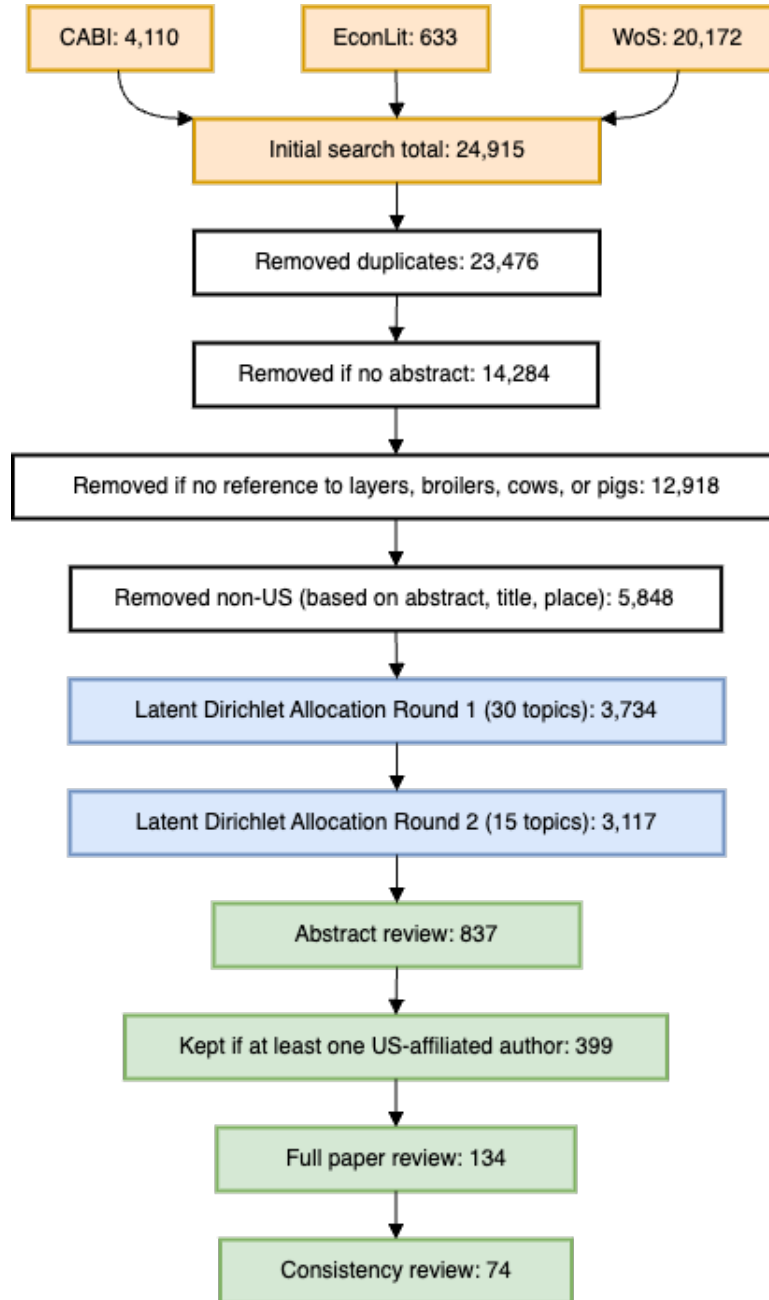
2.2.1 Information sources and searches

We developed a comprehensive search strategy to identify all available research pertaining to the use of farm practices that improve (worsen) animal welfare. We compiled an exhaustive list of all widely used farm practices that are (or have) alternatives which improve animal welfare. This resulted in 57 meaningfully different terms, including practices (e.g., “cage-free”, “teeth clipping”), humane labeling schemes (e.g., “Humane Certified”) which regulate some of the practices of interest, and umbrella terms like “animal welfare.” We categorized the practice terms into five mutually exclusive categories, forming a basis of our project’s scope of practices: outdoor access, confinement, enrichment, mutilation, and indoor environment. To limit the scope of our project, we did not search for practices such as the use of antibiotics, hormones, and selective breeding. While these practices affect animal welfare, their overall impact on animals—whether positive or negative—remains a topic of ongoing debate. We also did not include animal welfare-affecting transportation practices (e.g., the U.S. Twenty-Eight Hour Law, requiring confinement be under 28 consecutive hours without a minimum of 5 hours rest) to restrict our scope to on-farm practices (e.g., rearing and finishing).

We conducted searches in the following electronic databases: CAB Abstracts (access via CAB Direct); Web of Science Core Collection (access via Web of Science); and EconLit (access via EBSCOhost). Searches included variations of the same term (e.g., both “cage-free” and “cage free”). See Appendix Table B.B.1 for a list of all search terms. Our search resulted in 23,476 unique publications (Figure 2.1).

After downloading the metadata of our search results (including information such as title, authors, and abstract), we performed a number of exclusions using Stata. First, we removed duplicate publications. These were detected using title, abstract, and year of publication.

Figure 2.1: Exclusion and inclusion criteria for scoping review



When our code detected a duplicate, the citation priority order was EconLit, CAB Abstracts, and Web of Science. Second, we removed studies that did not have an abstract; the later machine-learning techniques we perform summarize the papers using information from the abstracts, so this information was necessary.¹ Third, to limit the scope of our paper to four

¹We are not concerned about dropping observations without abstracts as that likely signals it is a non-standard scientific paper and/or resides in a non-standard outlet.

industries, we removed studies that did not mention broilers, layers, cows, or hogs (or related terms) in their abstract. Lastly, we removed studies that were stated as taking place outside the United States based on title, abstract, or place of study (when available). These initial exclusions left us with 5,848 unique publications.

2.2.2 Study selection and eligibility criteria

Our goal in selecting our sample of papers was to find publications that study a relationship between at least one welfare-improving practice and at least one factor that producers would plausibly take into account when considering whether to adopt said practice. The latter included producer outcomes such as the price they could charge for the higher-welfare product, the cost of adopting the practice, and the productivity effects on the animals of adopting the practice. The paper selection process included two complementary techniques: machine learning (Latent Dirichlet Allocation) and manual review. We blend the machine learning strategy outlined by Asmussen and Møller (2019) with traditional manual review methods.

Latent Dirichlet Allocation

To minimize the labor-intensive task of reading abstracts, we took advantage of recent developments in machine learning methods. Latent Dirichlet Allocation (LDA) is a Bayesian network first proposed by Pritchard et al. (2000) and later applied to machine learning by Blei et al. (2003). At a high-level, LDA performs two interrelated tasks. First, the technique identifies some T number of topics that the papers cover; the number of topics that the algorithm identifies is specified by the researcher depending on how finely they want to separate the corpus. Formally, each topic is defined as a probability distribution over individual words. LDA then searches for the most likely combination of these topics that would produce each document of text. These documents are considered a single realization of draws from some mixture of these T topics. Overall, LDA is seeking to uncover the T distributions most likely to have generated the observed corpus.

The LDA algorithm functions iteratively, continuously adjusting topic definitions to maximize the probability that the observed document collection could be generated from these topics. For each iteration, the algorithm first determines the optimal mixture of topics that would likely produce each individual document, given the current topic definitions. It then updates the topic definitions themselves based on these assignments. This process repeats until convergence—when the overall probability that the entire corpus could be generated from the current set of topics reaches its maximum value. This mathematical approach allows LDA to identify latent thematic structures within large text collections without requiring pre-defined categories or training data.

The probability that token (word) i is assigned to topic j , $P(z_i = j)$, can be expressed as the following Gibbs sampling model:

$$P(z_i = j | z_{-i}, w_i, d_i) \propto \frac{C_{w_i j}^{WT} + \eta}{\sum_{w=1}^W C_{w j}^{WT} + W\eta} \times \frac{C_{d_i j}^{DT} + \alpha}{\sum_{t=1}^T C_{d_i t}^{DT} + T\alpha} \quad (2.1)$$

where z_{-i} represents the topic assignment of all other tokens; w_i is the word (index) of the i th token; and d_i is a document containing the i th token; C^{WT} is the word-topic matrix of other words; C^{DT} is the document-topic matrix; T is the number of topics; W is the total number of words in the set of documents; α is a parameter governing the topic distribution for the documents; and η is a parameter governing the topic distribution for the words. The programmer chooses T , η , α , and a randomization seed. A low α value places more weight on having each document composed of only a few dominant topics whereas a high value will return many more dominant topics per document. Because our purpose for using LDA was to separate papers into distinct topic categories with, ideally, little overlap, we chose small α values in both rounds of LDA ($\alpha = 10^{-8}$ and $\alpha = 10^{-7}$, over the two rounds). A low value for η places more weight on having each topic composed of only a few dominant words. Again, to limit the breadth of each topic, we chose small values of η in both rounds ($\eta = 10^{-8}$ and $\eta = 10^{-7}$).

LDA Rounds. In the first round of LDA, we specified $T = 30$, $\alpha = 10^{-8}$, $\eta = 10^{-8}$.² This analysis, by construction, generated 30 topic categories, of which 6 were clearly relevant to our study (e.g., “milk production,” “tie stalls,” “cage-free,” and “conventional dairy”). The remaining 24 appeared potentially irrelevant (e.g., “organic fertilizers,” “farmyard manure,” “plants grown,” “antibiotic resistance,” and “soil samples”). The LDA algorithm assigned each paper a similarity score (propensity or p score) for each topic, with approximately 300 papers falling into the 95th percentile for each topic. To test our intuitions about topic relevance, two team members reviewed a random sample of 60 abstracts (20% of papers with $p > 0.95$) for each of the 24 potentially irrelevant topics. If fewer than 10% of reviewed abstracts (six or fewer) were relevant to our research question, we classified that entire topic as irrelevant. Although 1,440 abstracts were selected for potential review, we only needed to read 1,022 to reach our decision thresholds. This process identified 13 irrelevant topics, allowing us to eliminate 2,114 papers that had high relevance to these topics (but not to any of the 17 topics we retained), reducing our sample from 5,848 to 3,734 papers.

The second round of LDA followed the same strategy but adjusted to accommodate fewer papers. In the second round of LDA, we specified $T = 15$, $\alpha = 10^{-7}$, $\eta = 10^{-7}$.³ Like in the first round, two team members read through a selection of abstracts—this time from all fifteen topics. With roughly 180 papers in the 95th percentile of each topic, team members reviewed no more than 40 abstracts from these subgroups ($p > 0.95$ for each topic). If fewer than a quarter of reviewed abstracts were relevant, we discarded the topic. Using this method, we identified only two irrelevant topics and dropped papers flagged with 95th percentile relevance to those topics that were not also flagged with 95th percentile relevance to one of the topics being kept (the other 13 topics), dropping 617 papers of the initial 3,734.

The words chosen by LDA to construct each topic are sensitive to the seed used. Experimenting with alternative seeds has resulted in alternative groups where, for example: 20 of the 30 topics had nearly perfect document overlap; five had a very different document mix; and five were somewhere between. If one were to rely on these topics as literature insights themselves, one would be better off constructing topics using many different seeds and syn-

²With a seed to 42, for replication purposes.

³With a seed of 99, for replication purposes.

thesizing the results.⁴ For our purposes, however, topical consistency across seeds is not of particular importance as we are interested only in predicting which papers are irrelevant to our analysis.

Benefits and costs of LDA. The success of this method is evident in the number of papers that LDA helped us identify as irrelevant without having to manually read every abstract. The two LDA rounds reduced our sample of eligible publications nearly in half—from 5,848 to 3,117. Notably, each consecutive LDA round became less useful. The first round allowed us to drop 2,114 papers with reasonable confidence, whereas the second allowed us to confidently exclude 617 papers. We conducted a third LDA round, but did not feel confident using its results to exclude any papers. This strategy was useful because our starting selection of papers was remarkably diverse, including epidemiology papers, most of which were not eligible for our purposes. Employing LDA allowed us to differentiate between eligible and ineligible papers rather than exclude all papers published in epidemiology journals.

However, using LDA for eligibility prediction does not come without costs. Because LDA assigns, and then uses, propensity scores to each paper for use in exclusion, our analysis may suffer from Type I Selection Error. To test the severity of Type I Selection Error due to LDA, we elicited a list of relevant papers from economists at the U.S. Department of Agriculture, Economic Research Service (USDA-ERS) outside of this study’s authorship list. All 35 of the papers provided by economists at USDA-ERS were present in our post-LDA sample. While this does not rule out the presence of Type I Selection Error, the test reassures us that the error is likely not pervasive.

Manual review

After completing the two LDA rounds, we implemented a two-stage manual review process to further refine our sample. First, we conducted an abstract-level screening to quickly identify and exclude papers that clearly fell outside our scope. This was followed by a comprehensive full-paper review of the remaining candidates to make final inclusion decisions based on a detailed assessment of their content and relevance to our research question.

Manual abstract review. We randomly distributed publication metadata to research team members using Excel spreadsheets. During this abstract review stage, we excluded papers that: (1) did not address practices within our five defined practice categories; (2) failed to mention producer-relevant outcomes; or (3) focused on contexts outside the United States. To ensure consistency in our exclusion criteria application, each team member first reviewed 20 papers, which were independently checked by another team member. A relatively small fraction of these 3,117 papers that survived the LDA rounds were deemed relevant—the manual abstract review further reduced our sample from 3,117 to 399 unique publications.

Manual full-paper review. With a large, but now manageable, set of papers, we began with a full and detailed review of each document. We once again randomly disseminated these to members of the research team. The purpose of this stage was to record for each study: (1) the independent variable(s); (2) the dependent variable(s); (3) the relationship

⁴Indeed, a major downside of relying only on LDA to develop exploratory insights about a body of literature is the unresolved question of how to account for topical variation across seeds.

(positive or negative, statistically significant or insignificant); (4) which practice category the humane practice studied belongs to; (5) whether the producer outcome is good or bad for producers⁵; (6) whether the practice is good or bad for animals⁶; and (7) whether the study was conducted outside the United States. Papers that were deemed eligible for the final sample were those (a) with an independent or dependent variable, one of which is a welfare-improving practice and the other a producer outcome and (b) that took place in the United States.

Before reviewing their full set of papers, each team member reviewed 10 papers, which were double-checked by another team member to ensure consistency between reviewers. The manual full-paper review further reduced our sample from 399 studies to 101 unique publications. Those nearly 300 papers that were dropped either took place outside of the United States⁷ or did not have relevant producer *and* animal-welfare outcomes. Collectively contained in these 101 publications are 794 different results, defined as any studied relationship between a dependent and independent variable. Restricting this sample to results where the independent variable is a humane/inhumane practice (rather than the dependent variable) yields 620 results among 86 papers. This restriction ensures that all results can be interpreted as the effect of adopting a humane practice on a producer-relevant outcome. Limiting these results to those with a sign (though not necessarily significant), yields 496 results among 74 unique papers. Of these, 310 results (among 57 papers) were statistically significant relationships.

Categorization. After the manual full-paper review was complete, one team member categorized all dependent variables (producer outcomes) into “economic factor” categories. The economic factor categories are intended to reflect profit function inputs: price (consumer WTP), productivity, sales, product quality, fixed cost, operation cost, farmer quality of life, animal health, and profit itself, if it was directly estimated. Another team member edited these categorizations and discussed changes with the team. See Appendix B B.3 for more information.

Consistency Review. With dependent variables now categorized into economic factor categories and practices into practice categories, we again conducted consistency reviews to ensure uniform exclusion and categorization. This was done in three stages. In each stage, adjustments were made to correct reviewer mistakes and inconsistencies. Overall, the consistency review removed 27 papers. What remain are 74 unique papers, 72 of which included results that could be interpreted as (dis-)incentives to adoption of a welfare-improving practice. These 72 papers constitute the final corpus of results and papers used to construct our figures and tables.

In the first stage of this final consistency check, one team member ensured that all data entries were logically consistent. A large number of results studying differences in willingness to pay for animal-welfare improvements across consumer demographics were discarded.

⁵As reviewers read and recorded variables for each paper, they flagged practices for which they did not know the valence for animals. The USDA-ERS team members reviewed these uncertain outcomes to assign them valence for producers, if any.

⁶A member of ASPCA not on our research team reviewed these uncertain practices to assign them a valence for animals, if any.

⁷Or did not have a single author with a U.S. affiliation.

These were not initially excluded by reviewers during the manual review process because such results usually include “willingness to pay” as a dependent variable, which is relevant to producers. However, the independent variables in these regressions are consumer demographics and not producer- or product-level implementation of a welfare-improving practice. Therefore, such findings were not informative about (dis-)incentives for, nor predictors of, welfare-improving practice adoption. Importantly, however, results studying raw differences in market prices or average consumer willingness to pay for products produced with/without a welfare-improving practice were included in our final corpus since price and willingness to pay can, in these cases, be interpreted as an incentive for practice adoption.

During the manual review process, reviewers were instructed to record whether the practice is presumably better for animal welfare than the alternative and, separately, whether the corresponding outcome (dependent variable) is presumably better for producers than the alternative. When uncertain, reviewers were encouraged to flag these with a “?”. In the second stage, we resolved flagged uncertainties. To resolve uncertainties as to whether the flagged producer outcomes were good or bad for them, every team member answered the question on their own in the form of a Google survey. If at least four of six team members agreed that the outcome was better (worse) for producers, then the outcome was assigned as better (worse). If four team members were still uncertain, then the outcome was deemed “uncertain” to producers and the result was dropped from our corpus. To resolve uncertainties about whether flagged practices were better or worse for animal welfare, we additionally requested the expert opinion of a farm animal welfare specialist at ASPCA.

In the third stage, the farm animal welfare specialist thoroughly reviewed our practice categorizations to ensure that they align with language used by industry, policy-makers, and advocacy groups. This resulted in the reclassification of 71 results (out of 496 in our final corpus).

2.3 Results

This section presents the findings from our systematic analysis of incentives and disincentives affecting farm animal welfare practice adoption. We begin by examining how different economic factors serve as motivators or barriers across welfare-improving practices, then analyze how these patterns vary by practice category and animal industry. We conclude by identifying critical knowledge gaps in the literature that limit our current understanding of producer decision-making regarding animal welfare improvements.

2.3.1 Incentives and disincentives for the adoption of more humane practices

The final set of 74 publications comprises papers that compare U.S. farmer outcomes or characteristics across livestock operations with and without more or less humane practices. Most analyses in this final set of papers take something like the form in Equation (2.2), at least conceptually.

$$\underbrace{y}_{\substack{\text{producer outcome} \\ \text{(e.g., operating cost)}}} = \beta_0 + \beta_1 \cdot \underbrace{x}_{\substack{\text{AW-affecting} \\ \text{practice}}} + \theta \cdot \underbrace{\mathbf{Z}}_{\text{controls}} + \mu. \quad (2.2)$$

When the dependent variable is a producer outcome in this way, that outcome can be interpreted as an incentive or disincentive to adopting the practice, depending on the sign of β_1 . Operation costs, for example, are a disincentive to adopting some welfare-improving practice, x , if β_1 is positive (conditional on the control variables, $\mathbf{Z}$). We do not assume that producers are directly motivated by animal welfare, though they may be. Instead, consistent with economic theory, we assume that producers make adoption decisions based on the perceived costs and benefits of those decisions. Thus, when categorizing producer outcomes that are studied as dependent variables, we refer to the categories as “economic factors.” In total, we identified nine categories of economic factors.

Figure 2.2 plots the number of significant results and total studies focused on each category of economic factors. Note that there are more individual results in the left panel of Figure 2.2 than papers in our review. This is because most publications present multiple results, which we report as separate findings in the left panel. Findings within a study are likely to be correlated; to ensure that a small number of papers with many statistical analyses do not account for the overall pattern of results, we also present the sign of the median result per paper in the right panel of this figure.

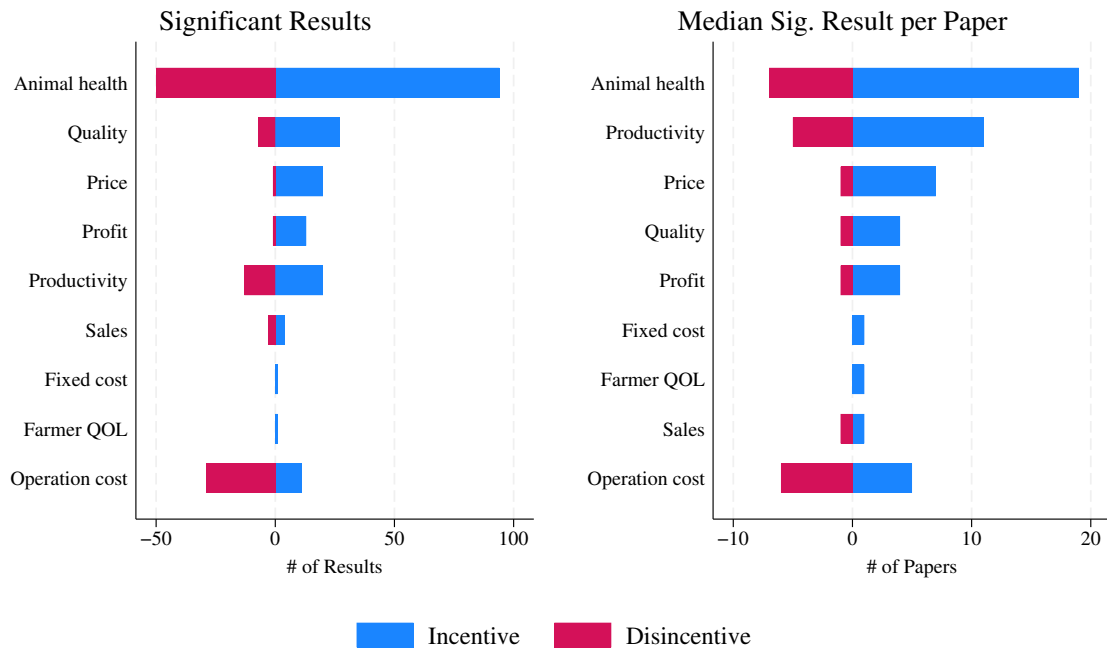
The literature in our sample identifies more incentives for the adoption of welfare-improving practices than disincentives. This is true both for the total number of significant results aggregated across studies, as well as the count of individual studies with at least one significant result in this direction. Of the nine categories of economic factors that we examine, animal health is, by a significant margin, the most frequently studied. While animal health is not always considered an “economic” factor in the production function of livestock operations, we take a wide view of what counts as an economic incentive. Animal health can influence costs and benefits associated with livestock production (e.g., veterinary costs, animal productivity). Insofar as producers care about animal health because of its effect on these costs and productivity effects, there are clear economic incentives to keep animals healthy.⁸ Chou et al. (2022), for example, find that lower density piglet litters reduce facial lesions and sow teat lesions; Cernicchiaro et al. (2012) find that daily manure management reduces E. Coli incidence.

As can be seen in the left panel of Figure 2.2, there are nearly 150 significant results relating to animal health. About 100 of these 150 identify benefits to animal health as an incentive for welfare-improving practice adoption. Conversely, about 50 identify deterioration in overall animal health as a disincentive to adoption of a welfare-improving practice. Cases where animal health is harmed by a welfare-improving practice include Hester et al. (2013a), which finds that availability of perches increases the incidence of keel bone fractures and broken claws during the laying phase.

Like animal health, productivity is well-studied and can serve as an incentive or disin-

⁸In an extreme case, imagine a farm with an extremely high premature mortality rate. The farmer would have an obvious economic stake in keeping his/her animals healthier.

Figure 2.2: Distribution of (dis)-incentive incidence across economic factors: Statistically significant results, total and median per paper



Notes: The nine economic factors examined are: animal health, product quality, price, profit, productivity, sales, fixed cost, farmer quality-of-life (QOL), and operation cost. The left panel examines the number of significant results across studies per economic factor. The right panel examines the number of studies that find more results pointing to an economic factor being an incentive versus a disincentive. In each panel, economic factors are ordered by incentives minus disincentives.

centive for welfare-improving practice adoption. More than 15 of the 74 papers reported a significant result about the productivity effects of a welfare-improving practice. Specific findings in this direction include Gunn et al. (2019a) and Weimer et al. (2019). The former finds that heat abatement increased milk production per cow; the latter finds that lower stocking density increased egg production per hen.

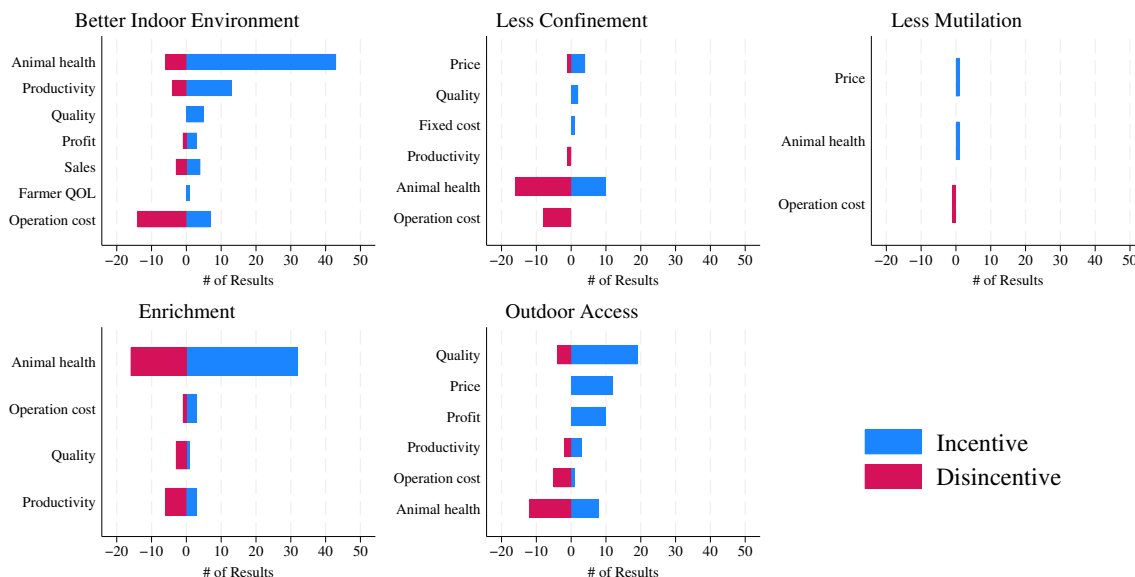
Price, profit, and product quality, although less-often studied, almost always represent incentives for welfare-improving practice adoption. It is well-known that consumers are generally willing to pay more for animal products from higher-welfare farms. This finding indeed appears in our corpus (see e.g., Tonsor et al., 2009; Wolf and Tonsor, 2017). Product quality likewise appears to increase in the studies that focus on this dimension. For example, Eusebio-Balcazar et al. (2018) find improved eggshell strength and weight in cage-free aviaries.

The other relatively well-studied (dis)-incentive to adoption of welfare improving practices are operation costs. Operating costs are much more likely to be a disincentive than an incentive to adopting a practice. This is not surprising: in almost all cases, better meeting the animals' needs requires additional resources. This is not always true—refraining from

mutilation does not directly require any additional resources—but providing more space, enrichment, or an improved indoor environment almost by definition requires additional resources.

In terms of how these different (dis-)incentives are clustered by various welfare-improving practices at a higher-level, Figure 2.3 separates these results by practice.

Figure 2.3: Distribution of (dis-)incentive incidence across economic factors: Statistically significant results, by practice category



Notes: For each of the five practice categories, only those economic factors (animal health, quality, price, profit, productivity, sales, fixed cost, farmer quality-of-life (QOL), and operation cost) having statistically significant results are displayed. For counts of median results per paper, see Appendix Figure B.B.1.

As can be seen, the distribution of results across these various welfare-improving practices differs considerably. Improving the animals’ indoor environment, providing them enrichment, and allowing them outdoor access are the three relatively well-studied welfare-improving practices. Confinement is behind these three categories, in terms of number of results, but not entirely absent. Practices related to mutilation are almost entirely unstudied among the papers within our corpus (only two papers were identified that analyzed correlates of mutilation practices).

Recall from Figure 2.2 that animal health is the most widely studied producer incentive. Studies on animal health are distributed across each of the four animal-welfare improving practice categories with non-trivial coverage.⁹ Better indoor environment and additional enrichment opportunities appear to improve animal health-related producer incentives. This

⁹We set aside mutilation because of its near-total absence.

suggests a dimension by which both animals and producers can benefit: improving the indoor environment of animals or providing them enrichment are correlated with outcomes that producers benefit from.

On the other hand, reducing confinement and improving outdoor access respectively appear more likely to negatively affect animal health than to improve it. When producers have less direct control over the environments that their animals encounter, it is more difficult to ensure the animals’ health is uncompromised. For example, dairy herds on summer pasture had higher rates of *Nematodirus* parasites relative to herds contained indoors (Sorge et al., 2015). Additionally, hygiene scores for dairy cows were poorer in compost-bedded-pack barns compared with free stall barns, though the prevalence of hock lesions and lameness was still significantly lower in the compost-bedded-pack barns (Lobeck et al., 2011).

An examination of the most studied producer (dis-)incentives—animal health, productivity, operation costs, and product quality—shows that adoption of a better indoor environment (e.g., ventilation, heating/cooling, natural light, sanitation) and enrichment practices seems especially beneficial to producers relative to other welfare-improving practice categories (Table 2.1) as these practices correlate with better animal health.¹⁰ Better indoor environments are additionally correlated with increased productivity, but also with increased operation costs.

Table 2.1: Counts of statistically significant results across the five practice categories, by the four most commonly-studied economic factors

	Animal health	Productivity	Operation costs	Quality
Indoor Environment	Increases (43-6)	Increases (13-4)	Increases (6-14)	Increases (5-0)
Outdoor Access	Decreases (8-12)	Ambiguous (3-2)	Increases (1-6)	Increases (9-4)
Less Confinement	Decreases (10-17)	Ambiguous (1-1)	Increases (0-8)	Increases (2-0)
Enrichment	Increases (32-16)	Decreases (4-6)	Decreases (3-1)	Decreases (1-3)
Less Mutilation	Ambiguous (1-0)	NA	Ambiguous (0-1)	NA

Notes: Counts of statistically significant results of incentives and disincentives are presented in parenthesis. For example, there were 43 (6) significant results indicating that indoor environment generally increases (decreases) animal health. If the difference between the increase and decrease counts is greater than one (less than minus one), the humane practice increases (decreases) the economic factor. The cell is labeled “Ambiguous” if the absolute value of the difference between the increase and decrease result count is one or zero.

Our compilation of results also suggests that increasing outdoor access or reducing confinement may be costly for producers in some cases. Twelve of 20 results in our sample identifying a relationship between outdoor access and animal health and 17 of 27 results

¹⁰“Beneficial” in this context is relative to the other practices we studied—it does not necessarily mean “profitable”.

identifying a relationship between reduced confinement and animal health found these to be correlated with decreased animal health. Most results indicate that providing outdoor access and reduced confinement increase operation costs. On the other hand, most results also indicate that providing outdoor access and less confinement can improve product quality.

2.3.2 Heterogeneity of (Dis-)Incentives across Industries

Substantial heterogeneity by animal industry exists in the number of significant results and the extent to which economic factors are incentives or disincentives. Figure 2.4 takes the results from Figure 2.2 and breaks them down by species, rather than practice category. Both the number of publications and the number of significant results are far higher for dairy cows and layers than for broilers and hogs. For hogs, nearly all studies on the economic (dis-)incentives for animal-welfare improvements find that they also improve producer-relevant outcomes, as is true for broilers. The exception to this is operation cost, a theme throughout this review. Welfare-improving practice adoption is correlated with higher operation costs for layers, dairy cows, and broilers, suggesting that operation costs are a common disincentive among nearly all industries and practices.

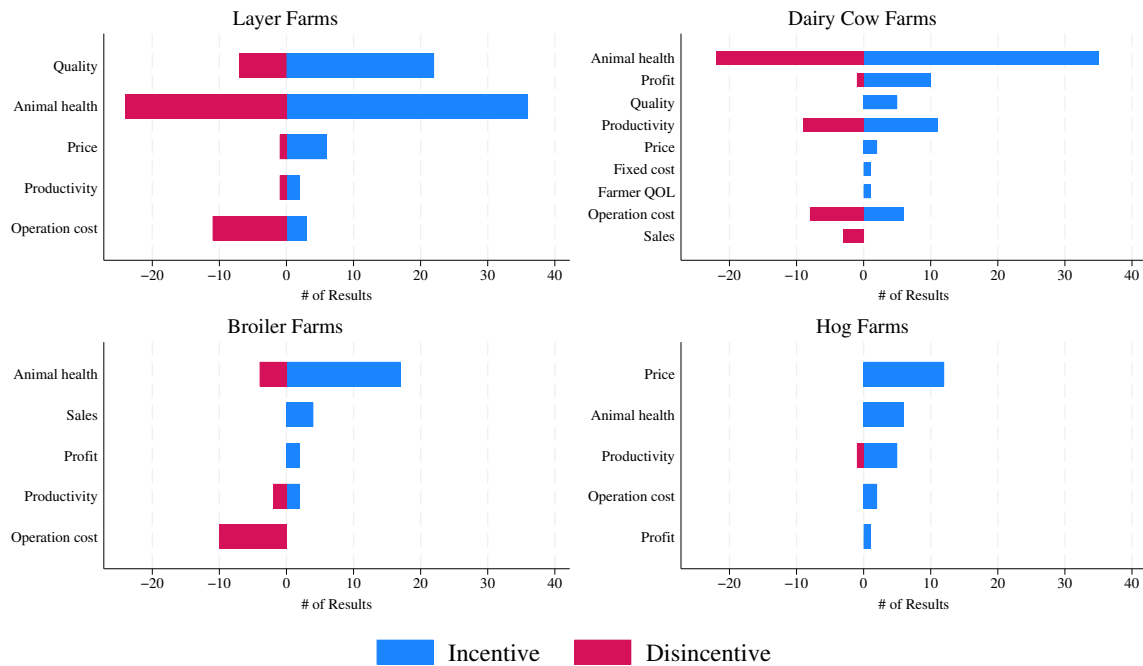
Across all four industries, significant results in our corpus indicate that animal health poses an incentive for welfare-improving practice adoption. In addition, we find substantial evidence that product quality is generally an incentive for welfare-improving practices affecting layers. Meanwhile, productivity, quality and profit are incentives for welfare-improving practices affecting dairy cows.

While comparisons across industries are critical for understanding high-level trends, some information is inevitably lost in any aggregation exercise. Figures B.3–B.6 in Appendix B break our results down by species and practice category. What emerges is substantial variation. Layer hen and dairy cow farms clearly dominate—40% (105/262) concern layer farms and 35% (92/262) concern dairy cow farms, while only 15% (39/262) concern broiler farms and 10% (26/262) concern hog farms. Furthermore, some practice categories are especially dominated by certain industries. For example, 65% (30/46) of statistically significant results about Confinement practices concern layer farms, while 28% (13/46) concern dairy cows and only 7% (3/46) concern hog farms. No results about Confinement practices for broilers were statistically significant.

Over time, the number of publications in our corpus was low for all animals of focus in 1991 but rose markedly in the ensuing 31 years (Figure 2.5). Increases in publications were especially notable for dairy cows, which rose to between seven and 17 studies per year, followed closely by layers. Broiler and hog publications, however, only slightly increased, from zero or one publications per year to roughly three to five publications per year.

These differences, and the associated knowledge gaps for broilers and hogs, may be attributable to differences in production practices at U.S. livestock farms and the methods for scientific publication in this literature. Hog and broiler farms are often contract operations, where an integrator owns the animals and the farmer raises them (MacDonald and McBride, 2009). Broilers and hogs are also grown and removed for slaughter in short time frames (e.g., 6–8 weeks for broilers). Dairy cows and layers, on the other hand, produce a

Figure 2.4: Distribution of (dis)-incentive incidence across economic factors: Statistically significant results, by industry

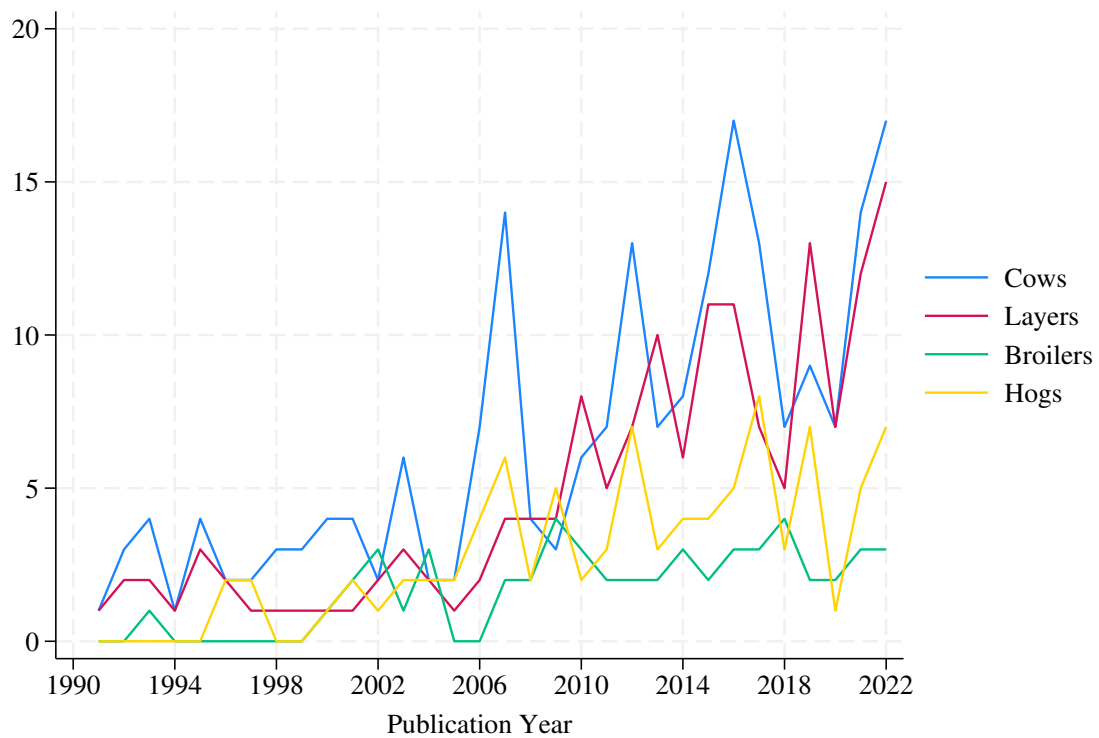


Notes: For each of the four industries, only those economic factors having statistically significant results are displayed. In each panel, economic factors are ordered by incentives minus disincentives. For counts of median results per paper, see Appendix Figure B.B.2.

secondary product (milk and eggs) and are not raised mainly for meat. Studies are primarily conducted at university or extension research farms which are better suited to study animal welfare practices of dairy cows and layers. Public attention on the treatment of layer hens and dairy cows may also be a driver for increased study within this time period (e.g., passage in 2018 of California's Proposition 12, banning the sale of eggs from caged layers).

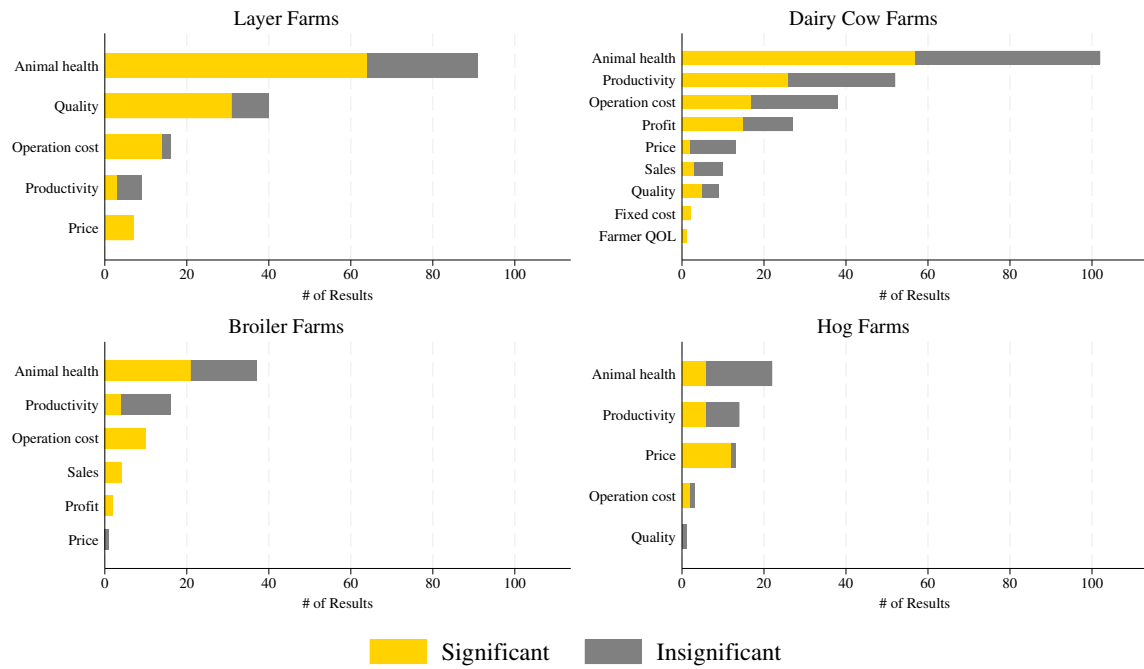
Finally, we conclude this section by noting that our findings regarding the relative research focus on each of these different sectors is not influenced by our presentation of only significant results. The ratio of results between sectors is qualitatively unchanged when we include insignificant results as well (Figure 2.6). There is robust evidence that dairy cows and layer hens are studied more intensively than broilers and hogs.

Figure 2.5: Counts of publications in the sample, by industry and year



Notes: The review encompassed publications concerning five practice categories (indoor environment, outdoor access, enrichment, confinement, and bodily mutilation) as they relate to nine economic factors (animal health, quality, price, profit, productivity, sales, fixed cost, farmer quality-of-life (QOL), and operation cost).

Figure 2.6: Counts of significant and insignificant results across economic factors, by industry



Notes: For each of the four industries, only those economic factors with publications that documented any relationship with the five practice categories of interest are displayed.

2.3.3 Knowledge gaps

Our analysis reveals fundamental gaps in the literature concerning both economic factors and welfare-improving practices. Fixed costs and farmer quality of life (QOL) are economic factors rarely studied in this literature. Fewer than five total significant relationships exist between each of these factors and welfare-improving practice adoption (Figure 2.2). These are significant omissions. It is plausible that farmer quality of life might be improved with more humane systems if it is more pleasant to tend animals who live better lives. If so, there is some reason to believe farmers might be willing to accept some compensating profit differential for this benefit. Whether and to what degree this is true appears almost entirely unstudied. Likewise, the difference between fixed costs and continuous operating costs of welfare-improving practices are crucial for policy design, and estimates of the total net-present-value for implementing improvements. We return to the structure of costs in Section 2.5.

In terms of practices, rather than incentives, there is almost no research on the economic costs and benefits of mutilation practices. It seems plausible that these represent the practices where the most acute changes in welfare may be had for potentially very little economic cost or benefits. It is not difficult to conjecture that there are cases where the economic costs of achieving most of the welfare-improvements would be quite low. As a proof of concept, in non-US markets it is not uncommon to avoid castration of piglets and instead provide a vaccine that prevents “boar taint”—the change in pork flavor coming from testosterone (Pluske, 2014). Better understanding whether there are significant quality changes associated with boar taint, or the costs of alternative strategies to avoid it, could be crucial inputs to eliminating practices with these acute welfare costs.

2.3.4 Other factors correlated with welfare-improving practice adoption

Our results primarily focus on producer (dis-)incentives for adopting more humane farm practices. By construction, all papers in our final sample explore correlations between a welfare-improving practice and a producer outcome *or characteristic*. We have omitted discussion of farm characteristics not because we omitted these papers from our corpus, but because only two of the 74 studies in the final set of papers focused on identifying the characteristics of farms that adopt welfare-improving practices.

That is, our paper selection criteria enabled us in principle to capture a broad range of factors associated with the adoption of more humane farming practices, such as farm, farmer, and practice characteristics.

Despite our inclusive search and selection process, our final sample included only two publications that identify characteristics associated with welfare-improving practice implementation. Dimitri and Nehring (2022) find that: (1) Northeast states have most available pasture per dairy cow (relative to Corn Belt, West, and Upper Midwest), and (2) dairy cows in the Upper Midwest spend the fewest months grazing on pasture, which suggests characteristics about the Upper Midwest (e.g., climate) may impede year-round pasture dairy production. Sorge et al. (2015) find that: (1) medium-sized conventional herds ($\geq$

200 cows) are least likely to have access to pasture relative to small-sized conventional herds and organic herds, while organic have most, and (2) medium-sized conventional herds have the lowest stocking density, suggesting that herd size is correlated with pasture access and stocking density.¹¹

The broader agricultural practice and technology adoption literatures identify multiple farm, farmer, and practice characteristics correlated with, and therefore likely influencing, practice adoption (Pineiro et al., 2020; Li et al., 2023; Prokopy et al., 2019; Pierpaoli et al., 2013). These factors are also likely to be important in the welfare-improving practice setting despite a relative lack of information about them. For example, farm size is an important predictor of technology and conservation practice adoption, with larger farms often having more resources to transition to newer technologies and systems (Pierpaoli et al., 2013; McFadden et al., 2023). Likewise, farmer characteristics such as farmer education, attitudes, awareness, and social networks have been cited as important factors influencing adoption decisions, though these did not emerge in our corpus (Pierpaoli et al., 2013; Pineiro et al., 2020; Prokopy et al., 2019; Rahm and Huffman, 1984; McFadden et al., 2022).

Returning to economic factors, several other potentially important factors are absent from this literature. Related work indicates that risk, uncertainty, and credit availability influence perceived economic costs of adoption (Feder et al., 1985; Foster and Rosenzweig, 2010; Suri, 2011; Li et al., 2023). Tenure also influences adoption decisions, with farmer-owners being more likely to adopt some practices than non-owners because of the associated longer-term benefits (Baumgart-Getz et al., 2012). While tenure did not emerge as an (dis)-incentive, we would expect contract farmers who rent their infrastructure, such as U.S. broiler producers, to be less likely to have incentives to adopt welfare-improving practices (MacDonald et al., 2004).

2.4 Discussion and Policy Implications

This section discusses the implications of our findings, contextualizing them within broader agricultural policy and research frameworks. We examine factors beyond direct economic incentives that influence adoption decisions, explore policy implications of our results, and assess the strengths and limitations of our methodological approach.

2.4.1 Policy Relevance and Implications

Our results suggest that producers have incentives to adopt welfare-improving practices, such as improved indoor environment, that enhance animal health and increase productivity. In these instances, farmers may not, therefore, require much additional economic benefits to encourage adoption. Results from Wolf and Tonsor (2017) support this “market approach” directly. The authors find that consumers’ willingness-to-pay (WTP) for dairy products produced using animal welfare-improving practices (e.g., no hitting, no tail docking, clean facilities) are high, while producers’ willingness-to-supply products using these practices,

¹¹See also recent work in Hutchins et al. (2025).

or costs, are low. Natural market forces with minimal policy intervention may therefore lead to greater adoption of these practices. The market approach is also consistent with findings from work that explores additionality in conservation practice adoption. This work demonstrates that producers more readily adopt practices that are beneficial to them, and thus require less intervention to stimulate their adoption (Canales et al., 2024; Claassen et al., 2018; Mason and Plantinga, 2013). If policymakers want to target these types of practices, technical assistance programs and outreach can be used to help farmers transition to using new practices and technologies.

On the other hand, larger scale interventions or incentives may be better employed in cases where policymakers wish to encourage the uptake of practices that are more challenging for farmers to implement such as increased outdoor access and less confinement. Because market incentives are less obvious for these practices, achieving their widespread adoption will likely depend more on government policy than on market forces.

Myriad market and non-market factors influence farmers’ decisions to adopt agricultural practices, and many of these have been neglected in the animal welfare-improving practice adoption literature. Existing policies or newly-designed programs that focus solely on economic incentives informed by the existing animal welfare literature may be limiting.¹² For example, confinement-enlarging mandates that do not consider the underlying demographic, attitudinal, or structural characteristics of independent livestock production could force some operations to economize on other production attributes (e.g., quality of feed, veterinary care) that could inadvertently, though possibly only temporarily, lower welfare. In other words, interventions that incentivize producers based on a more holistic approach to potential mechanisms—both economic and non-economic—could suffer from fewer adverse unintended consequences (McEwen et al., 2018; Fan et al., 2023).

Farm Animal Welfare Policy Typologies

However, the design of optimal policy instruments depends crucially on the underlying economic nature of the basic farm animal welfare problem (Sumner, 2023). Broadly, two economic interpretations prevail. One treats animal welfare as a *public good* underprovided by private markets. The other views poor animal welfare as a *negative externality* imposed on society and animals themselves. A wide variety of differing regulatory instruments align with both of these conceptual frames; in general, public goods approaches tend to emphasize voluntary incentives or direct public provision, while externality approaches highlight mandatory limits or price-based correction mechanisms (see Table 2.2).

Taken together, these examples show that while certain policy instruments align more naturally with specific conceptual frames—bans with externalities, subsidies with public goods—real-world policy design is frequently hybrid in nature. In the United States, especially at the state level, regulators are examining the potential to combine bans, fines, subsidies, and labeling requirements into multi-pronged regulatory packages.

¹²Most papers in our corpus represent animal science studies that examine the adoption of some animal welfare-improving practice and its impacts on various outcomes. Within the corpus, though, we identify 15 of the 72 studies that examine willingness-to-pay, economics, or policy directly.

The hybrid approach also reflects the complexity of consumer preferences surrounding farm animal welfare. Some consumers actively seek out higher-welfare products and willingly pay price premiums when labeling is clear and credible (see e.g., Thibault et al., 2022). Others may have ethical concerns about low-welfare practices but are unwilling to change purchasing behavior unless prompted by regulatory bans or excise taxes that embed welfare costs directly into prices.

Policy Evidence

Within our corpus, the studies that directly examine WTP, economics, or policy do so from both the public good and negative externality perspective. For the former, the literature focuses on information provision as a major policy tool used to address market failures and increase the quantities supplied of goods produced using animal welfare-improving practices. Tonsor et al. (2009) study WTP for pork, with an emphasis on pork produced under gestation crate bans. The authors find that command-and-control crate bans decrease consumer welfare because consumers are unaware that producers use the practice (i.e., consumers only see price increases). This information asymmetry can be remedied through information provision or labeling. Indeed, Tonsor et al. (2009) find that consumer WTP is highest for pork labeled voluntarily crate-free. McKendree et al. (2013b) also study WTP for pork products, and find similar effects. Consumers are willing to pay premiums for smoked ham and ham lunch meat produced using animal welfare-improving practices (e.g., individual crates). Importantly, WTP is highest for USDA-certified animal welfare-improving practices.

For eggs and poultry products, however, prior work suggests that consumer WTP for food produced using animal welfare-improving practices, such as cage-free eggs or free range chicken, is less than the mark-up of the products. The higher prices of organic and cage-free eggs, for example, lead to low sales of these products, suggesting that consumer WTP is lower than the price (Chang et al., 2010). Similarly, consumers are less likely to purchase free range chickens than conventionally raised chickens (Bernard et al., 2007a). Oh and Vukina (2022b) also suggest that consumer WTP for cage-free eggs is low. The authors find that California’s Proposition 12 resulted in annual consumer welfare losses of \$72m and industry profit losses of 18%.¹³ For egg and poultry products, then, information provision and labeling may not be as effective as for dairy and pork products. In any case, however, if animal welfare is a public good, then factual information and labeling will not be sufficient to achieve optimal welfare provision, and cost-benefit analyses that ignore the non-use value will be skewed towards under-supporting welfare-improving policies.

Next, our corpus contains studies that approach failing markets for animal welfare-improving produced goods from a negative externality viewpoint. Here, conventional products are overproduced (and animal welfare-improving products are underproduced) because the external costs of production are not internalized by the supplier. Davies (2012b) approaches the negative externalities of conventional pork production and increasing consolidation in the industry directly. The author discusses the implications of this style of pork

¹³Notably, however, Oh and Vukina (2022b) restrict their estimates to private use values (consumer WTP and profits) and do not calculate the public good or externality benefits of Prop 12.

production in terms of biosecurity, antimicrobial resistance, zoonotic disease prevention, and other external costs. The normative response to such externalities are Pigouvian taxes to decrease production.

Other work approaches market failures in food production and animal welfare-improving practices less directly. Gillespie et al. (2017a) study the effects of tunnel ventilation and evaporative cooling usage in broiler housing on operation-level costs and returns. The authors find that the use of tunnel ventilation and evaporative cooling, although more expensive than the alternative, produces higher revenues and increased operation-level profitability. Similarly, Gunn et al. (2019b) examine the cost-effectiveness of heat abatement strategies in dairy production and their impacts on productivity. The authors find that air conditioning in barns is expensive, but significantly increases cow-level yields. Organic production is also beneficial financially for operators, suggesting that incentives for organic certification can increase production (Holly et al., 2019b). Bakhtavoryan et al. (2021) find that organic and cage-free eggs are price elastic. As a result, small price changes, such as those from tariffs, decrease the quantity demanded and therefore consumer welfare.

Table 2.2: Typology of AW Policies in Agriculture under Public Good vs. Negative Externality Frames

Policy Tool	AW as Public Good	AW as Negative Externality
Administrative Fines	Rare; could apply to failure to adopt voluntary best practices.	Common; fines for violating minimum standards (e.g., cruelty, space/transport rules).
Bans	Bans on low-welfare practices to shift the industry toward higher norms.	Very common; bans used to eliminate high-externality practices.
Subsidies	Payments for voluntary adoption of high-welfare systems.	Subsidies to assist transitions away from harmful systems.
Taxes	Hypothetical: levy on non-adopters to fund AW education/research.	Emerging: welfare tax on low-welfare products to internalize moral harm (Espinosa and Treich, 2024).
Judicial Remedies	Rare; could apply if systemic poor AW erodes public trust.	Rare; could apply if poor AW triggers direct public harms (e.g., zoonotic spillover).
Information Provision	Labeling for voluntary practices; shift production toward these practices, minimize information asymmetries between suppliers and demanders.	Labeling for mandatory practices, less frequent; again minimize information asymmetries, pushes consumers toward true WTP.

Notes: Authors' synthesis of policy instruments commonly discussed in the public finance and environmental economics literature.

2.4.2 Strengths and Limitations of the Scoping Review Methodology

Using a comprehensive, tiered review process that adapted machine learning methods for an initial search of nearly 25,000 publications, our review sheds light on patterns among linkages between producer outcomes and animal welfare-improving farm practices. Beyond rigor, a key strength of our approach is replicability, and we invite researchers to modify and implement our methodology to broaden our understanding—especially for a non-U.S. setting and for practices and animals excluded from the analysis.

As is true of any scoping review that analyzes publications employing multivariate regression analyses, individual results from these analyses may suffer from various biases. Consistent with the literature on best practices for conducting scoping reviews, we do not evaluate methodological quality or bias of each study within the corpus (Tricco et al., 2016). Aside from being impractical, it introduces subjectivity on the part of the reviewers that is likely to introduce its own biases. This amounts to assuming that statistical biases of individual results are small, or equally likely to be positive or negative.

Beyond this are issues related to publication bias. It could be that novel, or surprising, results are more likely to get published than a replication of a result. So, the count of papers pointing in one direction or the other may come apart from the strength of the evidence for that directional result. Note that this is a distinct concern for quantitative publication bias, where results cluster around the 1% or 5% significance level. This is a qualitative issue regarding which results are deemed interesting, and publication worthy.

2.5 Future Research Directions

Beyond what the direct results may imply about agricultural policy design meant to improve animal welfare, there is a broader point that more research is needed to generate firmer conclusions. This section highlights some possible research directions that we believe could be particularly high value.

2.5.1 Data Collection & Availability

One key bottleneck in the production of research on these issues is the dearth of data available on welfare-improving practices in the United States and elsewhere. Government and industry data sources, for the most part, do not document which farms are undertaking which welfare-improving practices, making it difficult to evaluate humane production systems and the farmers who adopt them. Given increasing consumer demand for humane products, and producer response to this demand, there is an increasing need to better understand farmers' adoption of welfare-improving practices.

A potential solution to the current lack of comprehensive agricultural welfare data is to establish a centralized, open-access database documenting welfare practices across farms. Surveys conducted by the U.S. Census Bureau, such as the Management and Organizational Practices Survey (MOPS) and the Manufacturing Energy Consumption Survey (MECS),

provide valuable models for collecting detailed information on internal management, technology adoption, and efficiency practices. An agricultural welfare database could similarly document specific practices—such as housing systems, enrichment provisions, and veterinary care protocols—and systematically link these to productivity and economic outcomes.¹⁴

2.5.2 Interactions between market structure and documented incentives

It is one thing to understand the incentives faced by producers under the conditions of these respective studies that we review. However, the external validity of these findings depends on important facts about the market they operate in. For example, if consumers cannot identify which animal products come from farms that undertake a practice that they would be willing to pay a premium for, this willingness to pay may be irrelevant for producers. This would result in something like a market for lemons—the lowest quality products at the lowest price are the only viable offerings in equilibrium.

Likewise, the degree of competition in these markets could be relevant to which incentives are feasible to act on. A small number of large firms could potentially coordinate on an equilibrium with better treatment of animals, whereas a market with many firms may necessarily have defectors that result in dynamics that lead to poor animal treatment.¹⁵

While understanding market structure is distinct from the research question of our scoping review, it is plausible that these structures may interact with identified incentives and disincentives in crucial ways.

2.5.3 Welfare-Improving Practices in Aquaculture

Our review focused on land animals, ignoring welfare-relevant practices in aquaculture. This is because—even relative to the dearth of research on practices influencing land-animal welfare—we know of essentially no work on producer (dis-)incentives for improving the welfare of fish or crustaceans.

That said, this lack of research and academic interest may be consequential for at least two reasons. First, there is already discussion of fish and crustacean welfare in some policy areas. For example, several U.S. states have banned octopus farming, with a federal ban

¹⁴Several USDA surveys exist that provide partial information about these measures but are not fully comprehensive. For example, USDA’s Agricultural Resource Management Survey (ARMS), administered by the Economic Research Service (ERS) and National Agricultural Statistics Service (NASS), provides information about housing from its detailed surveys of broilers, beef cows, and hogs, but it does not tend to inquire about enrichment or veterinary care. By contrast, USDA’s National Animal Health Monitoring System (NAHMS) surveys, which are administered by the Animal and Plant Health Inspection Service (APHIS), do collect information about veterinary care and housing but not many productivity or economic outcomes. Neither of these datasets are currently able to be linked in a straightforward way to each other or to Census of Agriculture microdata.

¹⁵This would be an intriguing reversal of the belief, common among animal activists, that concentration in this market has led to worsened outcomes for animals.

being debated.¹⁶ Likewise, the UK’s recent Animal Welfare (Sentience) Act included decapod crustaceans—lobsters, crabs, shrimp, etc.—in their list of species that should be considered for protection. Policy can be path-dependent and long-lived (Freitas-Groff, 2024); we suspect that policies enacted early in these discussions may have disproportionate effects over long-run market outcomes.

Second, studying this topic may reveal opportunities that are so cost effective, that even with great uncertainty about whether we have any reason to treat fish and crustaceans better, society (or some subset of) may wish to undertake them. For example, an early study into shrimp welfare-practices has found that the operating cost increase of stunning before slaughter is trivial. At least one non-profit has begun purchasing stunners and distributing them to producers who commit to using them, estimating that on the order of 1,500 shrimp-deaths can be made painless, annually, per dollar invested.¹⁷

2.6 Conclusion

Our scoping review reveals both the state of knowledge and critical gaps regarding the incentives and barriers that producers face when considering welfare-improving practices for farm animals. Through a machine learning-aided approach that analyzed a diverse literature spanning multiple disciplines, we identified operating costs as a near-universal disincentive across most animal welfare improvements. Conversely, improved indoor environment and enrichment practices show promising benefits for animal health and productivity, suggesting potential interventions that might have negligible impacts on overall profitability. Interestingly, these findings vary considerably across species and practice categories, with some practices—such as improved indoor environment—presenting more favorable cost-benefit profiles than others like reduced confinement or outdoor access.

The paucity of research in several critical areas underscores the need for additional scholarship. Mutilation practices remain largely unstudied despite their potential for producing substantial welfare gains at minimal economic cost. Similarly, the limited research on broiler and hog welfare compared to layers and dairy cows represents a significant knowledge gap that requires attention. As public interest in farm animal welfare continues to grow, addressing these research gaps will be essential for developing evidence-based policies that balance improvements in animal welfare with economic viability for producers.

¹⁶The OCTOPUS Act, if passed, would ban commercial octopus farming in US waters as well as importation of commercially farmed octopus products (Jacquet et al., 2024).

¹⁷See: <https://www.shrimpwelfareproject.org/shrimpact>.

Chapter 3

Heterogeneous Trends of Animal Product Consumption in the US: Evidence from Grocery Purchase Data

3.1 Introduction

Is the end of meat on its way? The past two decades have seen rapid innovation in meat alternatives (Treich, 2021; Cuffey et al., 2023; Zhao et al., 2023) and growing economic debates related to farmed animal welfare (Malone and Lusk, 2016; Mullally and Lusk, 2018b; Lusk et al., 2019). Concern for animal welfare and climate change have led some to posit that the end of meat, factory farming, or animal agriculture entirely may be near (Krauthammer, 2015; Foer, 2020). At the same time, meat consumption in the US is near record highs and is growing worldwide (Parlasca and Qaim, 2022). This apparent contradiction raises two related questions: are aggregate trends masking meaningful changes across household subgroups, and are plant-based alternatives driving these changes or merely serving niche markets?

Methodological challenges have limited researchers' ability to address this question systematically. Self-reported dietary measures are vulnerable to social-desirability bias, and self-declared meat avoidance does not always align cleanly with consumption-based classifications (Mathur et al., 2021; Teh et al., 2023; Vinnari et al., 2009). Meanwhile, most observational data on food consumption are highly aggregated, obscuring potential heterogeneity in consumption trends among demographic subgroups (Tonsor and Lusk, 2022). These data limitations have made it difficult to determine whether stable aggregates mask offsetting changes across households that might hint at future changes in aggregate trends.

The primary goal of this chapter is to descriptively document trends in animal product grocery purchases over the last 20 years. We overcome biases from self-reporting and data aggregation by using granular supermarket data enhanced through machine-learning classification of product ingredients. In doing so, we provide new household-level evidence that a growing share of households purchase zero meat or animal products in a given month despite aggregate meat consumption remaining high. This helps reconcile aggregate evidence of persistently high meat consumption with the increasing visibility of meat avoidance: average

trends mask substantial heterogeneity across households.

Our strategy combines consumer panel data and product information to understand meat and animal product grocery purchases at the household level. Specifically, the NielsenIQ Consumer Panel (40,000–60,000 households from 2004–2020) details which products households buy and in what quantity, and NielsenIQ’s Label Insight records product labels, ingredients, and packaging. We merge the two datasets and train a machine-learning classifier on the Label Insight data to identify which household purchases are meat or animal products, obtaining a measure of whether households buy meat that is 98.9% accurate for purchases we observe. To our knowledge, no prior household-panel chapter combines ingredient-level product data with machine-learning-based classification to measure meat and animal-product purchases across the broader grocery universe. This matters in practice: using direct labels alone would classify only about 4.4% of grocery expenditure as meat and about 8.9% as animal products in our full sample, compared with about 8.2% and 16.4% under the full classifier.

Our findings are broadly consistent with prior work documenting self-reported meat reduction and growth in plant-based alternatives (Neff et al., 2018; Cuffey et al., 2023), but our analysis of detailed grocery purchase data from a household panel reveals patterns that are not visible in aggregate data. Relative to January 2005, meat’s grocery-weight share rises faster near the top of the household purchase distribution than near the bottom, while the share of households that do not buy meat in a given month increases from 5.0% to 6.2% by the end of 2019 and the share of households that do not buy animal products increases from 0.5% to 1.3%. These increases partially reverse in 2020, when pandemic conditions shift consumption back toward food at home. We also show that baseline levels and growth diverge across demographic groups: no-meat months are most common among high-income, well-educated households in Democratic-leaning cities, but growth is stronger among younger cohorts and Asian households. Because these patterns begin before the introduction of modern plant-based alternatives and PBMA adoption remains limited, PBMA are unlikely to explain more than a small share of the broader changes we document.

The remainder of this chapter proceeds as follows. Section 3.2 reviews the related literature and summarizes our contributions. Section 3.3 describes our data sources and the ingredient-based classification methodology. Section 3.4 documents aggregate trends, how meat and animal-product purchases change across the household purchase distribution, and how these trends vary across demographic groups. Section 3.5 concludes.

3.2 Related Literature and Contributions

Our chapter contributes to three related literatures by documenting how meat and animal-product purchases change across the household purchase distribution. First, we extend research on aggregate consumption trends by showing how population averages mask underlying polarization patterns. Second, we contribute to the literature on plant-based meat alternatives by placing their diffusion in the context of broader household-level changes in meat and animal-product purchasing, suggesting that PBMA appear too limited in scale to be the primary driver of those broader changes. Third, we inform the economics of animal

welfare by documenting how these trends vary across demographic groups and by showing the limits of aggregate statistics for tracking dietary change.

Previous research documents trends in meat consumption and its economic drivers in the aggregate. This work documents historically high and often rising meat consumption globally, alongside persistently strong and rising meat consumption in the United States over the last 60 years (Henchion et al., 2014; Sans and Combris, 2015; Godfray et al., 2018; Milford et al., 2019; Whitton et al., 2021; Parlasca and Qaim, 2022; Daniel et al., 2011; Tonsor and Lusk, 2022). Cross-country analyses find a positive correlation between GDP growth and increasing meat consumption in low- and middle-income countries, although this relationship weakens or disappears in high-income countries (Whitton et al., 2021; Sans and Combris, 2015). Using household-level data, Tonsor et al. (2021) study short-run pandemic-era changes in U.S. meat demand using a shorter household-level tracking survey and do not analyze broader non-meat substitution patterns.

We also contribute to a small but expanding literature that examines consumer demand for plant-based meat alternatives (PBMA) and their relationship to conventional meat demand using surveys, discrete choice experiments, and household data (see the review in Zhao et al. (2023)). Zhao et al. (2023) estimate demand elasticities between PBMA and various meat categories. More recently, Neuhofer et al. (2025) study weekly household scanner data from 2018–2020 and identify PBMA in a narrower ground-meat setting. Cuffey et al. (2023) study consumption behavior between 2014 and 2019 using the same household panel data as we do. They document that meat spending does not decrease in the first PBMA-purchase month and that total food spending jumps sharply at that time, suggesting that households often try PBMA as part of a broader temporary spending adjustment.¹

Related to the recent literature on PBMA demand, a parallel body of work examines demand for plant-based milk alternatives and documents the striking decline in dairy milk consumption over the past several decades. Stewart et al. (2020) use the NielsenIQ Consumer Panel for 2013–2017 to estimate that plant-based products replace dairy milk at approximately a one-to-one rate. Slade (2023) analyzes NielsenIQ Consumer Panel data for 2004–2018 and finds that almond milk adoption is associated with a reduction in dairy milk purchases by households. Dharmasena and Capps Jr (2014) and Capps and Wang (2024) use Tobit and the Quadratic Almost Ideal Demand System, respectively, to show that plant-based milk alternatives are substitutes for conventional milk.

Finally, our chapter contributes to a growing body of research on the economics of animal welfare and the interplay between ethics and consumer behavior. Existing work documents the economic impacts of animal welfare policies such as battery cage bans for egg-laying hens (e.g., California Prop 12) (Malone and Lusk, 2016; Mullally and Lusk, 2018b; Lusk et al., 2019; Lee et al., 2021). Our analysis complements both branches by documenting revealed preferences for animal products in observational data, identifying which demographic groups drive purchase changes, and showing patterns more consistent with a role for cultural and generational factors than with a major role for modern PBMA in shaping these changes.

¹Appendix Section C.2 reports a public-data replication benchmark based on the published description of the Cuffey et al. (2023) PBMA spending strength index (SSI) and first-purchase event-study framework, and then applies the same analysis using our ingredient-based product definition.

3.3 Data

To examine long-term trends in meat and animal product purchases, we draw on household grocery data from NielsenIQ’s linked Consumer Panel and Label Insight datasets.

3.3.1 Consumers

Our analysis focuses on household grocery purchases, which we measure using NielsenIQ’s Consumer Panel of US households (HMS). The panel records, for each shopping trip, the date, retailer, and store location, along with detailed information on each purchased item, including quantity, price, product attributes, and the Universal Product Code (UPC). The sample spans 2004–2020 and includes between 40,000 and 60,000 households at any point in time. Participating households report their demographic characteristics and scan their receipts in exchange for rewards.

3.3.2 Groceries

To describe household purchases, we link the NielsenIQ Consumer Panel with NielsenIQ Label Insight, which provides product names, labels, and ingredients for a subset of purchased UPCs in our sample.

Using the Label Insight data, we identify which products are meat (including fish), milk, eggs, or a plant-based alternative for one of these categories. Specifically, we manually identify all ingredients in the Label Insight data that correspond to a particular category of ingredient (e.g., synonyms for chicken) and create indicators for products that contain both the relevant ingredient and a related term in the product name (e.g., “chicken wings”).²

Since the Label Insight data cover only a subset of products in the Consumer Panel, we employ a machine-learning approach to impute labels for the full set of products. Label Insight covers roughly 45% of purchased Nielsen UPCs in our sample and accounts for 58% of expenditure over the sample period. Our classification procedure begins by using the Word2Vec algorithm to generate vector embeddings of each UPC’s abbreviated product description from the Consumer Panel data.³ We then train a logistic regression to predict the odds that a given UPC is in a particular category of meat, dairy, eggs or a plant-based alternative based on the UPC description and the brand.

Next, we merge these predicted labels with the HMS panel data to estimate category-level quantities purchased and to identify households with no purchases in each category. A product is assigned to a specific category when its predicted probability from the classifier exceeds a category-specific threshold chosen from validation tests. We choose these cut-offs to minimize misclassification. In validation tests using products observed in Label Insight,

²We also consider several alternative methods for classifying products, including all products with a relevant ingredient, all products with that ingredient in the top five, and all products with that as the primary ingredient. We find that the set of products identified by our method is largely in agreement with the set of products with the respective item as a top-five ingredient.

³The Word2Vec algorithm is a machine-learning model that uses the contexts in which a term appears to infer the meaning of the term (Bengio et al., 2003; Mikolov et al., 2013a,b; Ash and Hansen, 2023).

the selected cutoffs yield low type I and type II error rates and approximately minimize bias.⁴

We use higher thresholds for narrower categories because the risk of false positives is greater than for broader categories. Because recorded purchases are incomplete in Homescan (Einav et al., 2010), we study household meat avoidance only for household-months whose observed grocery spending exceeds a conservative lower bound for informative recorded purchases.⁵ Tables C.25–C.28 show the average amounts of various categories purchased overall and as a share of total grocery weight, respectively.

3.3.3 Data Limitations

A central limitation of our data is that they capture supermarket purchases rather than the full universe of food purchases. In particular, there is a steady trend away from food at home (that is, food purchased at a supermarket rather than a restaurant) during the period we study (Zeballos, 2020). To address this concern, we analyze trends in the share of grocery purchases—measured both by expenditure and weight—falling into each category. In addition, our grocery purchase data cover only products with a standard UPC, excluding fresh and in-store items. Where relevant, we use probability weights provided by NielsenIQ to ensure that our results are broadly representative of the US population.

We augment the HMS household panel with geographic and political data to study local correlates of purchase patterns. Household ZIP codes are linked to USDA Rural–Urban Commuting Area (RUCA) codes to proxy for urbanity, and counties are matched to the USDA Food Environment Atlas to obtain county-level measures of store density, food access, and demographics. We also incorporate Democratic vote shares at the county level from the MIT Election Data & Science Lab’s presidential returns (2000–2024), constructing an annual panel of vote share data through linear interpolation.

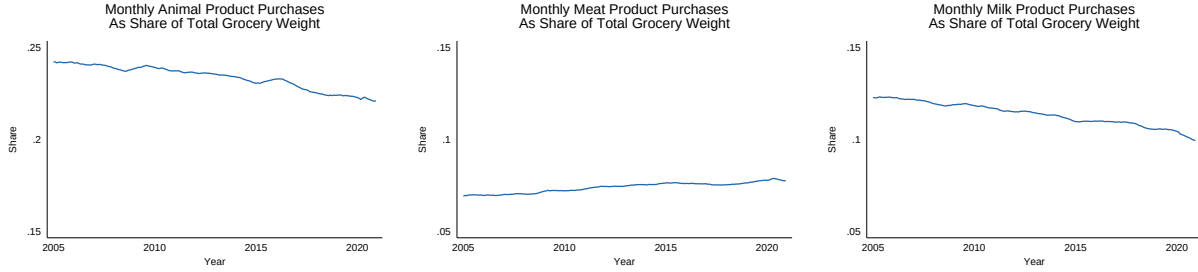
3.3.4 Comparison of Demographic and Socioeconomic Characteristics

Household demographics in the weighted panel are broadly similar to those of the US population on several key variables, though some race and education gaps remain. Table C.C.1 compares demographic and socioeconomic characteristics between the panelists (weighted and unweighted) and data from the US Census Bureau for 2020. The comparison indicates that the weighted NielsenIQ data align reasonably well with the general population on age,

⁴Appendix Figure C.C.6 shows the accuracy, error rates, and bias of the approach to classifying which households purchase meat in a given month, and Appendix Figure C.C.7 shows the performance of the predictions for a broader array of variables.

⁵Specifically, we begin with the April 2022 Thrifty Food Plan cost. We then scale this amount down using factors meant to convert that benchmark into a lower bound for plausibly informative recorded grocery spending: (i) 60% to allow for under-recording in Homescan, motivated by Einav et al. (2010); (ii) 90% to allow for online grocery purchasing; and (iii) 45% to translate total food spending into food-at-home spending. When excluding fresh and in-store items, we further multiply by 70%, reflecting the share of spending on non-magnet goods in our data. This restriction excludes approximately 1% of households from the sample.

Figure 3.1: Shares of grocery weight accounted for by meat, milk, and animal products



Notes: Each panel plots the 12-month moving average of the monthly household share of grocery purchase weight accounted for by animal products, meat, or milk. The sample is restricted to household-month observations with grocery spending above the paper's spending floor, and the series cover January 2005 through December 2020. Category definitions follow the product-classification procedure described in this chapter.

gender, and median household income. The NielsenIQ panel also aligns closely with the population's gender distribution and median household income. Income in the NielsenIQ data is reported in income brackets, with \$65,000 indicating that the median household income lies within the \$60,000–\$70,000 bracket, which also aligns with the census data.

The primary remaining differences are in race and education. NielsenIQ households are, on average, slightly more educated than the general population. A larger gap arises in the share of respondents identifying as white and those classified as “other.” Part of this discrepancy probably reflects survey design: the Census allows multiple racial identities and offers more detailed response categories, which we collapse into a single “other” category.

3.4 Descriptive Trends in Grocery Purchases of Animal Products

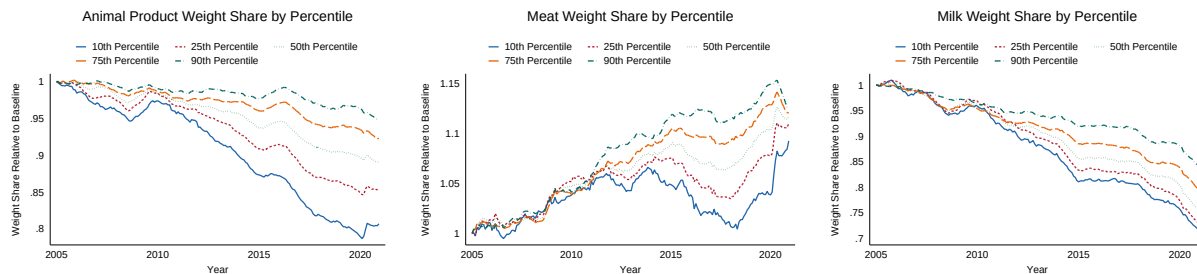
We first present descriptive evidence on food-at-home (FAH) purchases of animal products and plant-based analogs over our main pre-pandemic window, January 2005 through December 2019, and then treat 2020 separately as a pandemic stress test. Throughout, we plot 12-month moving averages to smooth seasonality; this implies a January 2005 baseline for indexed series.

3.4.1 Aggregate Consumption Trends

By the end of 2019, meat's share of grocery weight rises by 0.9 percentage points relative to January 2005. By contrast, milk and overall animal-product weight shares decline by about 1.8 and 1.9 percentage points, respectively (see Figure 3.1).

We use the weight-share measure because changes in food-at-home consumption complicate interpretation of levels. Specifically, per capita food-at-home (FAH) grocery volume declines by about 8.9% from 2005 to 2019, and Appendix Figure C.C.3 shows a sharp reversion in 2020 during the COVID-19 pandemic. This decline in grocery volume is consistent with broader evidence from the Economic Research Service of the U.S. Department of Agri-

Figure 3.2: Meat, milk, and animal-product grocery-share trends across the household purchase distribution



Notes: Each panel plots the 12-month moving average of the indicated percentile of the monthly household distribution of the corresponding grocery-weight share, normalized to its January 2005 value. The sample is restricted to household-month observations with grocery spending above the paper's spending floor. Category definitions follow the product-classification procedure described in this chapter.

culture that food-away-from-home spending has accounted for a growing share of total food spending over time (Zeballos, 2020; Saksena et al., 2018). Thus, while the share of groceries that are meat rises modestly over our main pre-pandemic window, our data show a decline in the average ounces of meat purchased (Appendix Figure C.C.4), indicating a biased measure of trends in households' overall meat consumption.

3.4.2 Trends Across the Household Purchase Distribution

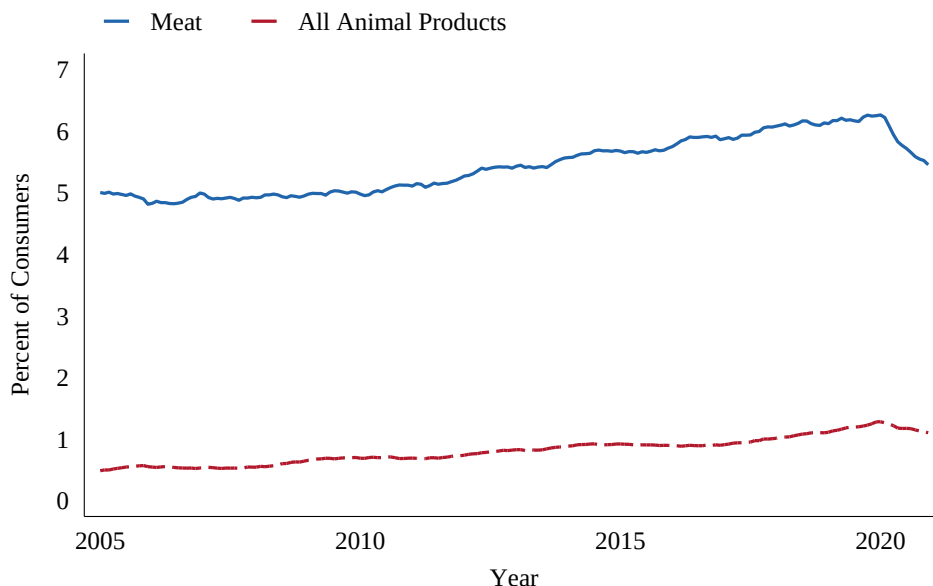
Our core descriptive finding is that aggregate trends mask large differences in how purchases change across households. Figure 3.2 plots selected percentiles of the monthly household distribution of meat's grocery-weight share, each indexed to January 2005. Relative to January 2005, meat's grocery-weight share rises much faster near the top of the household purchase distribution than near the bottom: by the end of 2019, the increase is 14.9% in the top decile, compared with 3.9% in the bottom decile. For milk, the grocery-weight share declines by about 23.9% in the bottom decile and 11.7% in the top decile. For broader animal products, the corresponding declines are about 20.8% in the bottom decile and 3.5% in the top decile.

3.4.3 Household-level non-purchasing

Moving beyond the intensive margin, our data enable us to investigate changes on the extensive margin: how frequently do households forego purchasing meat or animal products altogether?

Figure 3.3 plots the monthly share of households with no meat purchases and no animal-product purchases. Over our main pre-pandemic window, the share of households that do not buy meat increases from 5.0% to 6.2%, and the share not buying any animal products increases from 0.5% to 1.3%. These increases partially reverse in 2020, when pandemic conditions shift consumption back toward food at home. While these shares remain small in absolute terms, they represent substantial relative increases. In comparison, approximately

Figure 3.3: An increasing share of households does not buy meat or animal products in a given month



Notes: Each line plots the 12-month moving average of the share of household-month observations with no purchases in the indicated category. The sample is restricted to household-month observations with grocery spending above the paper's spending floor. Category definitions follow the product-classification procedure described in this chapter.

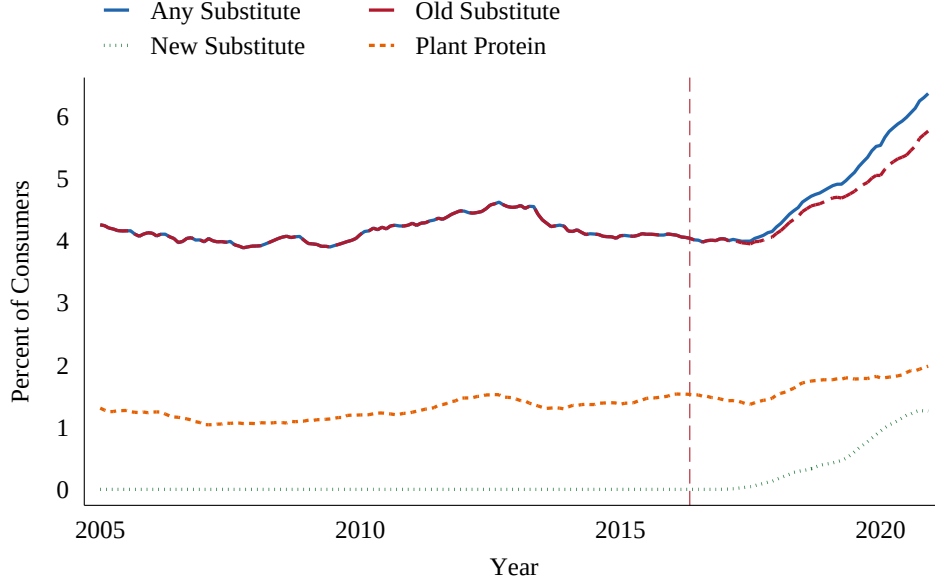
12.8% of households do not buy milk early in our data, which increases to 26.4% at the pre-pandemic peak.

A key concern is that these trends may reflect the secular decline in food-at-home (FAH) purchasing rather than changes in category-specific behavior. The 2020 pandemic provides a useful stress test: when restaurant closures pushed grocery purchases back toward their 2004 baseline, zero meat purchases still remained approximately 10.6% above baseline and zero animal product purchases remained about 2.3 times the baseline frequency. This indicates that declining FAH volume is not the sole explanation for the pre-pandemic rise in non-purchasing. We then estimate a descriptive counterfactual that relates purchase probability to grocery volume in 2004 and applies those coefficients in later years holding volume at 2004 levels. This volume-adjusted series materially attenuates the rise in meat non-purchasing, though it does not eliminate it; the attenuation is smaller for animal products (Appendix Figure C.C.3).⁶

Taken together, these descriptive checks suggest that declining grocery-purchase volume is an important part of the meat extensive-margin trend, but not a complete explanation; for animal products, the role of grocery-purchase volume appears smaller.

⁶See Appendix C.C.3 for a more detailed discussion.

Figure 3.4: Households purchasing meat alternatives



Notes: Each line plots the 12-month moving average of the share of household-month observations with purchases in the indicated category. The dashed vertical line marks the mid-2016 introduction of modern plant-based meat alternatives. The sample is restricted to household-month observations with grocery spending above the paper’s spending floor. Category definitions follow the product-classification procedure described in this chapter.

3.4.4 Adoption of Plant-Based Alternatives

The prominent introduction of modern plant-based meat alternatives (PBMA) such as Beyond and Impossible burgers during the 2010s coincides with a sharp rise in the share of households buying PBMA (Figure 3.4). However, both the timing and limited scale of these products suggest at most a limited role in the broader meat-purchasing trends we document.

At the start of the plotted sample, about 4.3% of households buy some PBMA in a given month, while about 1.3% buy traditional plant proteins and about 6.8% buy milk alternatives. After their introduction, newer PBMA, which are absent before then, grow rapidly, bringing the share of households buying any PBMA to about 6.4% by the end of the sample. This indicates real post-introduction momentum in modern PBMA, but household penetration remains limited.

Importantly, the timing and scale of PBMA adoption suggest that modern PBMA are unlikely to be the primary driver of the broader meat-purchasing trends we document. The frequency of meat-free months was already trending upward before the introduction of Beyond and Impossible products. PBMA purchases also remain small relative to meat purchases: by dollars, average meat purchases are about 44 times larger than purchases of meat alternatives in mid-2020, and by weight they are about 4 times larger. Although the share of households buying meat alternatives rises after the introduction of new PBMA, PBMA still account for only about 0.3% of grocery spending in mid-2020, up from about 0.2% in mid-2015. Thus, even under a one-for-one displacement benchmark, the post-2015 increase

would imply only about a 0.1% reduction in the share of groceries that are meat.⁷

3.4.5 Demographic Trends in Non-Purchasing

Appendix B.8.1 reports descriptive household characteristics for households at the top and bottom of the purchase distribution, including zero-purchase households and purchasers of plant-based meat and milk alternatives.

We then examine how purchase patterns correlate with demographic characteristics and how these correlations change over time using regression analysis. We estimate linear probability models where outcomes include indicators for the purchase groups described above, as well as grocery-purchase shares of meat and animal products more broadly. Key explanatory variables include household demographics (income, education, race, household composition, birth cohort) interacted with linear time trends to capture differential changes across groups over time. These regressions include geographic and time fixed effects along with controls for price and total grocery purchase volume, with full results reported in Appendix C.B.8.2 (see Appendix C.C.4 for more details).

Across these appendix comparisons, households purchasing little or no meat or animal products tend to be smaller, younger, more urban, more educated, and more racially diverse than heavy purchasers. PBMA purchasers share several of these characteristics, especially younger ages and higher education, though they tend to live in larger households and often also purchase plant-based milk. We treat these cross-sectional patterns as context for the main analysis below, which focuses on how purchasing patterns evolve over time.

Turning from levels to trends, baseline levels and growth do not always move together across demographic groups. High-income households have high baseline rates of meat-free months but declining meat-free months over time, and education groups differ much more in baseline levels than in growth rates. By contrast, the strongest increases in meat-free months are concentrated among younger cohorts and Asian households, suggesting that changing cohort and demographic composition likely contributes to the aggregate rise in meat-free months.

Figure 3.5 illustrates several striking patterns of meat- and other animal-product avoidance. While the highest income quartile maintains the highest frequency of meat-free months throughout the panel, it exhibits a downward trend over time. Combined with positive trends in other quartiles, this convergence reduces the gap between the highest and lowest income quartiles from approximately 3.3 percentage points to 0.9 percentage points by the end of 2019.

Our regression analysis helps quantify these subgroup differences while controlling for other household characteristics, prices, and total quantities purchased. We find no statistically significant difference in time trends between the highest and lowest income quartiles for meat non-purchasing. By contrast, Asian households show a statistically significant relative increase in meat non-purchasing of 0.17 percentage points per year compared with White households. More broadly, the meat regressions suggest substantial polarization among Asian

⁷See Appendix C.C.5 for a discussion of several causal inference analyses we conducted to estimate the effect of PBMA on meat purchases.

Figure 3.5: Animal Product Avoidance Trends by Demographic



Notes: The panels plot 12-month moving averages of the share of household-month observations with no meat purchases or no animal-product purchases by demographic group. The first row splits households by adjusted per-capita income quartile, the second by education group, the third by birth cohort, and the fourth by race/ethnicity group. The sample is restricted to household-month observations with grocery spending above the paper's spending floor.

households: relative to White households, they are more likely to appear both in the top and bottom deciles of meat purchasing and to have no-meat months, even though their average meat share is also higher overall. Household heads in the combined Millennial/Generation Z category exhibit the largest increase in no-meat months among the generational cohorts (see Appendix Tables B.8.2 and B.B.8.2).

For months without animal products, our regression results show higher baseline rates of animal-product non-purchasing among Black and Asian households relative to White households, but we do not find statistically significant differential time trends for either group in this outcome. We again observe substantial positive relative trends among household heads in the combined Millennial/Generation Z category for animal-product avoidance.

Our analysis highlights three persistent patterns. First, high-income and highly educated households, despite exhibiting high overall rates of non-purchasing, show flat or declining trends over time. Second, changes in meat- and animal-product non-purchasing are uneven across demographic groups rather than following a common pattern. Third, Asian households and household heads in the combined Millennial/Generation Z category show some of the strongest increases in meat- and animal-product-free months.

3.5 Conclusion

This chapter addresses a puzzle: aggregate U.S. meat consumption has remained high even as plant-based alternatives have become more popular. Using 2004–2020 household panel data linked to ingredient-level product information, we use an ingredient-based classification strategy that improves on existing retailer taxonomies and offers a more flexible way to measure ingredient-defined product groups, helping shed light on this puzzle. We provide three main substantive findings.

First, aggregate trends mask large differences in how purchases change across households: by the end of 2019, the average share of groceries that are meat by weight grows by 12.4%, while meat’s grocery-weight share rises much faster near the top of the household purchase distribution than near the bottom (14.9% vs. 3.9% relative to January 2005). Over the same pre-pandemic window, the share of households with meat-free months rises from 5.0% to 6.2%.

Second, we provide detailed characterization of households at purchase extremes. Zero-purchase months are concentrated among smaller, high-income, well-educated households and are especially common among Asian households.

Third, we reveal a disconnect between baseline levels and growth trends across demographic groups. While high-income and highly educated households exhibit relatively high rates of meat-free months, they show flat or declining trends over time. By contrast, some of the strongest increases in meat-free months occur among Asian households and younger cohorts.

Our descriptive counterfactuals also show that declining grocery-purchase volume is an important part of the meat extensive-margin trend without being a complete explanation. Together, these patterns suggest that both declining grocery-purchase volume and changing

cohort and demographic composition likely contribute to the aggregate rise in meat-free months in our data.

Our analysis has important limitations. Grocery-panel data exclude food away from home, so declines in grocery-purchase volume do not necessarily reflect equally large declines in total food demand. Because the data are observed at the household rather than individual level, they may also understate dietary change within households.⁸

These limitations point to important directions for future research on the drivers and implications of polarization in grocery purchases. Ultimately, our findings challenge simple narratives of uniform behavioral change toward lower meat purchasing and instead point to a more polarized pattern of food purchasing.

⁸See Appendix C.C.5 for causal inference analyses of PBMA's on meat purchases.

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Appendix A

Appendix for Chapter 1

A.1 Proposition 12 and Related Policies

Proposition 12 (2018) is part of a broader wave of farm-animal confinement legislation in the United States. This appendix provides institutional background on the policy and its predecessors.

A.1.1 Proposition 2 (2008)

California’s Proposition 2, approved by 63.5% of voters in November 2008, prohibited the confinement of calves raised for veal, pregnant sows, and egg-laying hens in enclosures that prevented them from lying down, standing up, fully extending their limbs, or turning around freely. The measure applied only to California producers and took effect on January 1, 2015. Several *ex ante* studies predicted that Prop 2 would raise egg production costs, shrink California’s egg industry as producers relocated, and raise retail egg prices for California consumers by 9–20%, with relatively modest reductions in consumption offset by imports from other states (Sumner, 2010).

Post-implementation evidence broadly confirmed these predictions. California’s in-state egg production declined substantially, with much of the deficit filled by imports from states without confinement requirements. Retail egg prices in California rose, though isolating the Prop 2 effect from contemporaneous supply shocks (e.g., the 2014–2015 HPAI outbreak) proved difficult.

A.1.2 Proposition 12 (2018)

Proposition 12 went further than Prop 2 in three respects. First, it established specific minimum space requirements (in square feet per animal) rather than vague behavioral standards. Second, it applied not only to California producers but to *any* eggs, pork, or veal sold in California, regardless of state of origin. Third, it required cage-free housing for laying hens by January 1, 2022—eliminating “enriched colony” cage systems that had been developed to comply with Prop 2’s looser standard.

The specific requirements for egg-laying hens were:

- By December 31, 2019: At least 1 square foot of usable floor space per hen.
- By January 1, 2022: Cage-free housing, defined as a system in which hens are free to roam within an enclosed area, with at least 1 square foot of usable floor space per hen.

For pork and veal, analogous space requirements were established, though the economic impact on these markets was expected to be much smaller because far fewer animals were affected (Sumner, 2021).

Prop 12 was approved by 63% of voters on November 6, 2018. It survived a legal challenge that reached the U.S. Supreme Court in *National Pork Producers Council v. Ross* (2023), in which the Court upheld California’s authority to regulate products sold within its borders.

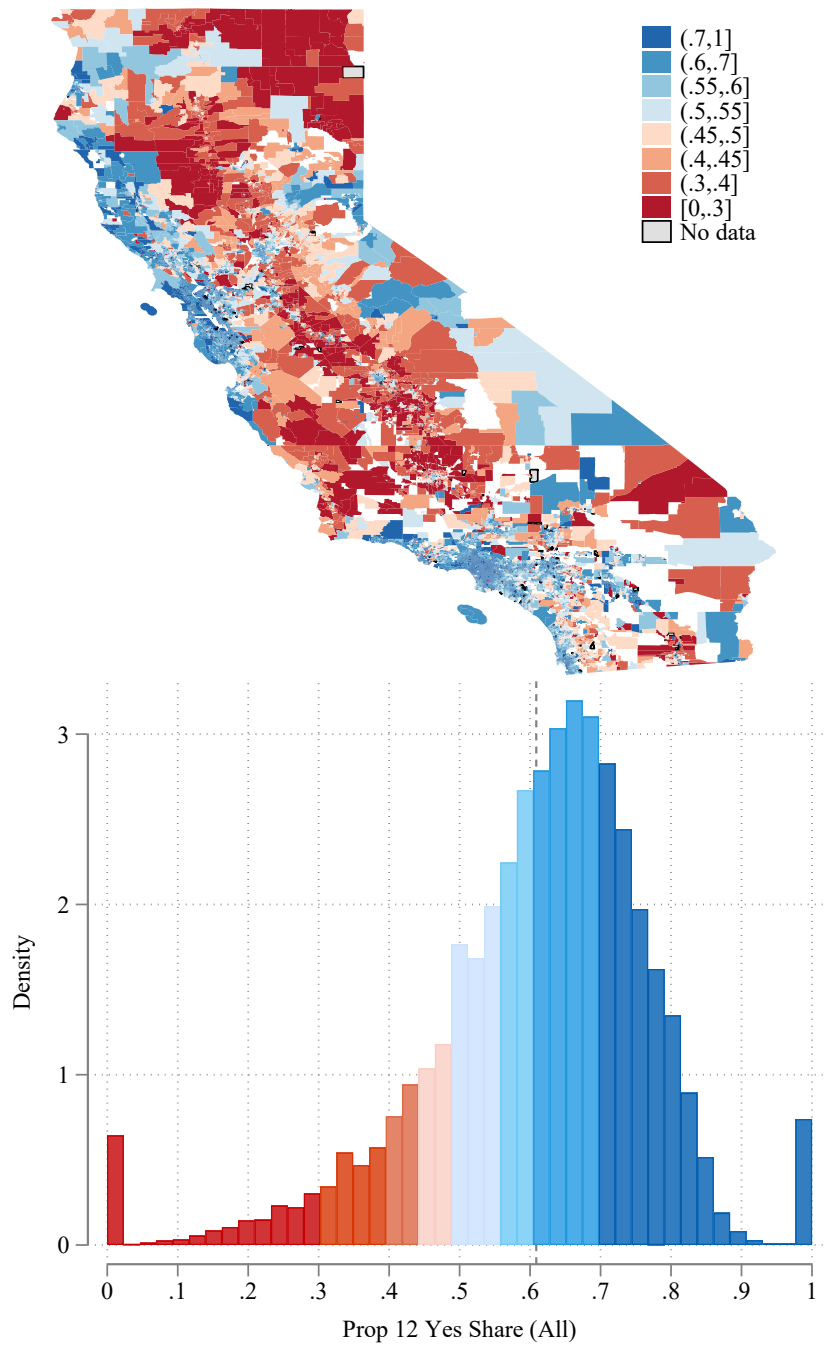
A.1.3 Similar legislation in other states

Following Prop 2’s passage, several other states enacted similar confinement standards, typically through ballot initiatives. Massachusetts Question 3 (2016) earned 77% of votes. State legislatures passed equivalent measures in Oregon, Washington, Michigan, and Colorado.

A.2 Exactness of the Use/Non-Use Decomposition

This appendix proves Proposition 1: that $WTP_i^{\text{total}} = WTP_i^{\text{use}} + WTP_i^{\text{non-use}}$ is exact for arbitrary (possibly non-separable) $V_i(q^{\text{free}}, q^{\text{conv}}, A)$, and that the market-revealed $MWTP_i^{\text{free}}$ correctly identifies WTP_i^{use} .

Figure A.1: Prop 12 “Yes” Vote Share by Precinct (All Precincts)



Note: Share of Proposition 12 “Yes” vote in each precinct (21,694 precincts). The distribution for the 19,061 precincts in the final analysis sample is nearly identical.

A.2.1 Setup

Consumer-voter i has quasi-linear utility $U_i = V_i(q_i^{free}, q_i^{conv}, A) + w_i$, where V_i is unrestricted and may be non-separable in (q, A) . The animal-welfare state $A = A(q_i^{free}, \mathbf{q}_{-i})$ depends on the consumption choices of all consumers.

Define two states:

- **State 0 (no policy):** Prices (P_0^{free}, P_0^{conv}) ; others choose $\mathbf{q}_{-i,0}$; animal-welfare state $A_0 = A(q_{0i}^{free}, \mathbf{q}_{-i,0})$.
- **State 1 (with policy):** Only cage-free eggs available at P_1^{free} ; others choose $\mathbf{q}_{-i,1}$; animal-welfare state $A_1 = A(q_{1i}^{free}, \mathbf{q}_{-i,1})$.

A.2.2 Definitions

Definition A.1 (Total WTP). $WTP_i^{total} = V_i(q_{1i}^{free}, 0, A_1) - V_i(q_{0i}^{free}, q_{0i}^{conv}, A_0)$.

Definition A.2 (Use WTP). The compensating variation for the consumption-bundle change, holding the animal-welfare state at its pre-policy Nash-equilibrium level:

$$WTP_i^{use} = V_i(q_{1i}^{free}, 0, A_0) - V_i(q_{0i}^{free}, q_{0i}^{conv}, A_0). \quad (\text{A.1})$$

Definition A.3 (Non-use WTP). $WTP_i^{non-use} = WTP_i^{total} - WTP_i^{use}$.

A.2.3 Result

Proposition 2. $WTP_i^{total} = WTP_i^{use} + WTP_i^{non-use}$ holds exactly, without approximation.

Proof. By the definitions:

$$\begin{aligned} WTP_i^{use} + WTP_i^{non-use} &= [V_i(q_{1i}^{free}, 0, A_0) - V_i(q_{0i}^{free}, q_{0i}^{conv}, A_0)] \\ &\quad + [V_i(q_{1i}^{free}, 0, A_1) - V_i(q_{1i}^{free}, 0, A_0)] \\ &= V_i(q_{1i}^{free}, 0, A_1) - V_i(q_{0i}^{free}, q_{0i}^{conv}, A_0) \\ &= WTP_i^{total}. \end{aligned} \quad (\text{A.2})$$

The $V_i(q_{1i}^{free}, 0, A_0)$ terms cancel exactly. □ □

A.2.4 Why Nash-Revealed MWTP Correctly Identifies Use WTP

The algebraic exactness of Proposition 2 holds by construction. The substantive economic content is that WTP_i^{use} , as defined in (A.1), is the object identified from market data—even when utility is non-separable in consumption and animal welfare.

In the pre-policy Nash equilibrium, consumer i takes others' choices $\mathbf{q}_{-i,0}$ as given and solves:

$$\max_{q_i^{free}, q_i^{conv}} V_i(q_i^{free}, q_i^{conv}, A(q_i^{free}, \mathbf{q}_{-i,0})) - P_0^{free} q_i^{free} - P_0^{conv} q_i^{conv}.$$

The first-order condition for cage-free consumption is:

$$\frac{\partial V_i}{\partial q_i^{free}} + \frac{\partial V_i}{\partial A} \cdot \frac{\partial A}{\partial q_i^{free}} = P_0^{free}. \quad (\text{A.3})$$

The left-hand side is the *total* marginal return to cage-free consumption. Her revealed MWTP $_i^{free}$ captures the full left-hand side of (A.3) minus the marginal value of conventional, regardless of whether the consumer values cage-free for taste, for moral satisfaction, or for any perceived contribution to animal welfare.¹

Because $\text{WTP}_i^{\text{use}} = V_i(q_{1i}^{free}, 0, A_0) - V_i(q_{0i}^{free}, q_{0i}^{conv}, A_0)$ is the integral of this total marginal return along the demand curve from the pre-policy to the post-policy bundle (holding A at A_0), it is correctly measured by $\text{MWTP}_i^{free} \times Q_i^1$ under the standard local-linearity approximation.

A.2.5 Decomposition of the Animal-Welfare Change

To see why the decomposition cleanly separates Nash-achievable from collectively-achievable value, decompose the change in A :

$$A_1 - A_0 = \underbrace{[A(q_{1i}^{free}, \mathbf{q}_{-i,0}) - A(q_{0i}^{free}, \mathbf{q}_{-i,0})]}_{\text{(a) } i\text{'s own switch to cage-free}} + \underbrace{[A(q_{1i}^{free}, \mathbf{q}_{-i,1}) - A(q_{1i}^{free}, \mathbf{q}_{-i,0})]}_{\text{(b) everyone else switching under mandate}}. \quad (\text{A.4})$$

Component (a) is the welfare improvement i could achieve unilaterally by changing her own consumption. The utility i derives from this channel is captured by her Nash first-order condition (A.3) and therefore absorbed into $\text{WTP}_i^{\text{use}}$.

Component (b) is the welfare improvement from all other consumers switching to cage-free under the mandate. This is the public-good component that i cannot achieve through private purchasing. Proposition 2 shows that $\text{WTP}_i^{\text{non-use}}$ captures component (b)—evaluated at the with-policy consumption bundle—with no residual interaction term.

Channel	Absorbed by
Direct consumption quality ($\partial V / \partial q$)	WTP^{use} (Nash-revealed MWTP)
Perceived own-purchase welfare impact ($\frac{\partial V}{\partial A} \frac{\partial A}{\partial q_i}$)	WTP^{use} (Nash FOC)
Others' welfare impact ($\frac{\partial V}{\partial A} \frac{\partial A}{\partial \mathbf{q}_{-i}}$)	$\text{WTP}^{\text{non-use}}$ (vote only)
Expressive utility from act of voting ($\delta_i \cdot \mathbb{1}[\text{yes}]$)	[Excluded by Assumption A.1]

The decomposition partitions the total utility change along the boundary between what the consumer can achieve unilaterally in Nash equilibrium (revealed by market data) and what requires collective action (revealed by the vote).

¹We return in Section A.2.6 to the distinct question of whether warm-glow attached to the *vote itself*, as opposed to the purchase, contaminates the residual.

A.2.6 Scope: Expressive Voting and the Interpretation of Non-Use WTP

The preceding subsections establish that $WTP_i^{\text{non-use}}$ captures component (b) of equation (A.4)—the public-good component of animal welfare that individual i cannot achieve unilaterally. This interpretation treats voting WTP as a revelation of $V_i(\cdot, A_1) - V_i(\cdot, A_0)$, the utility difference between policy states. One additional assumption is required to sustain this interpretation.

Assumption A.1 (No expressive voting utility). V_i depends on the policy only through the allocation $(q_i^{\text{free}}, q_i^{\text{conv}}, A)$ it induces. The act of casting a yes vote conditional on the realized state delivers no additional utility.

Without Assumption A.1, voting WTP contains a term $\delta_i \cdot \mathbb{1}[\text{yes}]$ attached to the *act* of voting yes rather than to the policy’s consequences. This term neither appears in market first-order conditions nor in the consequentialist welfare difference $V_i(\cdot, A_1) - V_i(\cdot, A_0)$, and is therefore absorbed into the residual $WTP_i^{\text{non-use}}$. It is analogous to the Kahneman-Knetsch “purchase of moral satisfaction” concern in stated-preference valuation Kahneman and Knetsch (1992), adapted to a revealed-preference voting context.

The concern is attenuated relative to survey settings. Proposition 12 voting was costly (time, cognitive effort, opportunity cost) and, from the pivotal-voter perspective, consequential in a way survey response is not. Nevertheless, expressive and ethical-signaling motives in large elections are well documented Brennan and Lomasky (1993); Feddersen et al. (2009), and we cannot rule out $\delta_i > 0$ on theoretical grounds. Under violations of Assumption A.1, $WTP_i^{\text{non-use}}$ is an upper bound on the consequentialist existence value of animal welfare.

A parallel point deserves brief mention. The Nash first-order condition (A.3) identifies the *total* marginal return to cage-free consumption, including any morally motivated willingness to pay arising from the consumer’s perceived influence on A through her own purchases. This is the correct quantity for WTP_i^{use} : the decomposition separates Nash-achievable value (whatever its psychological source) from the collective-action residual, not taste-based value from morally motivated value. Consequently, warm-glow attached to *purchasing* cage-free eggs is correctly absorbed into WTP_i^{use} and does not contaminate $WTP_i^{\text{non-use}}$. Only warm-glow attached to the *vote itself*—a distinct psychological channel—raises identification concerns, and that is the content of Assumption A.1.

A.3 The Median Voter Theorem and Prop 12

A.3.1 Statement of the Theorem

The *Median Voter Theorem* (MVT) is a foundational result in public choice theory stating that, under certain conditions, the policy preferred by the median voter will prevail in a majority-rule election. Formally, in a one-dimensional policy space where (i) all voters have single-peaked preferences, (ii) each voter’s utility decreases monotonically as the policy

outcome deviates from their most-preferred point, and (iii) decisions are made by simple majority rule, the Condorcet winner coincides with the preference of the median voter.²

A.3.2 Application to Proposition 12

California’s Proposition 12 (2018) presented voters with a binary choice over the adoption of a specific animal welfare and food labeling regulation. This structure aligns closely with the assumptions required for the MVT to hold:

1. **Unidimensionality.** Although Proposition 12 bundled several regulatory components, the central policy dimension—how much additional animal welfare regulation consumers are willing to support at a given cost—can be represented on a single latent continuum. Voters differ primarily in their marginal willingness to pay for improved farm-animal welfare.
2. **Single-peaked preferences.** Each voter faces a trade-off between moral satisfaction (or non-use value) from improved welfare standards and potential disutility from higher prices. The resulting utility function is single-peaked.
3. **Majority rule and binary choice.** Proposition 12 was decided by simple majority in a statewide referendum, with no alternative policy bundles on the ballot.
4. **Symmetric information and negligible strategic voting.** Given that the initiative was widely publicized and highly salient, each voter’s “yes” or “no” decision can be treated as a sincere expression of their WTP relative to the perceived cost of the policy.

Under these conditions, the aggregate voting outcome reveals the location of the median voter’s WTP threshold. The policy passes when the median voter’s WTP exceeds the policy cost. Hence, Proposition 12’s passage implies that the median Californian’s WTP for the policy’s animal welfare benefits was greater than its perceived cost.

A.3.3 Implications for Empirical Inference

The MVT’s relevance for Proposition 12 provides a bridge between individual-level welfare preferences and aggregate referendum outcomes. By treating the vote share function $V(p) = 1 - F(p)$ as a revealed-preference mapping, we can infer the median (and, under additional assumptions, the full distribution) of public WTP for the policy. This connection justifies interpreting Proposition 12’s aggregate voting behavior as a quasi-revealed preference measure of the social valuation of farm-animal welfare improvements.

²Black (1948); Downs (1957).

A.4 Rational Consumer-Voter Expectations

One of the critical identification assumptions is that voters are aware of and responsive to the personal costs that Prop 12 would impose. In my model, each voter expects to pay for Prop 12 in the form of higher egg prices. This appendix provides evidence supporting this assumption.

A.4.1 Information was widely disseminated

Evidence that voters expected Prop 12 to affect their personal grocery costs is abundant: state analysts, news outlets, and major opponents of the measure explicitly warned voters that egg prices were likely to rise if Proposition 12 passed in November 2018. Conventional consumers—70% of the California egg market—would, after Prop 12, be forced to buy the more expensive cage-free alternative.

The headline in the Official Voter Information Guide, written by the state government’s Legislative Analyst’s Office (LAO) and sent to every registered voter, reads “Consumer Prices Likely to Increase.” It explains that producers would have to remodel housing for hens, pork, and veal, “and much of these increased costs are likely to be passed through to consumers.”³

News coverage before Election Day also warned readers of price increases. An Associated Press wire report (October 2018) summarized the LAO’s conclusion, noting that Proposition 12 would likely result in higher prices for eggs, pork, and veal. The *Los Angeles Times* (August 29, 2017) cited an egg-industry study estimating that cage-free conversion would add one or two cents per egg. A *San Francisco Chronicle* editorial (September 21, 2018), urging a “No” vote, reminded readers that after the earlier hen-space law (Prop 2) took effect, egg prices had risen by 33 percent.

Organized opponents also highlighted the costliness of Prop 12 to consumers. The Association of California Egg Farmers (ACEF) and National Pork Producers Council stated that Prop 12’s housing mandates would “increase food prices and create meat and egg shortages.”

A.4.2 Precinct vote share was sensitive to local markup

Voters were responsive to the expected price increase. After controlling for relevant demographic and political variables identified in prior work (Sumner, 2010; Oh et al., 2025), precincts facing a higher cage-free price premium were significantly less likely to vote in favor of Prop 12 ($p < 0.01$; see Table 1.5.3, column 2). This is also evidence that voters considered how Prop 12 would affect them personally: if all voters expected the same price change regardless of location, regional variation in the cage-free premium would not predict vote patterns conditional on demographics.

³California Secretary of State, *Official Voter Information Guide*, Proposition 12 Title, Summary, and Analysis, 2018. Available at <https://vig.cdn.sos.ca.gov/2018/general/pdf/prop12-title-sum-analysis.pdf>.

A.4.3 Marginal cost of voting on Proposition 12

Proposition 12 appeared seventh on a twelve-measure ballot in the November 2018 general election. The share of gubernatorial voters who also voted on Prop 12 averages 94.9% across precincts, comparable to the 95–96% completion rates for other salient propositions on the same ballot. This is consistent with near-zero marginal cost of completing the Prop 12 question conditional on having started the ballot.

A small number of precincts (683, or 3.2%) recorded more Prop 12 votes than gubernatorial votes, suggesting a subset of voters who skipped the governor’s race but completed the propositions. These precincts tend to be small (mean registered voters: 463 vs. 934 for other precincts) and exhibit a vote-share distribution that is statistically indistinguishable from the full sample.

A.5 Use Value Estimation Supplement (MWTP)

This appendix reports the distribution of marginal willingness to pay (MWTP) for the cage-free egg attribute and alternative demand estimation strategy (BLP) that provides a robustness check to the linear IV specification included in the body.

A.6 Control-function GLM First-Stage

The control-function GLM instruments the non-use price with supply-side variables. For the local-price specification, the excluded instrument is the cage-free retailer assortment propensity ($F = 14.9$). For the state-level specification, the excluded instrument is food stores per household ($F = 9.5$). Table A.6 reports both first-stage regressions.

A.7 Robustness to Non-use Price Construction

This appendix reports the sensitivity of the main model to alternative definitions of non-use price and presents the distribution of cage-free markup, the primary driver source of regional non-use price variation.

Figure A.2: MWTP for Cage-free Attribute

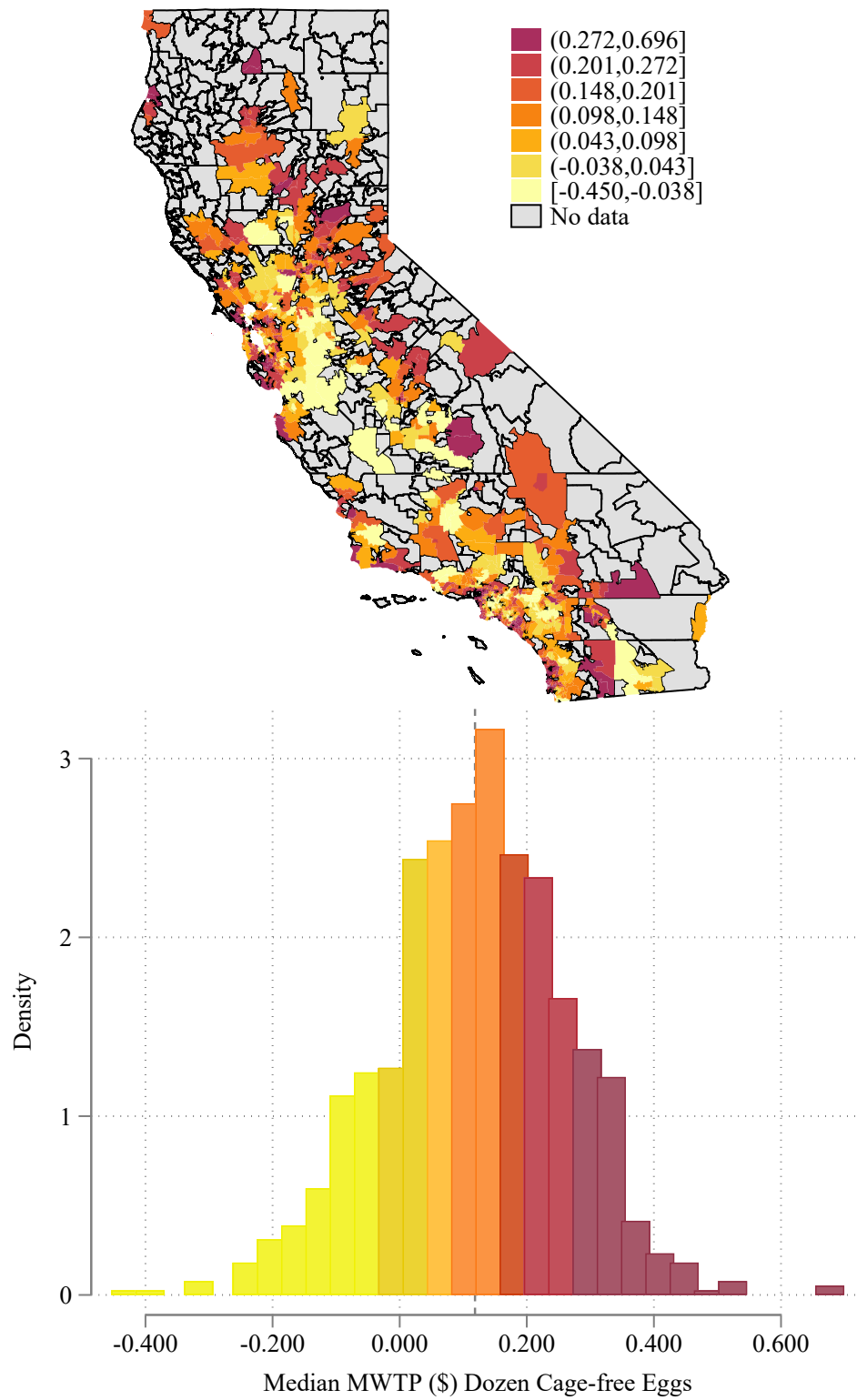


Table A.1: MWTP for Cage-free Attribute — BLP Approach

	(1)	(2)	(3)	(4)
Mean utility				
cons	3.121 (2.550)	3.001 (271.198)	2.583 (975.527)	2.659 (1.693)
Cage-free or above	0.246 (0.709)	0.177 (26.922)	0.240 (13.626)	0.209*** (0.038)
Free-range or above	0.528 (0.973)	0.444 (49.236)	0.629 (37.860)	0.569*** (0.033)
Pasture-raised	1.276 (1.149)	1.224 (7.692)	1.377 (59.757)	1.353*** (0.084)
Organic	1.646 (1.078)	1.565 (33.071)	1.779 (84.003)	1.725*** (0.121)
Fertile	-1.025 (0.763)	-1.018 (65.968)	-1.239 (81.681)	-1.214*** (0.095)
Extra large	-0.299 (0.414)	-0.379 (23.481)	-0.372 (2.528)	-0.413*** (0.022)
Jumbo	0.966*** (0.192)	0.941 (109.515)	0.980 (143.974)	0.948*** (0.290)
Medium	-3.338 (2.406)	-3.411 (28.478)	-3.428 (36.248)	-3.467*** (0.072)
Size unlisted	10.076 (9.677)	9.909 (1426.225)	11.013 (942.629)	10.781*** (1.186)
Price (\$/dozen)	-1.545 (2.435)	-1.498 (87.121)	-1.644 (20.462)	-1.615*** (0.041)
Housing tier $\times$ ln(income)		0.088 (183.710)		-0.557 (0.647)
Housing tier $\times$ education		0.956 (92.235)		0.854*** (0.129)
Median HH income			0.000 (0.014)	0.000 (0.000)
Total households (ZIP)			-0.000 (0.003)	-0.000*** (0.000)
Price (\$/dozen)				
dm_lnincome	0.055 (1.733)	-0.012 (69.530)	0.006 (256.610)	0.004 (0.521)
SD	0.000 (1169.933)	0.000 (31043.679)	0.000 (9174.886)	0.000 (.)
Month FE	Y	Y	Y	Y
County FE	Y	Y	Y	Y
Observations	113402	113402	113402	113402
Adjusted (R^2)				

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

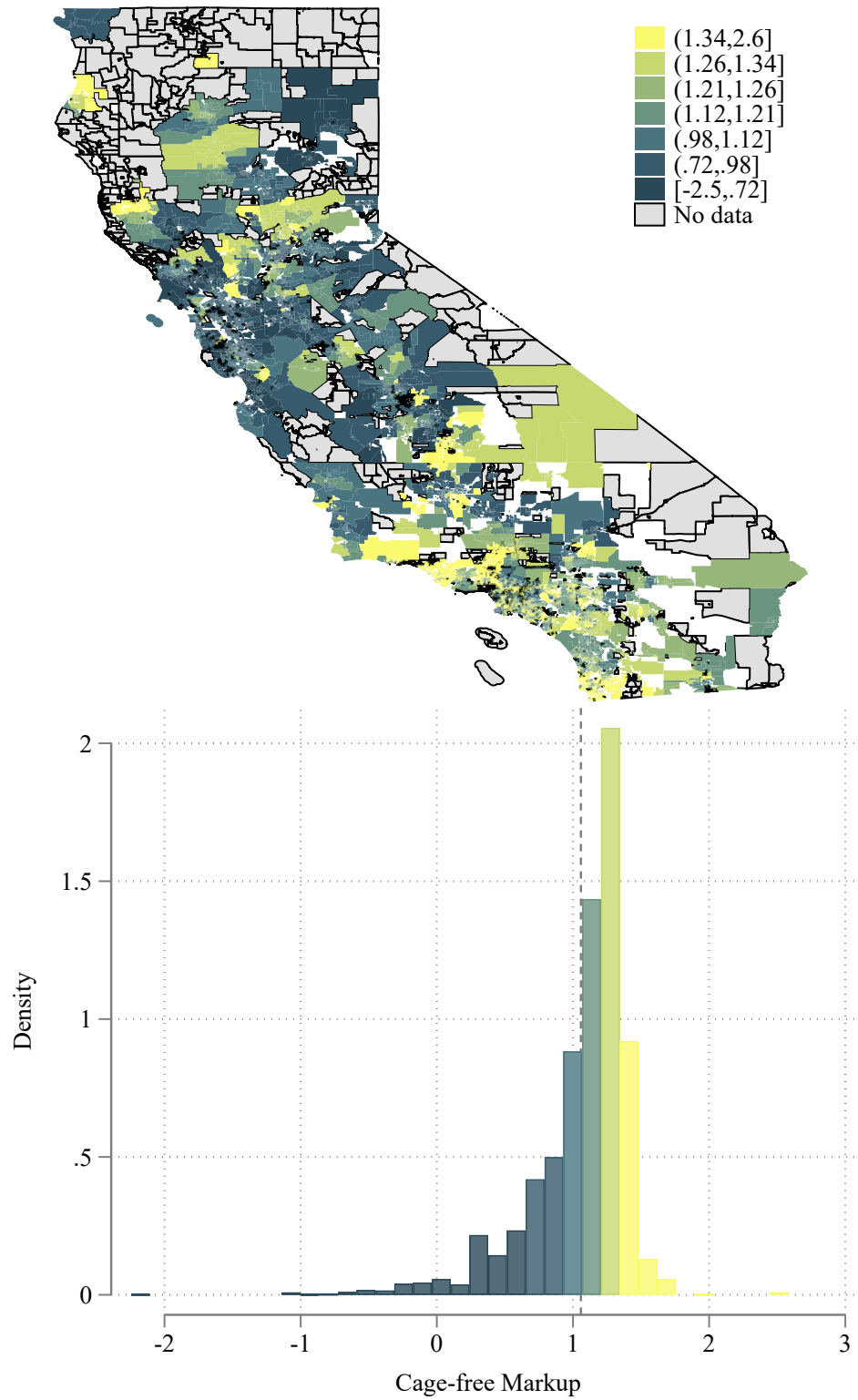
Table A.2: Control Function GLM - First Stage

	(1)	(2)
	Policy Price (local $\mathbb{E}[P]$)	Policy Price (state $\mathbb{E}[P]$)
LOO retailer assort. (free)	48.1013*** (7.9973)	
% Dem. governor vote	-14.1563*** (3.8332)	-10.2730*** (1.6704)
% Right-wing registered	-12.5679*** (4.4035)	-5.1615*** (1.8565)
% Bachelor's degree+	-39.3050** (15.2947)	-22.5569*** (4.0309)
% Workforce in agriculture	13.8435*** (4.3638)	11.2800*** (2.1906)
Gini index	-11.8374*** (2.7633)	-5.2365*** (1.1196)
Median HH income (\$100K)	-1.1724* (0.6195)	-0.1593 (0.2472)
ln(adult population)	0.5610** (0.2269)	0.2602** (0.1077)
% voters Female	-4.5178 (2.7471)	-0.5763 (1.6159)
% voters Hispanic	0.1108*** (0.0114)	0.0748*** (0.0077)
% voters Asian	-0.0104 (0.0201)	-0.0001 (0.0091)
N stores per HH		-688.1346*** (233.8097)
Constant	11.4309** (5.2078)	33.8284*** (2.1146)
Observations	19061	19061

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Figure A.3: Cage-free Markup



A.7.1 Alternative Non-use Price Specifications

The main specification assumes that voters expect the post-policy egg price to equal the 2018 cage-free price observed at their local grocery stores (“local price expectations”) and that the own price elasticity of egg demand is 0.14, the USDA’s preferred estimate.

However, voters may have expected a uniform 30% increase in the conventional egg price, as stated in the Official Voter Information Guide. Cross-precinct variation in the non-use price arises only through differences in conventional prices and MWTP, not through the cage-free markup. Results are reported in Table A.7.1. The coefficient on the non-use price remains negative and significant.

A.8 Policy WTP among Conventional Consumer-voters

By construction, my empirical estimation of willingness to pay for Prop 12 is restricted to conventional consumer-voters. More specifically, the subset of voters for whom I directly construct WTP estimates (my final sample of precinct-level observations) is comprised entirely of the median voters—one for each precinct—because, by the Median Voter Theorem, the vote outcomes in a given precinct reflect the preferences of the median voter in that precinct.

Figure A.4 displays the (logarithmically smoothed) raw CDFs of Prop 12 WTP estimates. This figure directly follows from the estimates in Table 1.5.3.

The WTP curves in Figure A.5 are constructed to represent the preferences of all conventional consumer-voters, not just of median voters. The values of Figure A.5 are extrapolated from those in Figure ??.

A.9 Optimal Cost Recovery for Quasi-Public Goods under Use and Non-Use Valuation

Let N denote a population of individuals indexed by i . A subset $U \subseteq N$ are *users* of a quasi-public good with provision cost C ; the complement $NU \equiv N \setminus U$ are *non-users*. The government recovers C through a combination of user fees and general taxation parameterized by $\alpha \in [0, 1]$.

Willingness to pay. Each individual i has total willingness to pay $WTP_i \geq 0$, decomposed additively into use value and non-use value:

$$WTP_i = WTP_i^{use} + WTP_i^{non-use}, \quad WTP_i^{use}, WTP_i^{non-use} \geq 0,$$

with $WTP_i^{use} = 0$ for all $i \in NU$. Aggregate values are:

$$WTP^{use} \equiv \sum_{i \in U} WTP_i^{use}, \quad WTP^{non-use} \equiv \sum_{i \in N} WTP_i^{non-use}, \quad W \equiv WTP^{use} + WTP^{non-use} > 0.$$

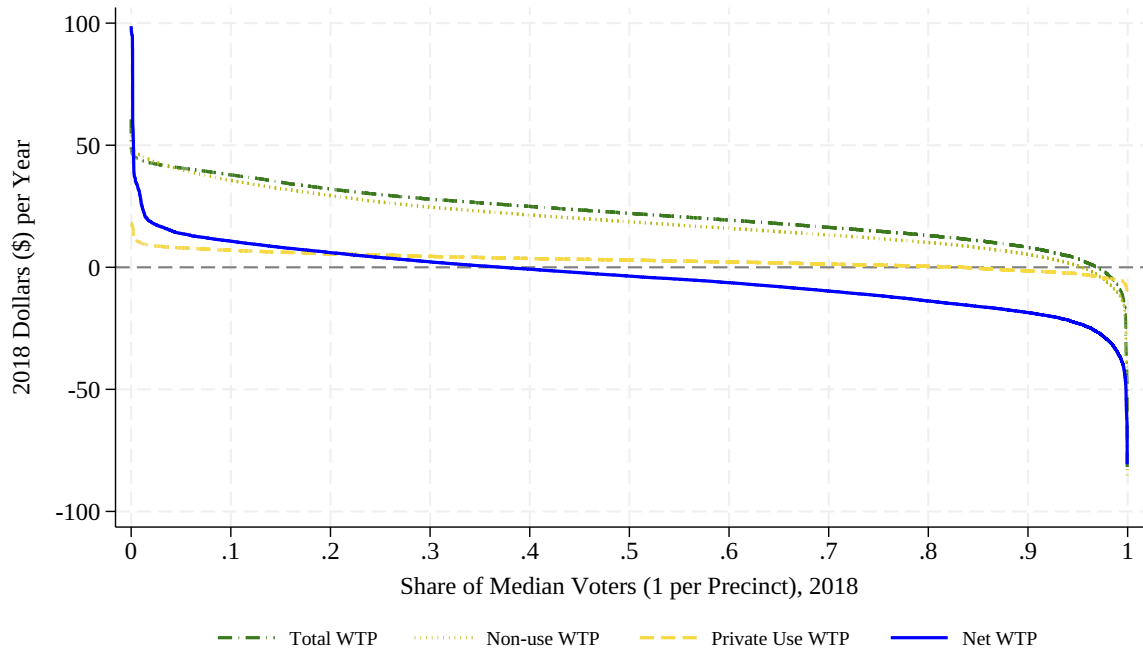
Table A.3: Comparison: Naive vs IV Approaches

	(1) Naive GLM	(2) CF-GLM	(3) 2SLS Linear
Non-use price (state $\mathbb{E}[P]$)	-0.0483*** (0.0110)	-0.1214*** (0.0448)	-0.0253*** (0.0088)
% Dem. governor vote	1.5919*** (0.5306)	0.8612 (0.6243)	0.2589 (0.1591)
% Right-wing registered	-2.5232*** (0.4593)	-2.8901*** (0.4815)	-0.5600*** (0.1047)
% Bachelor's degree+	-1.2062 (0.9693)	-2.8176** (1.4186)	-0.5787* (0.3427)
% Workforce in agriculture	-0.2919 (0.4666)	0.5145 (0.8075)	0.1264 (0.1500)
Gini index	-0.3485 (0.2696)	-0.7260** (0.3495)	-0.1331 (0.0888)
Median HH income (\$100K)	-0.1179* (0.0617)	-0.1278** (0.0605)	-0.0295** (0.0140)
ln(adult population)	0.0775*** (0.0277)	0.0976*** (0.0313)	0.0196*** (0.0060)
% voters Female	0.9152*** (0.3033)	0.8765*** (0.3130)	0.1490*** (0.0527)
% voters Hispanic	0.0011 (0.0017)	0.0066** (0.0029)	0.0014 (0.0009)
% voters Asian	-0.0035** (0.0014)	-0.0035** (0.0014)	-0.0009*** (0.0003)
Control f residual		0.0734* (0.0445)	
Constant	-0.4685 (0.5320)	1.9465 (1.4590)	0.8640*** (0.3291)
Observations	19061.0000	19061.0000	19061.0000

Standard errors in parentheses

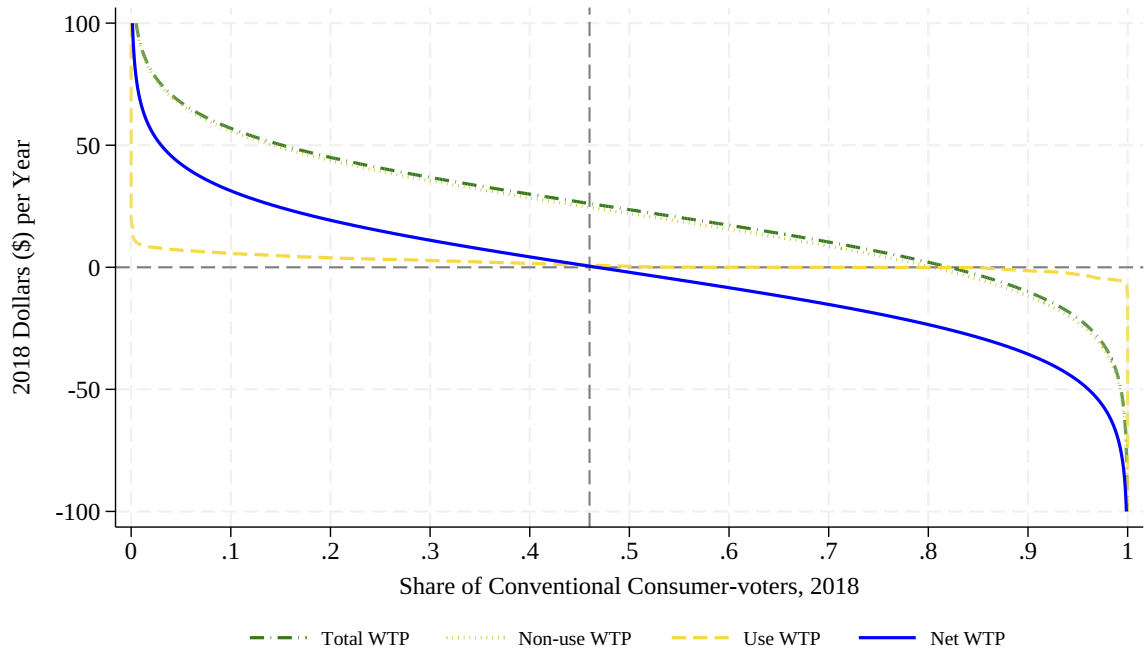
* $p < .10$, ** $p < .05$, *** $p < .01$

Figure A.4: WTP for Prop 12: Median Voters



Note: Inverse CDFs of precinct-level WTP estimates from the control-function fractional logit (Table A.7.1, column 2). Each precinct contributes one observation (its median voter), weighted by votes cast. “Total WTP” = non-use + use WTP. “Net WTP” = total WTP – gross annual cost. The \$0 dashed line marks indifference. See Section 1.5.4 for construction.

Figure A.5: WTP for Prop 12: All Conventional Consumer-voters



Note: Inverse CDFs of precinct-level WTP estimates from the control-function fractional logit (Table ??, column 2). Each precinct contributes one observation (its median voter), weighted by votes cast. “Total WTP” = non-use + use WTP. “Net WTP” = total WTP – gross annual cost (i.e., full policy price). The \$0 dashed line marks indifference. See Section 1.5.4 for construction.

Define the non-use share $\theta \equiv \text{WTP}^{non-use}/W \in [0, 1]$.

Cost-recovery rule. Given α , cost is allocated as follows. A user fee τ_u is charged equally to all users, and a general tax τ_g is levied equally on all individuals:

$$\tau_u(\alpha) = \frac{\alpha C}{|U|}, \quad \tau_g(\alpha) = \frac{(1 - \alpha)C}{|N|}.$$

Note that $\sum_{i \in N} t_i(\alpha) = C$ for all α , so the rule is revenue-neutral by construction.

Optimal cost-recovery parameter. Because total collected revenue equals C for any α , choosing α to maximize aggregate net surplus $\sum_i (\text{WTP}_i - t_i(\alpha))$ yields no interior solution—the objective is constant in α . The economically meaningful criterion is instead *benefit-proportional cost sharing*: each group should bear a share of total cost equal to its share of total willingness to pay.

Users collectively receive benefit WTP^{use} and bear cost αC ; non-users collectively receive benefit $\text{WTP}^{non-use}$ and bear cost $(1 - \alpha)C$. Requiring that cost shares equal benefit shares for both groups gives the single condition:

$$\frac{\alpha C}{C} = \frac{\text{WTP}^{use}}{W},$$

which solves immediately to:

$$\alpha^* = \frac{\text{WTP}^{use}}{W} = 1 - \theta.$$

Therefore, the optimal user-fee share equals the aggregate use-value share of total WTP. As the non-use share θ rises, α^* falls and a larger fraction of cost is optimally borne through general revenue. In the polar case $\theta = 1$ (pure non-use value), the good should be fully tax-financed; when $\theta = 0$ (pure use value), full cost recovery through user fees is optimal.

A.10 Ban vs. Pigouvian Tax under Use and Non-Use Valuation

This appendix compares the consumer deadweight loss under a product ban (as implemented by Prop 12) with the deadweight loss under an equivalent Pigouvian tax, showing that the efficiency gap between the two instruments depends on the share of total WTP attributable to use value.

Under a ban, the conventional product is eliminated entirely. The consumer-surplus loss for a conventional consumer is the full trapezoidal area between P_0^{conv} and the quality-adjusted post-policy price $\tilde{P}_1$. Under a per-unit Pigouvian tax set at $\tau = P^{free} - P^{conv}$ (the markup), the consumer retains access to the conventional product at price $P^{conv} + \tau = P^{free}$, and the consumer-surplus loss is the standard Harberger triangle. The difference in consumer

DWL between the ban and the tax is:

$$\Delta\text{DWL} = \text{DWL}_{\text{ban}} - \text{DWL}_{\text{tax}} = \text{WTP}_i^{\text{use}} \cdot Q_i^1, \quad (\text{A.5})$$

which is proportional to use value. As $\text{WTP}^{\text{use}}/\text{WTP}^{\text{total}} \rightarrow 0$ (i.e., as non-use value dominates), the consumer forgoes less surplus on infra-marginal units under the ban relative to the tax, and the two instruments converge in efficiency. In my estimates, use value accounts for less than 15% of total WTP, implying that the efficiency cost of the ban relative to a tax is small.

A.11 Conditions for Benefit–Cost Analysis

The WTP estimates in this chapter pertain to the median voter in each precinct. Extending these to a full benefit–cost analysis requires assumptions about whose welfare the social planner counts. This appendix discusses the representativeness of the estimated WTP distribution for several populations of interest.

A.11.1 Registered voters in California

The distribution of WTP I estimate is, by construction, a distribution over precinct medians. For this to represent the WTP distribution of all registered voters, the cross-precinct distribution of medians must approximate the individual-level CDF. This holds exactly when precincts are homogeneous ($\text{Var}(W_i \mid p) = 0$) and precincts are weighted by population. In practice, the logistic within-precinct heterogeneity model (Section 1.3.5) provides a structural correction: the individual-level WTP distribution is constructed as a mixture of logistics, explicitly accounting for within-precinct dispersion. The validation check—that the full-population net-WTP distribution crosses zero at 64%, matching the 63% Yes vote—supports the adequacy of this correction.

A remaining concern is selection into voting. If the decision to vote is correlated with Prop 12 preferences, voters may not represent registered voters. The 94.9% completion rate for Prop 12 among those who voted in the governor’s race (Appendix A.4.3) suggests that conditional on appearing at the polls, nearly everyone voted on Prop 12. The relevant selection margin is therefore turnout for the election as a whole, not Prop 12-specific turnout.

A.11.2 All California residents

Extending to the full adult population requires the additional assumption that registered-voter preferences are representative of non-registrant preferences. Non-registrants are disproportionately younger, lower-income, and less politically engaged, which could shift the WTP distribution in either direction. Poststratification using ACS demographics could partially address this, but is beyond the scope of the current analysis.

A.11.3 Non-Californians

Prop 12 may generate benefits for non-Californian populations through at least two channels. First, economic spillovers: if Prop 12 raises egg prices outside California (through supply-chain adjustments or interstate trade effects), non-Californian consumers experience welfare changes that should enter a complete BCA. Second, political spillovers: Prop 12's passage may encourage other states to adopt similar policies, generating additional animal-welfare improvements.

A.11.4 Animals

A complete utilitarian welfare accounting would include the welfare of the affected animals. The scientific consensus is that birds are sentient—capable of experiencing pain and pleasure—making them morally relevant within consequentialist frameworks.⁴ Prop 12 affected approximately 15–20 million laying hens per year in California by transitioning them from cage to cage-free housing. Even modest per-animal welfare gains, when aggregated across this population, could dominate the consumer-side welfare calculations. However, monetizing animal welfare is beyond the scope of this chapter.

⁴The Cambridge Declaration on Consciousness (2012) affirmed that birds and other non-human animals possess the neurological substrates of conscious experience.

Appendix B

Appendix for Chapter 2

B.1 Search Terms

Table B.1 contains a full list of search terms used in the CAB Abstracts, Web of Science Core Collection, and EconLit databases.

Table B.1: Search terms.

Note: Columns separate AND statements and “|” represent OR statements.

Term 1 (Practice)	Term 2 (Animal Food)	Term 3 (Misc.)	CAB papers	EconLit papers	WoS papers
concrete wire wood dirt floor	all species		70	0	124
cooling	all species		206	0	338
housing shelter	all species	shelter	2255	44	2417
indo/ space	all species		3	0	0
ventilation	all species		214	1	512
aviary	broiler layer chicken poultry hen		39	2	461
side curtain	broiler layer chicken poultry hen		1	0	1
vent boxes	broiler layer chicken poultry hen		0	0	0
calf hutch	dairy cow		5	0	7
corral	dairy cow	size	14	3	10
lot	dairy cow	size	9	3	79
milking parl/ stall	dairy cow		137	2	354
tether	dairy cow	milk	114	4	246
tie-stall tie stall	dairy cow		48	0	17
			109	0	339

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Term 1 (Practice)	Term 2 (Animal Food)	Term 3 (Misc.)	CAB papers	EconLit papers	WoS papers
veal	dairy cow	crate pen hut	0	1	40
farrow	hog pig pork sow swine	crate pen hut	48	22	1256
gestat	hog pig pork sow swine	crate pen hut	23	11	584
slotted	hog pig pork sow swine	floor	3	0	10
sun-shade sun shade	hog pig pork sow swine		0	0	0
cage free cage- free			12	22	48
feedlot			133	56	632
natural light	broiler layer chicken poultry hen		23	0	6
nest box	broiler layer chicken poultry hen		7	0	121
perch	broiler layer chicken poultry hen		23	0	629
automatic take- off	dairy cow		1	0	2
calf-cow separat	dairy cow		0	0	41
dry period	dairy cow		203	0	456
wash	dairy cow	udder	27	0	11
wean	dairy cow	weight	83	3	50
bird-proof	hog pig pork sow swine		0	0	5
environmental enrichment			33	0	394
live shackle			0	0	0
welfare quality			51	1	223
tail dock	all species (except hen)		38	0	8
beak cut trim	broiler layer chicken poultry hen		49	0	12
debeak	broiler layer chicken poultry hen		40	0	0
dehorn disbud	dairy cow		32	1	27
teeth clip	hog pig pork sow swine		5	0	53

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(Table B.1 continued from previous page)

Term 1 (Practice)	Term 2 (Animal Food)	Term 3 (Misc.)	CAB papers	EconLit papers	WoS papers
pasture out-door	access		400	18	729
organic	all species		2341	61	4201
paddock	dairy cow		104	1	524
all-in	hog pig pork sow swine	all-out	9	2	159
American Grassfed Association	As-		0	0	0
American Humane	Hu-		1	1	2
Animal Care Program	Care		3	0	3
Animal Welfare			2041	276	4701
Better Chicken Project			0	0	0
Certified Humane	Hu-		0	0	3
Food Alliance			0	2	7
free range free-range			318	27	567
Global Animal Partnership	Animal		1	0	7
grassfed			0	11	85
Humane			84	7	288
One Health			161	48	609
pasture raised pasture-raised			6	3	30

B.2 Latent Dirichlet Allocation

Tables B.2 and B.3 present the topic phrases used in the Latent Dirichlet Allocation (LDA) machine learning model. The tables include the LDA model output (“LDA Topic Phrases” are the LDA model output), our team’s paraphrasing of the LDA topic phrases (“Simplified Topic”), whether a random sample of abstracts with a 95th percentile propensity score for that topic were reviewed for relevance (“Review?”), and whether the papers’ 95th percentile propensity score for that topic were deemed relevant to our scoping review (“Relevant?”).

Table B.2: LDA Round 1 Topics.

Simplified topic	Relevant?	Review?	LDA Topic Phrases
dairy practices	Y	N	milk production housing system tie stalls stall housing housing systems loose housing stall barn dairy cows free stall tie stall
milk samples	Y	N	dairy herds cross sectional samples collected logistic regression milk production subclinical mastitis dairy farms factors associated milk samples risk factors
ventilation, air pollution	Y	Y	air quality temperature relative humidity age first temperature relative emission rates ventilation rate milk yield dry period air temperature relative humidity
milk yield, lameness	Y	Y	lactating dairy cows lactating dairy early lactation holstein cows time spent lying time milk production center dot milk yield dairy cows
digestion	N	Y	reduced tillage physical chemical organic matter content chemical properties cattle manure matter content nutrient digestibility zea mays soil physical organic matter
fertilizers, plant	N	Y	organic fertilizers growth yield farmyard manure chemical fertilizers field experiment yard manure farm yard manure farm yard organic manures poultry manure
plants	N	Y	60 days plant height neem cake per plant seed yield randomized block design randomized block poultry manure block design cow dung
water access, enrichments	Y	Y	two groups treatment groups ad libitum daily gain live weight average daily weight gain control group feed intake body weight
antimicrobial, one health, air quality	N	Y	antimicrobial resistance amr resistance amr public health one health approach health approach antimicrobial use farm animals human animal antimicrobial resistance one health
dairy practices	Y	Y	united states life cycle assessment cycle assessment herd health weaning weight wk age life cycle body condition score condition score body condition
economics	Y	Y	cage free dairy cattle farm animal welfare animal based willingness pay welfare assessment health welfare farm animal welfare quality animal welfare
random health	N	Y	plants grown health care cattle manure rice husk cu zn organic pig holstein friesland heavy metals chicken manure poultry litter
economics	Y	Y	developing countries livestock farms public health organic dairy dairy products environmental impacts farm level human health food production food safety

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(Table B.2 continued from previous page)

Simplified topic	Relevant?	Review?	LDA Topic Phrases
undetermined	Y	Y	chemical oxygen demand chemical oxygen dairy farm component analysis principal component analysis organic milk oxygen demand principal component dairy farming organic dairy
disease, de-horning,	N	Y	organic farm infectious diseases pig slurry dairy cattle antibiotic resistant health welfare animal health antibiotic use use antibiotics antibiotic resistance
broilers, layers	Y	N	egg production perch use body weight day old feather pecking housing systems laying hen broiler chickens weeks age laying hens
coli	N	Y	extended spectrum coli isolates dairy farm producing coli esbl producing poultry house poultry farm escherichia coli animal production drinking water
cages, density	Y	N	conventional cages dust bath furnished cages egg weight water use stocking density egg production laying hens nest boxes nest box
soil	N	Y	soil samples 10 cm 20 cm soil quality soil layer soil organic carbon cm soil long term organic carbon soil organic
humidity, heat	N	Y	temperature humidity index humidity index temperature humidity gas chromatography delta 15 mass spectrometry per thousand parts per thousand parts per heat stress
sustainability, ghg	N	Y	samples collected dairy farms management practices animal health livestock production bulk tank milk tank milk bulk tank ghg emissions production systems
dairy practices	Y	N	conventional dairy digital dermatitis stall dairy milk flow free range small scale organic dairy milking parlor dd lesions dairy farms
methane, bio-gas	N	Y	chemical composition methane yield biogas production pig farms dairy manure co digestion pig manure fatty acid fatty acids anaerobic digestion
crops, soil, weeds	N	Y	poultry manure 40 ha research farm split plot management practices grain yield nutrient management 20 ha cow urine per cent
grazing nutrition, crops	Y	Y	matter dm cow day milk fat dry matter intake cow per matter intake crude protein cows fed per day dry matter
milking	Y	N	milk production automatic milking milk samples dairy farms udder health milking parlor somatic cell count cell count milk yield somatic cell
enrichments, housing	Y	Y	bone fractures hy line basal diet wood shavings bull calves environmental enrichment meat quality weeks age free range keel bone

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(Table B.2 continued from previous page)

Simplified topic	Relevant?	Review?	LDA Topic Phrases
dairy practices	Y	Y	quality milk organic dairy dairy industry dairy cattle raw milk dairy cows dairy farms dairy farmers milk yield milk production
undetermined	N	Y	organic production production systems cover crop hydrogen sulfide volatile organic compounds volatile organic cover crops organic compounds weed control organic farming
organic, ghg emissions	Y	Y	greenhouse gas conventional farms livestock farming nitrous oxide organic farms farming system n20 emissions organic farming farming systems organic conventional

Table B.3: LDA Round 2 Topics.

Simplified Topic	Relevant?	Review?	LDA Topic Phrases
feed, production	Y	Y	cows fed dry matter intake per day matter intake body condition score condition score dry matter dairy cows milk production body condition
milk yield	Y	Y	per cow milk protein yield milk daily milk control group milk fat dry period milk production dairy cows milk yield
ventilation, temperature	Y	Y	temperature relative humidity temperature relative organic compounds ammonia emission nh3 emissions ventilation rate emission rates air temperature air quality relative humidity
feed, weight	Y	Y	daily gain growth performance days age crude protein feed intake dry matter average daily broiler chickens body weight weight gain
dairy systems	Y	Y	dairy herds management practices factors associated stall housing organic dairy dairy cows dairy farms tie stall free stall risk factors
welfare, safety	Y	Y	livestock production farm animal welfare welfare quality animal health animal production farm animals food safety farm animal production systems animal welfare
dairy systems	Y	Y	dairy farming use efficiency conventional milk organic milk pasture based dairy farmers organic farming raw milk farming systems per cent

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(Table B.3 continued from previous page)

Simplified Topic	Relevant	Review?	LDA Topic Phrases
housing	Y	Y	housing conditions loose housing tie stall housing system dd lesions cage free dairy cattle nest boxes housing sys- tems nest box
random	Y	Y	serum samples wk age access perches management prac- tices ventilation system life cycle tail docking feeding management dairy cattle milk production
manure, ghg	Y	Y	manure management anaerobic digestion greenhouse gas locomotion score milking systems pig manure automatic milking milk production dairy farms milking parlor
grazing	N	Y	organic matter perennial ryegrass dm intake wk age white clover fatty acids dry matter cows fed fatty acid feed in- take
layers	Y	Y	feather pecking feed conversion laying hen stocking den- sity body weight keel bone egg production weeks age free range laying hens
random	Y	Y	organic dairy cow manure results showed united states poultry houses management practices poultry litter dairy farm poultry production pig farms
soil	N	Y	soil organic matter soil organic carbon management prac- tices n2o emissions organic farming long term poultry ma- nure organic carbon soil organic organic matter
mastitis	Y	Y	clinical mastitis subclinical mastitis udder health milk samples dairy cows somatic cell count cell count organic dairy somatic cell dairy farms

B.3 Categorization

The first table below displays the categorization that was a result of the manual full-paper review; team members categorized all dependent variables into economic factors. The second table shows categorization of practices. Finally, the third table identifies the count of significant results for the (1) animal welfare-improving categories and (2) economic factors of the final 72 papers in the analysis sample.

Table B.4: List of dependent variables.

Note: Sorted by Market Factor and number of results for given dependent variable. Dependent variables have been simplified for aggregation. For complete list, see raw data file.

Economic tor	Fac-	Dependent Variable	Good for Pro- ducer?	N
animal health		Lameness	N	23
animal health		Indoor NH3 (ammonia)	N	10
animal health		Muscle deposition	Y	10
animal health		Bone mineral content	Y	9
animal health		Bone mineral density	Y	9
animal health		Indoor PM	N	9
animal health		Early mortality (percent)	N	8
animal health		Hock lesions	N	8
animal health		Indoor CO2	N	7
animal health		Poor hygiene	N	7
animal health		Respiration rate	N	7
animal health		Keel bone injuries	N	6
animal health		Prevalence of <i>Pryptosporidium parvum</i> (parasitic disease)	N	6
animal health		Prevalence of mastitis	N	6
animal health		Foot condition	Y	5
animal health		Hygiene	Y	5
animal health		Reticulorumen temperature	N	5
animal health		Cull rate	N	4
animal health		Fluctuating asymmetry of tibia length	N	4
animal health		Indoor air temperature	N	4
animal health		Udder health score (ranking where higher values= dirtier udders)	N	4
animal health		Antibody response to SRBC in the last 10 d of growth	Y	3
animal health		Body condition score	Y	3
animal health		Bursa weight	Y	3
animal health		E coli	N	3
animal health		Facial lesions	N	3
animal health		Health score	Y	3
animal health		Heterophil:lymphocyte ratios	N	3
animal health		Indoor air relative humidity	N	3
animal health		Indoor air temperature-humidity heat stress	Y	3
animal health		Panting score	N	3

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(Table B.4 continued from previous page)

Economic tor	Fac-	Dependent Variable	Good for Pro- ducer?	N
animal health		Pathogen concentration	N	3
animal health		Prevalence of Moniezia parasites	N	3
animal health		Prevalence of Strongyle parasites	N	3
animal health		Prevalence of Trichuris parasites	N	3
animal health		Sow teat lesions	N	3
animal health		Spleen weight	Y	3
animal health		Rumination time	Y	3
animal health		Attempts to induce tonic immobility (immediate, delayed)	Y	2
animal health		Broken claws	N	2
animal health		Crude protein concentration (grams/kilogram of dry matter)	Y	2
animal health		IDC (inhalable dust concentration)	N	2
animal health		Mean age of air	N	2
animal health		Mean claw length	N	2
animal health		Mean feather score	Y	2
animal health		Presence of Moniezia parasite eggs in fecal samples	N	2
animal health		Prevalence of Capillaria spp. (parasite)	N	2
animal health		Prevalence of Cryptosporidium spp. (parasite)	N	2
animal health		Prevalence of Dispharynx nasuta (parasite)	N	2
animal health		Prevalence of Heterakis gallinarum (parasite)	N	2
animal health		Prevalence of Hyperkeratosis	Y	2
animal health		Prevalence of Nematodirus parasites	N	2
animal health		Prevalence of Strongyloides avium (parasite)	N	2
animal health		Percentage of cows in the herd that died or were sold	N	2
animal health		Air velocity magnitude (m/sec)	N	1
animal health		Beak condition	N	1
animal health		Bone area	Y	1
animal health		Cage air exchange effectiveness	Y	1
animal health		Coliform infection	N	1
animal health		Comb wounds	N	1
animal health		Disease risks	N	1
animal health		Ear health scores (high is bad)	N	1
animal health		Ease of identifying sick pigs	Y	1
animal health		Efficacy of teat sanitization measures (drying and cleaning teats)	Y	1
animal health		Environmental streptococci	N	1

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(Table B.4 continued from previous page)

Economic	Fac-	Dependent Variable	Good	N
tor			for Pro-	
			ducer?	
animal health		Eye health	Y	1
animal health		Fecal score	Y	1
animal health		Feeding time (minutes/day)	Y	1
animal health		Frostbite	Y	1
animal health		Gestation duration	Y	1
animal health		Hide dirtiness	N	1
animal health		Immunity	Y	1
animal health		Indoor H2S concentrations	N	1
animal health		Lying time (minutes/day)	Y	1
animal health		Manure spreading on pasture	Y	1
animal health		Nasal health score (high is bad)	N	1
animal health		Odor concentration	N	1
animal health		PPRS virus infection	N	1
animal health		Presence of Strongyle parasite eggs in fecal samples	N	1
animal health		Presence of Trichuris parasite eggs in fecal samples	N	1
animal health		Prevalence of Ascaridia galli (parasite)	N	1
animal health		Prevalence of Eimeria spp. (parasite)	N	1
animal health		Prevalence of fever	N	1
animal health		Prevalence of tapeworms	N	1
animal health		Removal rate	N	1
animal health		Risk of food borne disease	N	1
animal health		Risk of injuries	N	1
animal health		Teat condition	Y	1
animal health		In vitro digestible organic matter concentration	Y	1
farmer QOL		Farmer satisfaction	Y	1
fixed cost		Initial cost	N	1
operation cost		Total operating costs	N	10
operation cost		Unpaid labor	N	10
operation cost		Cows per full time employee	Y	5
operation cost		Energy use	N	3
operation cost		Feed cost (\$)	N	3
operation cost		Heat cost	N	3
operation cost		Producer marginal cost	N	3
operation cost		Supplemental heat	N	3
operation cost		Percentage of cows in the herd that died or were sold	N	2
operation cost		Accuracy of detecting hens on floor given a camera	Y	2
operation cost		Cost per stall (\$)	N	2

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(Table B.4 continued from previous page)

Economic	Fac-	Dependent Variable	Good	N
tor			for Pro-	
			ducer?	
operation cost		Crop expenses	N	1
operation cost		Debt-asset ratio	N	1
operation cost		Depreciation	N	1
operation cost		Difficulty determining dry matter intake	N	1
operation cost		Feed efficiency	Y	1
operation cost		Feed expenses	N	1
operation cost		Feed utilization	N	1
operation cost		Insurance expenses	N	1
operation cost		Intake as a percentage of predicted intake (less food waste)	Y	1
operation cost		Interest expenses	N	1
operation cost		Maintenance and repair expenses	N	1
operation cost		Procedure labor	N	1
operation cost		Replacement costs (\$)	N	1
operation cost		Total cash expenses	N	1
operation cost		Total fixed cash expenses	N	1
operation cost		Total variable expenses	N	1
operation cost		Utilities expenses	N	1
operation cost		Variable other costs (\$)	N	1
price		Consumer willingness to pay	N	21
price		Milk price	Y	10
price		Price (\$)	Y	3
price		Consumer ikelihood of purchasing broiler meet (10-point scale)	Y	1
price		Demand elasticity	N	1
price		Marketing options	Y	1
productivity		Body weight	Y	14
productivity		Milk yield per cow	Y	11
productivity		Hen-day egg production	Y	7
productivity		Milk yield per herd	Y	7
productivity		Average daily gain	Y	4
productivity		Number of piglets weaned	Y	4
productivity		Rumination time	Y	3
productivity		Pregnancy rate	Y	3
productivity		Gain to feed ratio	Y	2
productivity		Growth	Y	2
productivity		Hen-house egg production	Y	2
productivity		Milk production	Y	2

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(Table B.4 continued from previous page)

Economic tor	Fac-	Dependent Variable	Good for Pro- ducer?	N
productivity		In vitro digestible organic matter concentration	Y	1
productivity		12th rib fat thickness, cm	Y	1
productivity		Average DMI (dry feed plus milk replacer)	Y	1
productivity		Body weight at birth	Y	1
productivity		Dressing percent	Y	1
productivity		Dry matter intake	Y	1
productivity		Ease of loading pigs for slaughter	Y	1
productivity		Farrowing rate (percent)	Y	1
productivity		Feedlot arrival bodyweight, kg	Y	1
productivity		Foraging	Y	1
productivity		KPH, %	Y	1
productivity		LM (ribeye) area, cm ²	Y	1
productivity		Marbling score	Y	1
productivity		Number of calvings	Y	1
productivity		Number of cows that have not finished milking at end of rotation	N	1
productivity		Number of times cow is milked	Y	1
productivity		Nursery pig growth	Y	1
productivity		Ruminal development (BHBA blood concentra- tions)	Y	1
productivity		Technical efficiency	Y	1
productivity		Weaning BW, kg	Y	1
productivity		Weight gain	Y	1
profit		Net farm income (\$)	Y	11
profit		Net return (\$)	Y	11
profit		Profit (\$)	Y	3
profit		Income over variable expenses (\$)	Y	1
profit		Price minus marginal cost	Y	1
profit		Profit per acre basis	Y	1
profit		Profit per cow	Y	1
profit		Profit per hundredweight	Y	1
quality		Somatic cell count	N	8
quality		Vitamin concentration in fresh yolk	Y	6
quality		Cracked eggs	N	3
quality		Egg weight	Y	3
quality		Dirty eggs	N	2
quality		Docosaehexaenoic acid concentration (% of total fatty acids)	Y	2

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(Table B.4 continued from previous page)

Economic	Fac-	Dependent Variable	Good for Pro- ducer?	N
quality		N-3 docosapentaenoic acid concentration (% of total fatty acids)	Y	2
quality		Percent good shell	Y	2
quality		Shell thickness	Y	2
quality		Shell weight	Y	2
quality		Total carotenoids in eggs (micrograms per gram of fresh yolk)	Y	2
quality		Total monounsaturated fatty acids (% of total fatty acids)	Y	2
quality		Alpha-linolenic acid concentration (% of total fatty acids)	Y	1
quality		Conjugated linoleic acid concentration (% of total fatty acids)	Y	1
quality		Eggshell strength	Y	1
quality		Manganese concentration in yolk	Y	1
quality		Mean difference in pig value	Y	1
quality		Milk fat content (percent)	Y	1
quality		Milk protein content (percent)	Y	1
quality		Myristic acid (% of total fatty acids)	Y	1
quality		Odd-chain fatty acid concentration (% of total fatty acids)	Y	1
quality		Oleic acid (% of total fatty acids)	Y	1
quality		Total branched-chain fatty acids (% of total fatty acids)	Y	1
quality		Total phenols in yolk	Y	1
quality		Total polyunsaturated fatty acids (% of total fatty acids)	Y	1
quality		USDA yield grade	Y	1
sales		Gross farm income (\$)	Y	12
sales		Broiler income (\$)	Y	1
sales		Calf sales (\$)	Y	1
sales		Cull sales (\$)	Y	1
sales		Milk sales (\$)	Y	1
sales		Other farm income (\$)	Y	1

Table B.5: List of Practices.

Note: Sorted by Species, Practice Category, and number of results about given practice. Practices have been simplified for aggregation. For complete list, see raw data file.

Industry	Pract. Category	Practice	N	Better?
Broiler	Enrichment	Access to barrier perch	10	Y
Broiler	Enrichment	Availability of horizontal perches (relative to no perch at all)	5	Y
Broiler	Indoor Env	Higher density	11	N
Broiler	Indoor Env	Lower density	6	Y
Broiler	Indoor Env	Tunnel ventilation and evaporative cooling cells	16	Y
Broiler	Outdoor Access	Additional rotations	7	Y
Broiler	Outdoor Access	Free range	1	Y
Broiler	Outdoor Access	Size of outdoor enclosure	6	Y
Dairy Cow	Confinement	Calving pens relative to bedding pack	1	Y
Dairy Cow	Confinement	Free stall (cubicle) relative to tie stall	1	Y
Dairy Cow	Confinement	Free-stall barn relative to tie-stall barn	1	Y
Dairy Cow	Confinement	Free-stall housing relative to tie-stall housing	5	Y
Dairy Cow	Confinement	Group housing relative to individual housing	6	Y
Dairy Cow	Confinement	Tie stall (vs free stall)	1	N
Dairy Cow	Confinement	Tiestall housing (reference is free stall)	1	N
Dairy Cow	Enrichment	Contact between adult cattle and calves	1	Y
Dairy Cow	Enrichment	Cross-ventilated vs naturally ventilated free-stall barns	7	Y
Dairy Cow	Enrichment	Fans and sprinklers relative to neither	2	Y
Dairy Cow	Enrichment	Free-stall barn with mattress relative to one with sand	1	Y
Dairy Cow	Enrichment	Freestall herd with sand stall relative to one with mattress stall	1	Y
Dairy Cow	Enrichment	Herringbone parlor (compared with stall)	1	Y
Dairy Cow	Enrichment	Sprinkler use (to cool cows)	1	Y
Dairy Cow	Indoor Env	Parallel parlor (compared with stall)	1	Y
Dairy Cow	Indoor Env	Adequate bedding management given compost barn	1	Y

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(Table B.5 continued from previous page)

Industry	Pract. Cate- gory	Practice	N	Better?
Dairy Cow	Indoor Env	Adequate ventilation given compost barn	1	Y
Dairy Cow	Indoor Env	Changing bedding greater than one week intervals	1	Y
Dairy Cow	Indoor Env	Compost barn relative to tie-stall or free-stall barn	4	Y
Dairy Cow	Indoor Env	Compost bedded pack barn (vs sand freestall barns)	6	Y
Dairy Cow	Indoor Env	Compost bedded-pack barns (vs natural ventilation)	8	Y
Dairy Cow	Indoor Env	Compost-bedded-pack barns (vs Cross-ventilated freestall barn)	8	Y
Dairy Cow	Indoor Env	Concrete floor in the calving area	1	Y
Dairy Cow	Indoor Env	Daily addition of bedding (preweaning)	1	Y
Dairy Cow	Indoor Env	Daily disposal and cleaning of bedding (preweaning)	1	Y
Dairy Cow	Indoor Env	Deep-bedded freestalls relative to freestalls with mattresses	6	Y
Dairy Cow	Indoor Env	Fewer cows on farm	1	Y
Dairy Cow	Indoor Env	Four- and six-row free-stall barns relative to two- and three-row	1	N
Dairy Cow	Indoor Env	Four-row free-stall barns relative to three-row free-stall barns	1	N
Dairy Cow	Indoor Env	Four-row free-stall barns relative to six-row free-stall barns	1	Y
Dairy Cow	Indoor Env	Free stall with sand (relative to free stall with mattress)	1	Y
Dairy Cow	Indoor Env	Good ventilation (relative to fair or poor)	1	Y
Dairy Cow	Indoor Env	Heat abatement	1	Y
Dairy Cow	Indoor Env	Higher density	2	N
Dairy Cow	Indoor Env	Inorganic bedding	2	Y
Dairy Cow	Indoor Env	leaning of soiled bedding (postweaning)	1	Y
Dairy Cow	Indoor Env	Lower brisket board height	1	Y
Dairy Cow	Indoor Env	Lower density	1	Y
Dairy Cow	Indoor Env	Manure management	1	Y
Dairy Cow	Indoor Env	Manure solids as bedding material	2	N
Dairy Cow	Indoor Env	Number of calves per group	2	N
Dairy Cow	Indoor Env	Palpation rails relative to self-locking headgates	1	Y
Dairy Cow	Indoor Env	Parallel (vs herringbone) milking parlor	2	N

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(Table B.5 continued from previous page)

Industry	Pract. Category	Practice	N	Better?
Dairy Cow	Indoor Env	Presence of positive pressure ventilation tube	1	Y
Dairy Cow	Indoor Env	Replacing bedding in back of stalls	1	Y
Dairy Cow	Indoor Env	Sand flooring relative to non-sand flooring	7	Y
Dairy Cow	Indoor Env	Slatted floors relative to other manure removal methods	1	N
Dairy Cow	Indoor Env	Stall stocking density	13	N
Dairy Cow	Indoor Env	Sand flooring relative to non-sand in tie-stall housing	3	Y
Dairy Cow	Indoor Env	Ventilation in calf rearing areas (preweaning)	1	Y
Dairy Cow	Indoor Env	Ventilation system	1	Y
Dairy Cow	Mutilation	No tail docking	2	Y
Dairy Cow	Mutilation	Tail docking	1	N
Dairy Cow	Outdoor Access	Access to pasture due to organics requirements	1	Y
Dairy Cow	Outdoor Access	Rotating pasture access relative to continuous	4	N
Dairy Cow	Outdoor Access	Allowing entire herd to have access to pasture (i.e., organic)	12	Y
Dairy Cow	Outdoor Access	Allowing entire herd to have any access to pasture	3	Y
Dairy Cow	Outdoor Access	Allowing entire herd to have continual access to pasture	4	Y
Dairy Cow	Outdoor Access	Area devoted to grazed pastureland (hectares)	1	Y
Dairy Cow	Outdoor Access	Continuous vs rotational access to pasture	1	Y
Dairy Cow	Outdoor Access	Length of grazing season	1	Y
Dairy Cow	Outdoor Access	Management-intensive grazing (vs. confinement)	10	Y
Dairy Cow	Outdoor Access	Management-intensive grazing (vs. Semi-confinement)	6	Y
Dairy Cow	Outdoor Access	Nongrazing relative to size-matched grazing	1	Y
Dairy Cow	Outdoor Access	Outdoor (vs confinement)	6	Y

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Industry	Pract. Category	Practice	N	Better?
Dairy Cow	Outdoor Access	Outdoor (vs Semi-confinement)	6	Y
Dairy Cow	Outdoor Access	Outdoor access	2	Y
Dairy Cow	Outdoor Access	Outdoor vs indoor bedding	5	Y
Dairy Cow	Outdoor Access	Pasture access	3	Y
Dairy Cow	Outdoor Access	Semi-confinement (vs confinement)	6	Y
Layer	Confinement	Cage free (vs caged)	7	Y
Layer	Confinement	Aviary (vs cage)	14	Y
Layer	Confinement	Enriched colony (vs cage)	3	Y
Layer	Enrichment	Access to barrier perch	29	Y
Layer	Enrichment	Perch vs no perch during laying phase	12	Y
Layer	Enrichment	Perch vs no perch during pullet phase	16	Y
Layer	Indoor Env	Acid-treated build-up litter vs. untreated build-up litter	1	Y
Layer	Indoor Env	Forced molting	5	N
Layer	Indoor Env	Frequent manure removal	1	Y
Layer	Indoor Env	Frequently replaced bedding vs. untreated build-up litter	1	Y
Layer	Indoor Env	Higher density	4	N
Layer	Indoor Env	Higher density (given enriched colony cage system)	6	N
Layer	Indoor Env	House lighting	3	Y
Layer	Indoor Env	Improved ventilation	15	Y
Layer	Indoor Env	Lower density	2	Y
Layer	Indoor Env	Lower stocking density and access to amenities	12	Y
Layer	Indoor Env	Manure pit cleanouts	3	Y
Layer	Indoor Env	Natural ventilation system	1	Y
Layer	Indoor Env	Roof sprinkler cooling system	1	Y
Layer	Outdoor Access	Pasture raised	1	Y
Layer	Outdoor Access	Free-range (vs conventional fresh)	1	Y
Layer	Outdoor Access	Pasture-raised relative to cage-free	23	Y

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Industry	Pract. Cate- gory	Practice	N	Better?
Hog	Confinement	Crate free	2	Y
Hog	Confinement	No gestation crate	1	Y
Hog	Indoor Env	Large pens relative to small pens	3	Y
Hog	Enrichment	Enrichment materials (edible, chewable, safe)	1	Y
Hog	Enrichment	Enrichment/nesting materials	2	Y
Hog	Indoor Env	Air filtration system relative to none	1	Y
Hog	Indoor Env	Avoid large litter (decrease density)	2	Y
Hog	Indoor Env	Bark filter	3	Y
Hog	Indoor Env	Filtration of incoming air	1	Y
Hog	Indoor Env	Tunnel (vs natural) ventilation	4	Y
Hog	Indoor Env	Air filtration system vs none	8	Y
Hog	Mutilation	Immunocastration (vs. surgical castration)	3	Y
Hog	Mutilation	No tail docking	2	Y
Hog	Mutilation	Teeth clip	2	N
Hog	Outdoor Access	Pasture access	1	Y
Hog	Outdoor Access	Pasture access relative to individual crates/stalls	9	Y

Table B.6: Practice Categories and Economic Factors for the 72 Corpus Papers

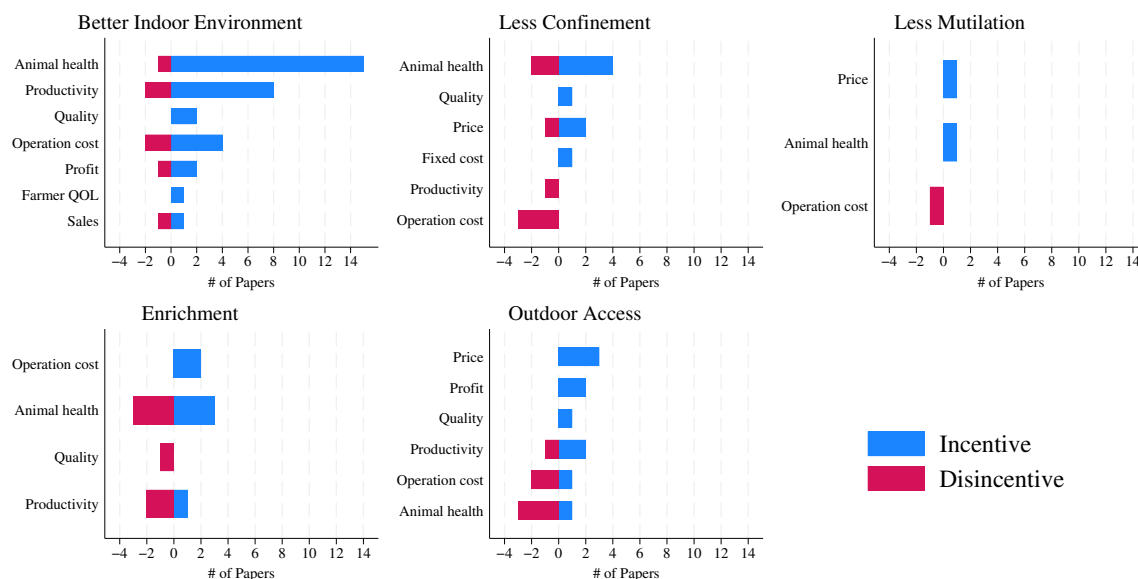
Reference	<u>Practice category</u>					<u>Economic factors</u>								
	Outdoor Access	Indoor Enrich.	Env.	Mutil.	Conf.	Anim. Health	Farm. QOL	Fixed Cost	Oper. Cost	Price	Prod.	Profit	Prod. Qual.	Sales
Allison et al. (2021)	1	0	0	0	0	0	0	0	0	0	0	1	0	0
Alonso et al. (2013)	0	0	9	0	0	2	0	0	0	0	5	1	1	0
Bartlett et al. (1992)	0	0	0	0	2	2	0	0	0	0	0	0	0	0
Bakhtavoryan et al. (2021)	0	0	0	0	1	0	0	0	0	1	0	0	0	0
Beaver et al. (2016)	1	0	0	0	0	1	0	0	0	0	0	0	0	0
Bernal-Rigoli et al. (2012)	0	0	0	0	6	2	0	0	0	0	4	0	0	0
Bernard et al. (2007b)	1	0	0	0	0	0	0	0	0	1	0	0	0	0
Bewley et al. (2001a)	0	2	5	0	3	3	1	1	2	0	2	0	1	0
Bewley et al. (2001b)	0	3	1	0	0	0	0	0	2	0	2	0	0	0
Brumm (2004)	0	0	2	0	0	1	0	0	0	0	1	0	0	0
Cernicchiaro et al. (2012)	0	1	2	0	0	3	0	0	0	0	0	0	0	0
Chang et al. (2010)	2	0	0	0	0	0	0	0	0	2	0	0	0	0
Chou et al. (2022)	0	2	2	2	0	6	0	0	0	0	0	0	0	0
Cook (2004)	0	0	1	0	1	2	0	0	0	0	0	0	0	0
Cook (2003)	0	0	5	0	8	12	0	0	0	0	1	0	0	0
Cornell et al. (2022)	13	0	0	0	0	13	0	0	0	0	0	0	0	0
Davies (2012a)	0	0	1	0	0	1	0	0	0	0	0	0	0	0
De Vries et al. (2016)	0	0	13	0	0	0	0	1	4	0	4	1	0	3
Eckelkamp et al. (2016)	0	0	6	0	0	4	0	0	0	0	0	0	2	0
Espejo and Endres (2007)	0	0	1	0	0	1	0	0	0	0	0	0	0	0
Espejo et al. (2006)	0	0	1	0	0	1	0	0	0	0	0	0	0	0
Eusebio-Balcazar et al. (2018)	0	0	0	0	11	6	0	0	0	0	1	0	4	0
Gillespie et al. (2017b)	0	0	16	0	0	0	0	0	10	0	0	2	0	4
Grinter et al. (2023)	0	5	0	0	0	4	0	0	0	0	2	0	0	0
Gunn et al. (2019a)	0	0	1	0	0	0	0	0	0	0	1	0	0	0
Hanson et al. (2013)	4	0	0	0	0	0	0	0	0	0	0	4	0	0

Hardie et al. (2014)	2	0	0	0	0	0	0	0	1	0	1	0	0	0
Harwood and Drake (2020)	1	0	0	0	0	0	0	0	0	1	0	0	0	0
Heckert et al. (2002)	0	5	10	0	0	12	0	0	0	0	3	0	0	0
Hester et al. (2013a)	0	28	0	0	0	28	0	0	0	0	0	0	0	0
Hester et al. (2013b)	0	28	0	0	0	10	0	0	3	0	4	0	12	0
Holly et al. (2019a)	58	0	0	0	0	0	0	0	20	10	0	21	0	7
Husfeldt and Endres (2012)	0	0	6	0	0	6	0	0	2	0	0	0	0	0
Janni et al. (2007)	0	0	2	0	4	4	0	0	0	0	1	0	1	0
Jorgensen et al. (2017)	0	0	5	0	0	5	0	0	0	0	0	0	0	0
Kaffe et al. (2015)	0	0	3	0	0	3	0	0	0	0	0	0	0	0
Lai and Yue (2020)	1	0	0	0	1	0	0	0	0	2	0	0	0	0
Lally and Edwards (2001)	0	0	4	0	0	1	0	0	2	0	1	1	0	0
Leonardi and Armentano (2007)	0	0	0	0	1	0	0	0	1	0	0	0	0	0
Li et al. (2013)	0	0	11	0	0	11	0	0	0	0	0	0	0	0
Lilburn et al. (2019)	0	1	0	0	0	1	0	0	0	0	0	0	0	0
Lobeck et al. (2011)	0	0	15	0	8	23	0	0	3	0	0	0	0	0
Lombard et al. (2010)	0	0	0	1	0	1	0	0	0	0	0	0	0	0
Mathews et al. (1994)	4	0	0	0	0	3	0	0	0	0	2	0	0	0
Mohammed and Carpenter (1991)	0	0	3	0	0	0	0	0	0	0	3	0	0	0
McKendree et al. (2013a)	9	0	0	0	0	0	0	0	0	9	0	0	0	0
Mohammed et al. (1999)	0	0	5	0	0	5	0	0	0	0	0	0	0	0
Mora (2019)	0	1	0	5	0	2	0	0	1	1	2	0	0	0
Neill et al. (2019)	0	1	0	0	0	0	0	0	0	0	1	0	0	0
Oattes et al. (2021)	0	17	0	0	0	1	0	0	0	0	15	0	1	0
Oh and Vukina (2022a)	0	0	0	0	4	0	0	0	1	2	0	1	0	0
Patel et al. (2019)	0	0	3	0	1	4	0	0	0	0	0	0	0	0
Pereira et al. (2013)	1	0	0	0	0	0	0	0	1	0	0	0	0	0
Potter et al. (2022)	0	3	0	0	0	2	0	0	0	0	1	0	0	0

Pozo et al. (2012)	1	0	0	0	1	0	0	0	0	2	0	0	0	0
Predicala et al. (2000)	0	0	6	0	0	6	0	0	0	0	0	0	0	0
Rowbotham and Ruegg (2015)	0	0	5	0	0	0	0	0	0	0	1	0	4	0
Sergin et al. (2022)	23	0	0	0	0	0	0	0	0	0	0	0	23	0
Sjostrom et al. (2019)	5	0	0	0	0	4	0	0	0	0	1	0	0	0
Snider et al. (2022)	1	0	0	0	0	0	0	0	0	0	1	0	0	0
Sorge et al. (2015)	15	0	0	0	0	15	0	0	0	0	0	0	0	0
Thomas et al. (1996)	0	0	2	0	0	0	0	0	0	0	2	0	0	0
Tong et al. (2019)	0	0	15	0	0	15	0	0	0	0	0	0	0	0
Tonsor et al. (2009)	0	0	0	0	2	0	0	0	0	2	0	0	0	0
Ventura et al. (2010)	0	10	6	0	0	12	0	0	0	0	4	0	0	0
Ventura et al. (2012)	0	0	1	0	0	0	0	0	0	0	1	0	0	0
Weimer et al. (2019)	0	0	8	0	0	6	0	0	1	0	1	0	1	0
Wheeler et al. (2008)	0	0	2	0	0	2	0	0	0	0	0	0	0	0
Wolf and Tonsor (2017)	2	0	0	2	0	0	0	0	2	2	0	0	0	0
Yang et al. (2022)	0	1	1	0	0	0	0	0	2	0	0	0	0	0
Zhao et al. (2015)	0	0	0	0	12	12	0	0	0	0	0	0	0	0
Zhao et al. (2013)	0	0	3	0	6	0	0	0	9	0	0	0	0	0

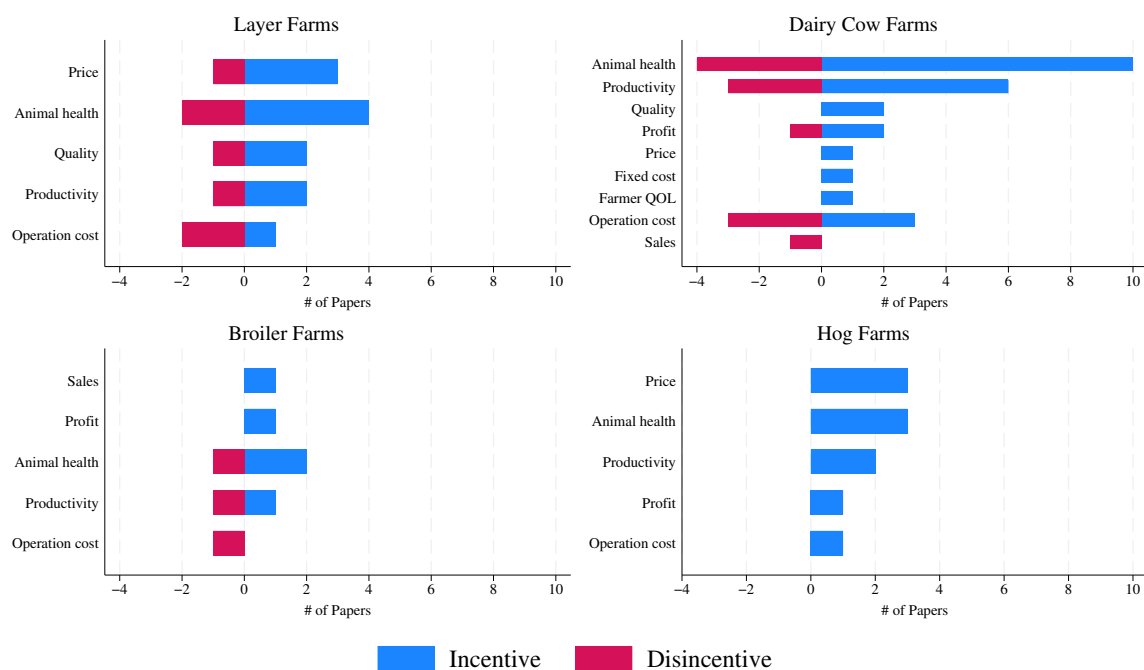
B.4 Supplementary Results

Figure B.1: Distribution of (dis)-incentive incidence across economic factors: Median significant result per paper, by practice category



Notes: The nine economic factors examined are: animal health, product quality, price, profit, productivity, sales, fixed cost, farmer quality-of-life (QOL). Each panel examines the number of publications in which the given economic factor is found to be an incentive (disincentive) in the majority of results studied in that publication. For example, if a single publication presents two results showing that a welfare-improving practice correlates with higher operation costs (two disincentives) and one result showing that the welfare-improving practice correlates with lower operation costs (one incentive), then the median result of the publication is that operation costs are a disincentive to the welfare-improving practice. In each panel, economic factors are ordered by incentives minus disincentives.

Figure B.2: Distribution of (dis)-incentive incidence across economic factors: Median significant result per paper, by industry



Notes: The nine economic factors examined are: animal health, product quality, price, profit, productivity, sales, fixed cost, farmer quality-of-life (QOL). Each panel examines the number of publications in which the given economic factor is found to be an incentive (disincentive) in the majority of results studied in that publication. For example, if a single publication presents two results showing that a welfare-improving practice correlates with higher operation costs (two disincentives) and one result showing that the welfare-improving practice correlates with lower operation costs (one incentive), then the median result of the publication is that operation costs are a disincentive to the welfare-improving practice. In each panel, economic factors are ordered by incentives minus disincentives.

Figure B.3: Distribution of (dis)-incentive incidence across economic factors: Statistically significant results for Dairy Cow Farms

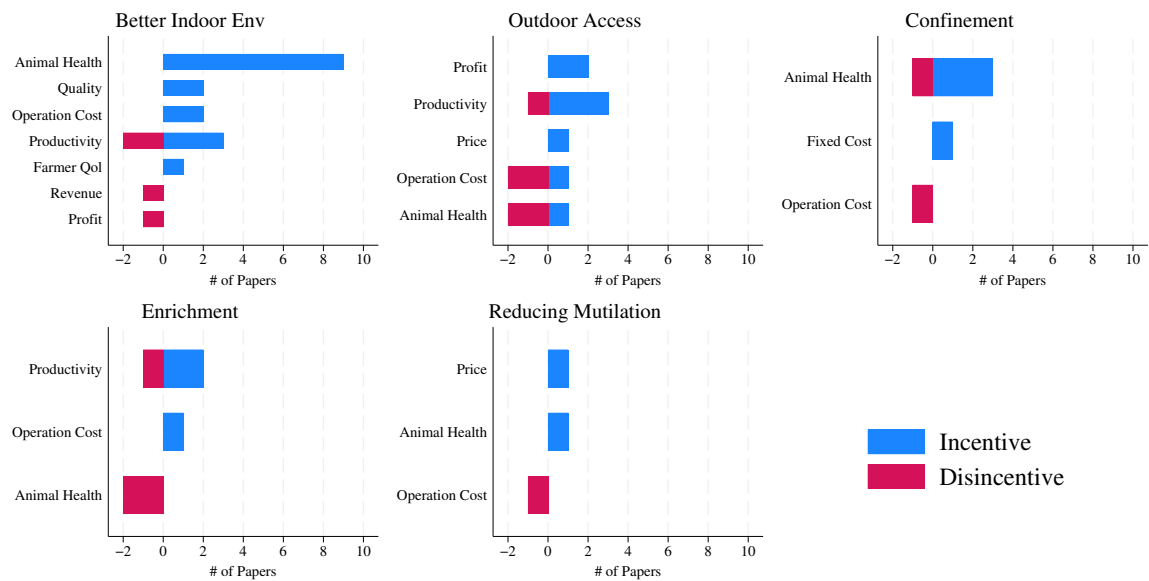


Figure B.4: Distribution of (dis)-incentive incidence across economic factors: Statistically significant results for Layer Hen Farms

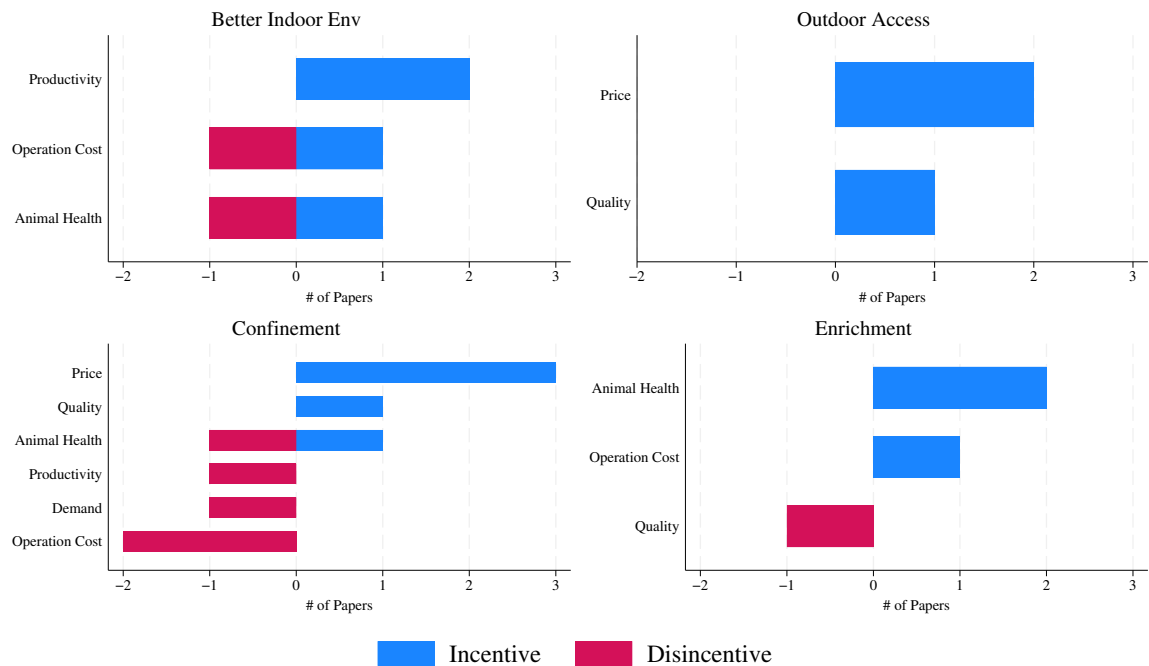


Figure B.5: Distribution of (dis)-incentive incidence across economic factors: Statistically significant results for Broiler Farms

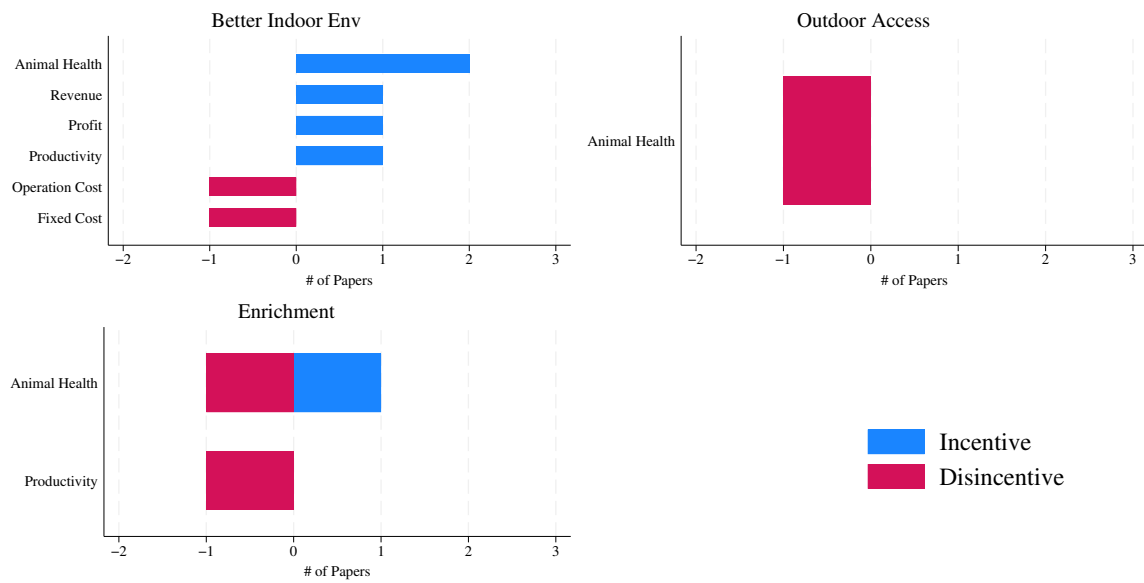


Figure B.6: Distribution of (dis)-incentive incidence across economic factors: Statistically significant results for Hog Farms

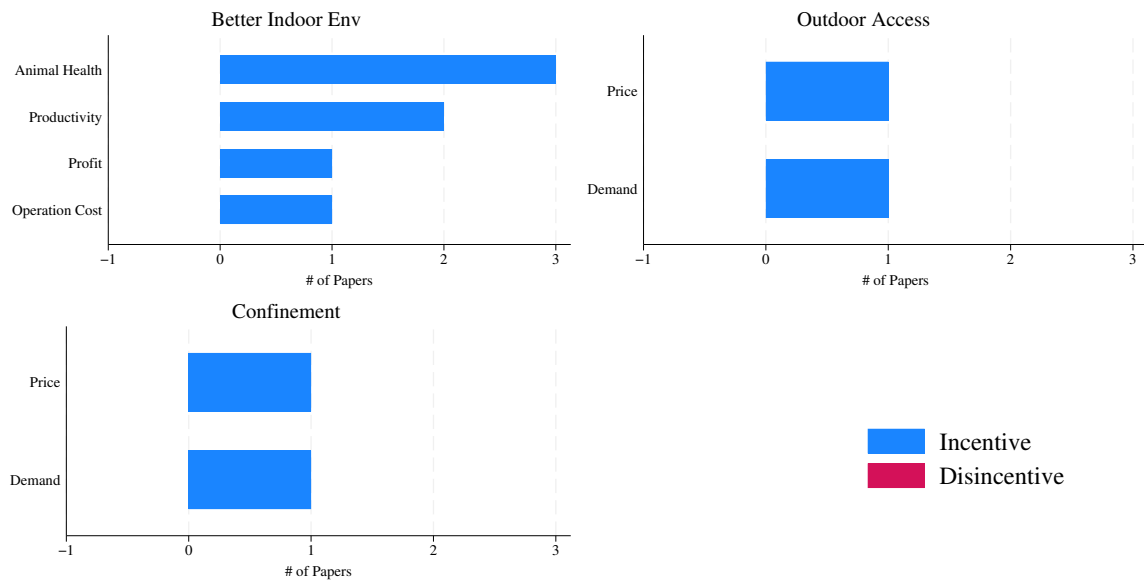


Table C.1: Comparison of weighted panel and U.S. demographic characteristics

	Unweighted	Weighted	US
Median Age	50.00	41.00	38.80
Fraction of Women	0.54	0.51	0.51
Median Income	65000	65000	67521
<i>Education</i>			
Didn't Graduate High School	2.78	4.11	9.77
Graduated High School	24.11	31.14	27.84
Some College	28.61	29.80	27.60
Graduated College	30.44	23.16	22.13
Post College Grad	14.07	11.79	12.66
<i>Race</i>			
White	79.04	74.30	61.63
Black	11.65	12.58	12.40
Asian	4.10	4.88	6.00
Other	5.21	8.25	19.97

Appendix C

Appendix for Chapter 3

C.1 Summary Statistics

C.2 Benchmark Comparison with Cuffey et al. (2023)

The following benchmarks our public-data implementation of the Cuffey et al. (2023) plant-based meat alternative (PBMA) spending strength index (SSI) and first-purchase

event-study framework, and then applies the same framework using our ingredient-based PBMA definition. The benchmark retains 51,598 analytic households and 2,928,168 household-months, compared with 52,022 and 2,953,044 reported in Cuffey et al. (2023), and includes 8,372 event-study households versus 8,496 in the chapter.

We then hold fixed the household-month panel, event timing, controls, and downstream expenditure-share outcomes from the original event-study design, and replace only the PBMA treatment definition with our ingredient-based classifier. Under this overlay, event-study eligibility falls from 8,372 to 7,088, and the number of SSI non-spenders rises from 36,906 to 38,270. At the same time, the headline first-purchase PBMA spending pattern remains similar: month-0 PBMA expenditure rises from 7.10 to 7.38 USD, and month-0 PBMA expenditure share rises from 1.90 to 2.01 percentage points.

C.3 Robustness of Non-Purchasing Trends to Food-at-Home Volume Changes

This section examines whether the rise in household non-purchasing of meat and animal products reflects category-specific behavior or instead more mechanical effects of the secular decline in food-at-home (FAH) purchasing over our sample period.

Figure 3.3 plots the monthly share of households with no meat purchases and no animal-product purchases. Over our main pre-pandemic window, the share of households that do not buy meat increases from 5.0% to 6.2%, and the share not buying any animal products increases from 0.5% to 1.3%.

A key concern is that these trends may reflect the secular decline in food-at-home purchasing rather than changes in category-specific behavior. As households increasingly consume food away from home, their grocery purchases naturally decline, potentially creating mechanical increases in zero-purchase months.¹ We present three descriptive checks.

First, when the pandemic began in 2020, many households shifted from food away from home (FAFH) back toward FAH, bringing grocery purchases back toward their 2004 baseline. This surge in FAH coincides with a visible decline in the share of households who do not purchase meat or animal products. Nevertheless, extensive-margin nonparticipation remains elevated.

Second, we estimate a descriptive counterfactual that relates the household’s purchase indicator for meat (or animal products more broadly) to total grocery volume in ounces using 2004 data and apply those coefficients in later years, holding grocery volume fixed at 2004 levels. Figure C.3 plots the complement of these counterfactual purchase probabilities together with the observed non-purchasing shares. This volume-adjusted series materially attenuates the rise in meat non-purchasing, though it does not eliminate it; the attenuation is smaller for animal products.

¹We limit our analysis of household meat avoidance to households whose grocery spending exceeds the minimal cost of a healthy diet according to the US Department of Agriculture, adjusted for a reasonable degree of underreporting as outlined in Section 3.3.

Finally, we stratify households into bins based on total volume of grocery purchases and plot non-purchase rates within each bin (Figure C.3). As expected, households with lower grocery volumes are more likely to record a month without meat or animal-product purchases. Importantly, however, the share of non-purchasing months rises over time across nearly all volume bins.

Taken together, these descriptive checks suggest that declining grocery-purchase volume is an important part of the meat extensive-margin trend, but not a complete explanation; for animal products, the role of grocery-purchase volume appears smaller.

C.4 Regression Analysis of Heterogeneity

We study how households’ meat and animal-product purchasing varies with prices, demographics, and local market structure using linear probability/linear share models. For household i in DMA (market) r and month t , our baseline specification is

$$y_{irt} = \alpha + \beta_m \ln p_{rt}^m + \beta_o \ln p_{rt}^o + \gamma' X_i + \delta' L_{rt} + \tau_t + \varepsilon_{irt}, \quad (\text{C.1})$$

where y_{irt} is either (i) a weight share (e.g., meat share of FAH purchases) or (ii) an indicator (e.g., no meat purchased this month); $\ln p_{rt}^m$ and $\ln p_{rt}^o$ are log prices for the grocery group and the complement aggregates in market r and month t ; X_i collects household characteristics (education, income per capita, race/ethnicity, composition, birth cohorts, household size); L_{rt} are local retail and environment covariates (e.g., democratic vote share, poverty measures, store densities, access measures); and τ_t are month and year fixed effects (FE) absorbing aggregate seasonality and trends. We estimate (C.1) by weighted OLS using population weights and report standard errors clustered at the DMA level to allow arbitrary within-market correlation over time. We also report an instrumental-variables (IV) version using Hausman-style “leave-one-market-out” price shifters that exploit price movements in other DMAs as instruments.

To assess how results change when restricting to a linear time trend rather than full year/month fixed effects, we estimate:

$$y_{irt} = \alpha + \beta_m \ln p_{rt}^m + \beta_o \ln p_{rt}^o + \gamma' X_i + \phi t + \psi'(X_i \times t) + \mu_r + \kappa_{\text{month}} + \varepsilon_{irt}, \quad (\text{C.2})$$

where t is a continuous time index (years since 2004), μ_r are DMA (market) fixed effects, κ_{month} are month fixed effects, and interactions $X_i \times t$ allow the slopes of time trends to differ by household characteristics.

C.5 Causal Inference Analysis of Plant-Based Meat Introductions

Given the dramatic increase in plant-based meat purchases during our sample period, we conduct complementary analyses to estimate the extent to which plant-based meats

displace animal-based meats following previous literature in an earlier version of the chapter. We emphasize that exogeneity tests indicate that neither design supports strong causal claims. We follow Zhao et al. (2023) and Liu and Ansink (2024) in estimating elasticities and Cuffey et al. (2023) in estimating an event study around the first purchase of plant-based alternatives.

We find that price-based substitution patterns from an Almost Ideal Demand System (AIDS) specification are fragile to specification and instrumentation. The difficulty of identification is consistent with the event-study evidence in Cuffey et al. (2023), where total food spending jumps sharply in the first PBMA-purchase month. In our setting, the combination of nonrandom adoption, problematic pretrends, and placebo failures makes it difficult to find credible comparison observations. Some of the estimated elasticities imply that plant-based alternatives are complements to meat.

As an alternative measure of displacement of animal products by plant-based alternatives, similarly to Cuffey et al. (2023), we study how consumers' purchases of animal products change after they first purchase a plant-based alternative and compare them to similar consumers using a variety of event-study designs. We consider (i) a traditional two-way fixed effect estimator, (ii) an adjusted two-way fixed effect (TWFE) estimator that predicts the change in purchases for a consumer who first purchases a particular alternative during a surge in demand, and (iii) the matrix completion strategy outlined in Athey et al. (2021) as implemented by Liu et al. (2024).² There are problematic pretrends in many cases, and a now-substantial literature gives reason to worry about whether the effects from the TWFEs are interpretable without the strong assumptions of a homogeneous effect and parallel trends across households (De Chaisemartin and d'Haultfoeuille, 2020; Sun and Abraham, 2021; Callaway and Sant'Anna, 2021; Athey and Imbens, 2022). While the matrix completion approach allows for some trends over time that may vary by consumer in a flexible but unobserved way, placebo tests indicate that the estimates produced by this strategy are substantially confounded by unobserved differences between consumers.

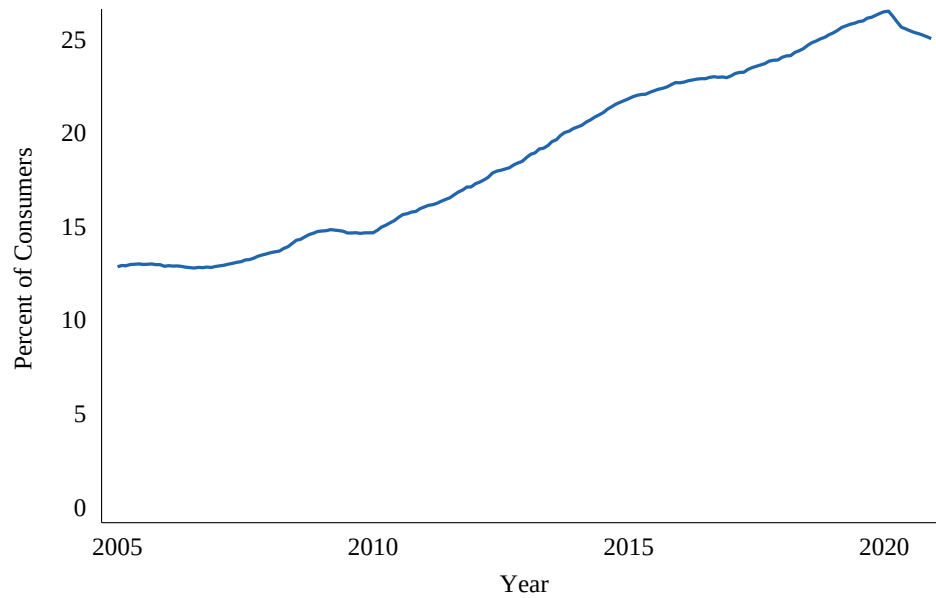
For milk alternatives, we obtain statistically significant and sensible estimates of displacement, but identification concerns remain. In the case of milk alternatives, we find 0.73–0.74 or 0.89–0.93 units of milk displaced per unit of plant-based milk depending on whether the outcome is share of grocery weight or ounces. This is similar to but smaller than the estimate in Stewart et al. (2020).

C.6 Additional Figures

C.7 Classifier Diagnostics

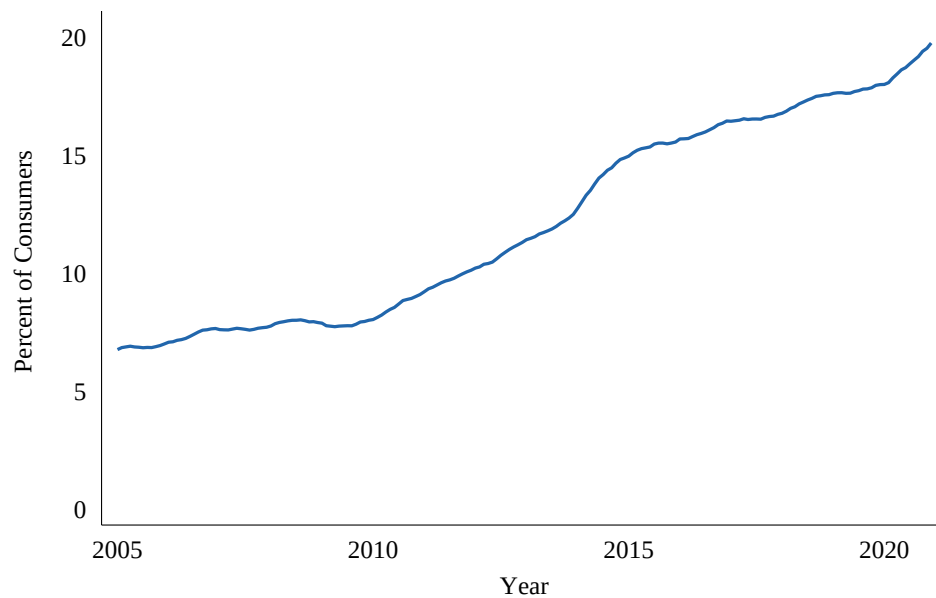
²This method is similar to synthetic controls Abadie et al. (2015) and synthetic difference-in-differences Arkhangelsky et al. (2019) but does not require parallel trends across units.

Figure C.1: An increasing share of households does not buy milk in a given month



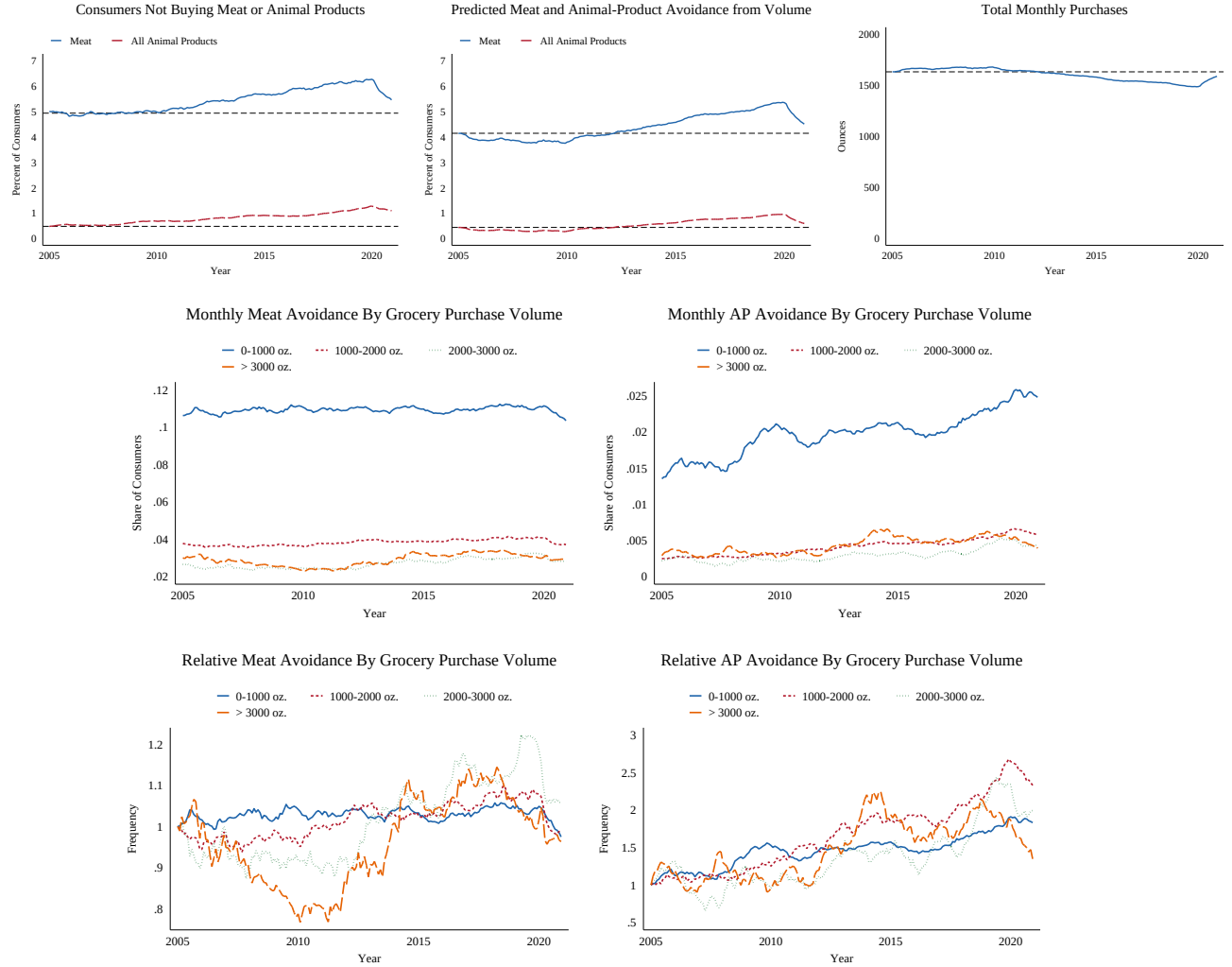
Notes: The line plots the 12-month moving average of the share of household-month observations with no milk purchases. The sample is restricted to household-month observations with grocery spending above the paper's spending floor. Category definitions follow the product-classification procedure described in this chapter.

Figure C.2: Households purchasing milk alternatives



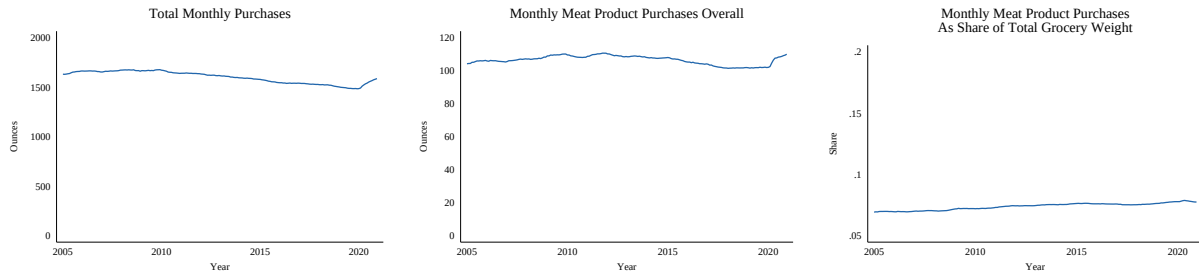
Notes: The line plots the 12-month moving average of the share of household-month observations with purchases of milk alternatives. The sample is restricted to household-month observations with grocery spending above the paper's spending floor.

Figure C.3: Food-at-home volume and non-purchasing robustness checks



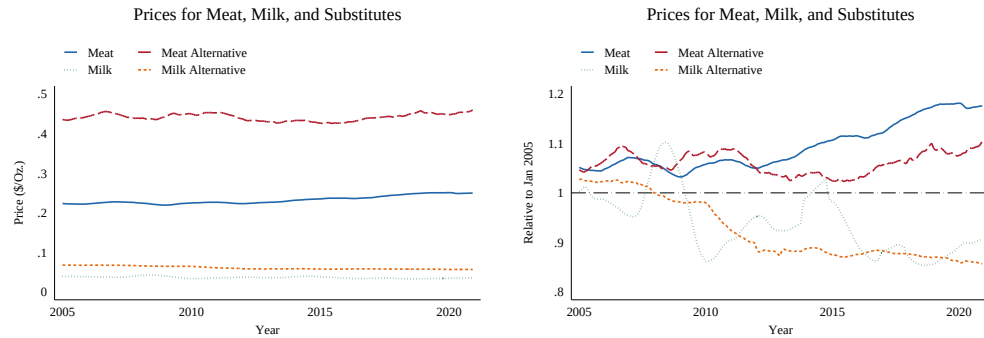
Notes: All panels plot 12-month moving averages. The left panel in the first row reproduces Figure 3.3 with dashed horizontal lines showing the 2004m1–2005m1 baseline mean. The middle panel shows the predicted shares of household-month observations with no meat purchases based on grocery-purchase volume alone. The right panel shows total monthly grocery purchase volume. The second row shows meat and animal-product avoidance by monthly grocery-purchase volume group. The third row shows the same volume-group series normalized to their January 2005 values.

Figure C.4: Grocery purchasing volume, meat purchases, and meat share



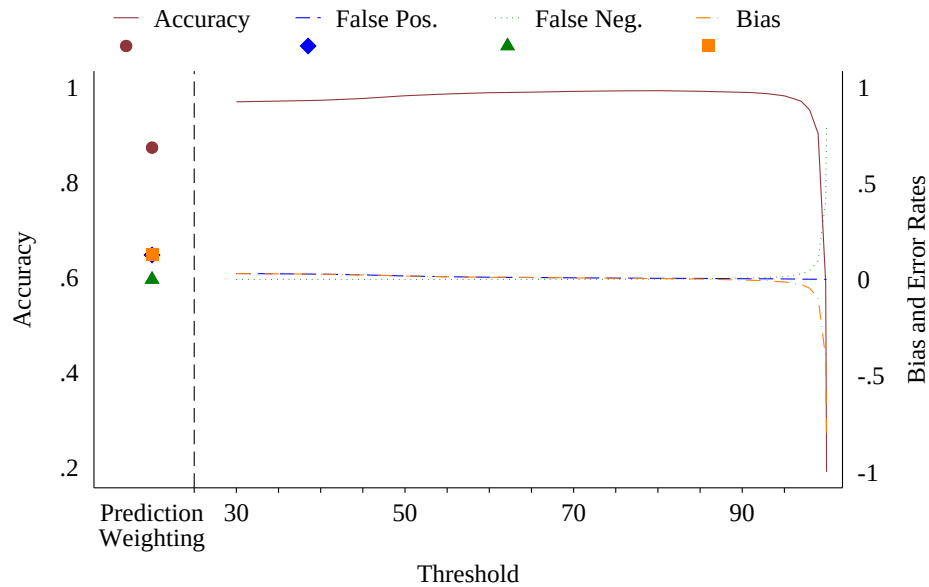
Notes: The first two panels plot 12-month moving averages of average total grocery purchases and average meat purchases, measured in ounces. The third panel plots the 12-month moving average of the meat share of total grocery purchase weight.

Figure C.5: Prices for meat, milk, and their alternatives



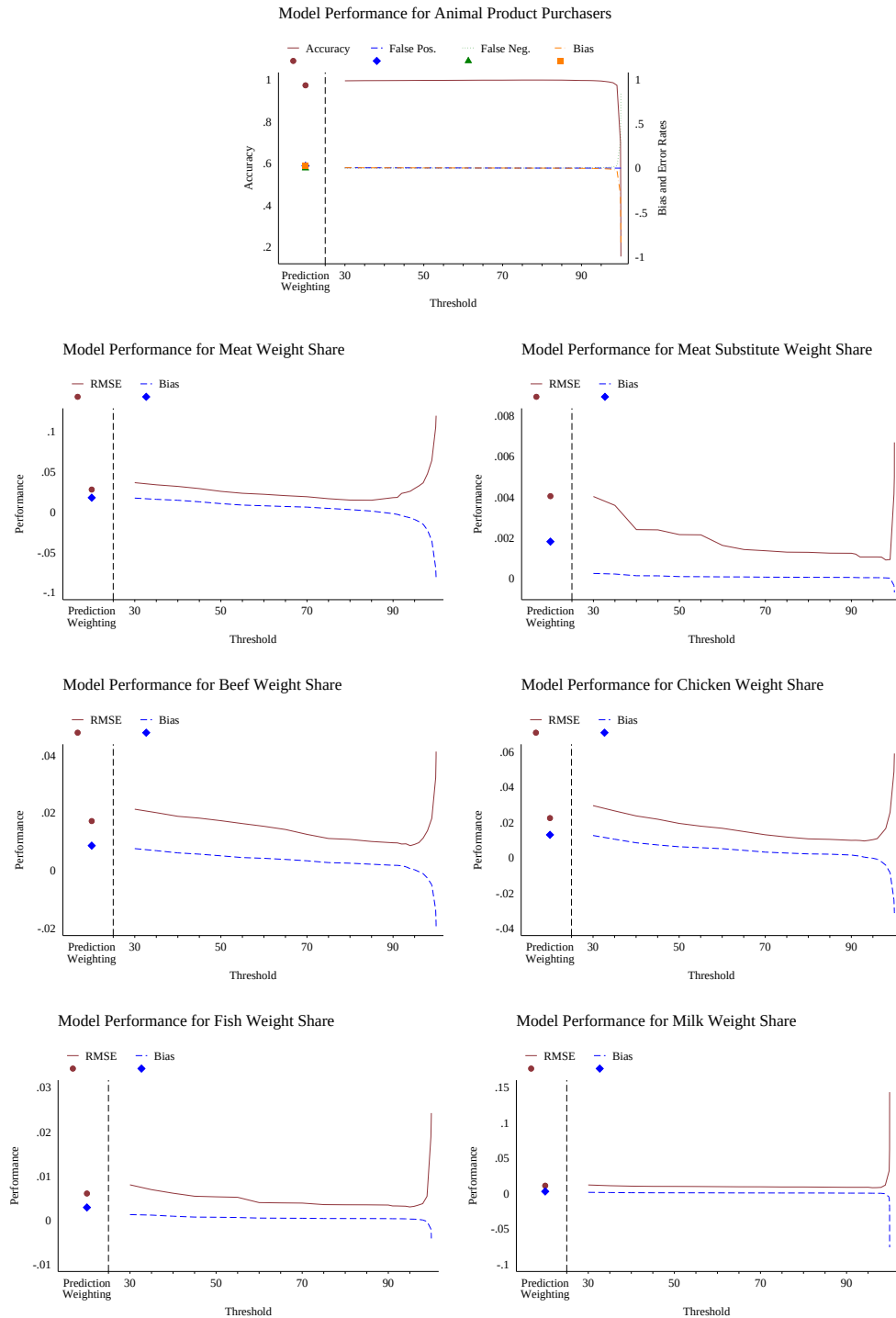
Notes: The left panel plots 12-month moving averages of average prices per ounce for meat, meat alternatives, milk, and milk alternatives. The right panel plots the same series normalized to their January 2005 values.

Figure C.6: Classifier diagnostics for monthly meat-purchaser identification



Notes: Diagnostics are computed on a random 0.1% subsample of household-month observations with Label Insight coverage. The dots to the left of the dashed vertical line show the prediction-weighting benchmark, while the lines to the right show hard-threshold alternatives. Accuracy is plotted on the left y -axis. False-positive and false-negative rates, and bias in the predicted share of meat purchasers, are plotted on the right y -axis.

Figure C.7: Additional classifier diagnostics for animal-product purchasers and category shares



Notes: These panels extend the same diagnostics to animal-product purchasers (top panel) and to category weight shares (remaining panels). The dots to the left of the dashed vertical line show the prediction-weighting benchmark, while the lines to the right show hard-threshold alternatives. The top panel reports purchaser-level accuracy, false-positive and false-negative rates, and bias. The remaining panels report root mean squared error and bias for each category's weight share.

C.8 Appendix Tables

B.8.1 Household Characteristics

Meat Purchases

Table C.2: Top-decile meat share — household & location characteristics by year

	All years	2004	2012	2019	2020
Household size	2.13	2.13	2.13	2.14	2.14
Income per capita	40,554	34,633	40,219	49,279	51,666
No college	30.9	30.8	31.8	28.3	27.2
Some college	33.5	36.7	32.9	31.6	32.1
College grad	24.2	22.5	24.9	26.6	26.8
Post-grad	11.4	9.9	10.5	13.5	14.0
Avg age of HH heads	54.33	54.14	53.93	55.05	55.76
Age < 35	11.7	10.2	12.2	11.9	10.7
Age 35-49	25.9	30.2	24.8	23.9	23.7
Age 50-64	35.9	33.8	38.9	34.4	33.4
Age 65+	25.8	25.1	23.3	29.0	31.4
Female HH head	31.9	30.9	32.0	33.2	32.0
Male HH head	33.1	32.5	34.4	30.3	31.3
Married HH heads	35.0	36.6	33.6	36.5	36.6
White	70.7	75.3	70.4	68.0	67.0
Black	14.4	14.0	14.6	13.6	14.3
Asian	3.2	1.6	2.9	4.4	4.9
Hispanic	9.0	7.3	9.5	10.7	10.5
Other	2.7	1.8	2.5	3.2	3.3
County Dem. vote share	50.5	48.5	51.0	50.7	51.2
RUCA (higher=rural)	2.02	2.09	2.01	1.95	1.99
Low access pop. (2015)	22.78	22.49	22.68	22.89	22.90
Ounces bought (Avg)	1837.20	2059.91	1841.21	1597.24	1788.84
Ounces meat (Avg)	364.70	379.86	370.65	339.22	373.78
Ounces milk (Avg)	156.52	195.49	157.41	116.36	126.29
Ounces animal products (Avg)	549.86	608.71	551.87	484.30	536.11
Bought PBMA	2.0	2.1	2.0	2.4	2.9
Bought plant-based milk	7.5	3.3	7.5	11.6	12.2
Ounces meat substitutes (Avg)	0.60	0.63	0.55	0.60	0.79
Ounces plant-based milk (Avg)	10.95	6.99	10.46	15.24	17.46

Notes: Characteristics of households in the Nielsen Homescan panel based on purchasing behavior. All entries are in percent unless otherwise indicated. RUCA is the Rural–Urban Commuting Area code (1-10, higher is more rural). County Democratic vote share is linearly interpolated for non-election years. Low access population is the percent of the population in a census tract that is low access to a supermarket, as measured in 2015.

Table C.3: Bottom-decile meat share — household & location characteristics by year

	All years	2004	2012	2019	2020
Household size	1.92	1.97	1.93	1.88	1.92
Income per capita	48,891	40,686	48,401	58,985	60,585
No college	26.2	26.6	26.9	23.4	23.8
Some college	28.9	31.4	29.0	27.6	27.1
College grad	27.4	25.5	26.9	29.0	28.4
Post-grad	17.6	16.5	17.2	20.1	20.7
Avg age of HH heads	54.36	54.40	53.90	54.75	54.20
Age < 35	12.3	10.6	13.2	13.0	13.4
Age 35-49	24.3	27.7	23.1	22.9	24.4
Age 50-64	36.6	34.7	39.3	33.8	33.3
Age 65+	26.1	26.3	23.5	29.4	28.2
Female HH head	35.0	32.9	34.9	36.6	36.5
Male HH head	32.1	31.1	32.1	32.1	31.3
Married HH heads	32.9	36.0	32.9	31.3	32.2
White	74.0	80.4	74.0	69.0	67.7
Black	8.7	7.9	8.7	9.6	9.5
Asian	4.1	1.9	3.8	6.1	6.7
Hispanic	10.3	7.9	10.2	12.0	12.4
Other	3.0	2.0	3.2	3.4	3.7
County Dem. vote share	52.8	50.6	52.8	53.5	54.2
RUCA (higher=rural)	1.97	2.05	1.99	1.85	1.87
Low access pop. (2015)	21.27	20.87	21.47	21.35	21.48
Ounces bought (Avg)	2097.01	2308.32	2111.07	1794.12	1961.25
Ounces meat (Avg)	6.46	8.85	6.50	3.34	4.38
Ounces milk (Avg)	216.08	278.67	216.94	149.17	162.98
Ounces animal products (Avg)	354.98	430.91	358.65	261.96	289.60
Bought PBMA	7.1	5.4	6.6	10.1	10.4
Bought plant-based milk	11.6	5.7	11.5	17.5	17.0
Ounces meat substitutes (Avg)	3.72	2.80	3.51	5.84	6.26
Ounces plant-based milk (Avg)	24.07	13.83	26.17	33.09	34.58

Notes: Characteristics of households in the Nielsen Homescan panel based on purchasing behavior. All entries are in percent unless otherwise indicated. RUCA is the Rural–Urban Commuting Area code (1-10, higher is more rural). County Democratic vote share is linearly interpolated for non-election years. Low access population is the percent of the population in a census tract that is low access to a supermarket, as measured in 2015.

Table C.4: No-meat consumers — household & location characteristics by year

	All years	2004	2012	2019	2020
Household size	1.71	1.67	1.72	1.75	1.77
Income per capita	52,261	43,599	51,544	61,075	63,026
No college	24.6	25.0	25.5	22.3	22.7
Some college	27.9	30.8	28.1	26.7	26.0
College grad	28.4	26.2	27.7	29.7	29.2
Post-grad	19.2	18.0	18.7	21.3	22.1
Avg age of HH heads	54.66	55.29	54.10	54.63	54.11
Age < 35	13.1	10.0	14.0	14.1	14.7
Age 35-49	22.7	25.5	22.1	22.3	23.8
Age 50-64	36.3	35.5	38.6	33.0	32.1
Age 65+	27.4	28.5	24.6	30.0	28.9
Female HH head	36.7	35.2	36.5	37.9	37.8
Male HH head	36.8	38.6	37.1	34.6	34.2
Married HH heads	26.5	26.2	26.4	27.5	27.9
White	73.3	80.4	73.4	68.7	67.1
Black	9.0	8.4	9.0	9.6	9.7
Asian	5.0	2.3	4.7	7.0	7.8
Hispanic	9.5	6.9	9.6	11.3	11.7
Other	3.1	2.0	3.3	3.4	3.8
County Dem. vote share	53.8	51.5	53.8	54.3	55.1
RUCA (higher=rural)	1.89	1.98	1.91	1.78	1.79
Low access pop. (2015)	20.92	20.46	21.07	21.02	21.17
Ounces bought (Avg)	1518.49	1631.28	1547.59	1401.32	1485.70
Ounces meat (Avg)	0.00	0.00	0.00	0.00	0.00
Ounces milk (Avg)	162.91	207.12	167.52	122.44	130.70
Ounces animal products (Avg)	267.85	317.56	275.40	214.13	230.17
Bought PBMA	7.9	6.0	7.5	10.5	10.9
Bought plant-based milk	12.2	6.1	11.9	17.0	16.6
Ounces meat substitutes (Avg)	4.19	3.32	4.02	5.99	6.61
Ounces plant-based milk (Avg)	24.94	14.64	26.56	31.99	33.33

Notes: Characteristics of households in the Nielsen Homescan panel based on purchasing behavior. All entries are in percent unless otherwise indicated. RUCA is the Rural–Urban Commuting Area code (1-10, higher is more rural). County Democratic vote share is linearly interpolated for non-election years. Low access population is the percent of the population in a census tract that is low access to a supermarket, as measured in 2015.

Animal-Product Purchases

Table C.5: Top-decile animal-product share — household & location characteristics by year

	All years	2004	2012	2019	2020
Household size	2.24	2.26	2.26	2.27	2.28
Income per capita	42,518	34,735	42,175	52,132	55,038
No college	28.4	29.7	28.3	26.1	24.8
Some college	31.2	34.5	31.0	29.3	29.8
College grad	26.0	23.4	26.6	27.1	28.0
Post-grad	14.4	12.4	14.1	17.5	17.4
Avg age of HH heads	54.83	55.11	54.40	55.13	55.70
Age < 35	13.0	12.1	13.8	12.2	12.1
Age 35-49	25.2	28.4	23.8	25.3	24.5
Age 50-64	31.7	27.1	34.7	30.5	29.4
Age 65+	29.3	31.6	26.9	31.4	33.1
Female HH head	27.3	26.8	27.6	27.3	26.0
Male HH head	31.4	29.6	32.0	29.7	30.0
Married HH heads	41.3	43.6	40.4	43.0	44.0
White	80.7	84.9	80.9	77.5	77.5
Black	4.7	4.3	4.8	4.7	4.7
Asian	3.2	1.5	2.9	4.5	5.1
Hispanic	9.1	7.6	9.1	10.6	10.1
Other	2.3	1.7	2.2	2.7	2.6
County Dem. vote share	50.0	48.3	50.3	49.9	50.8
RUCA (higher=rural)	2.09	2.13	2.13	2.04	2.03
Low access pop. (2015)	22.84	22.59	22.86	22.89	23.02
Ounces bought (Avg)	1975.14	2202.70	1978.11	1766.48	1937.72
Ounces meat (Avg)	171.29	173.74	171.11	170.35	182.41
Ounces milk (Avg)	590.37	685.38	599.25	492.78	524.86
Ounces animal products (Avg)	979.94	1081.65	986.14	874.35	956.52
Bought PBMA	1.9	1.8	1.9	2.2	2.8
Bought plant-based milk	4.4	1.9	4.2	7.3	7.3
Ounces meat substitutes (Avg)	0.56	0.57	0.54	0.59	0.75
Ounces plant-based milk (Avg)	5.81	3.23	5.35	8.62	10.29

Notes: Characteristics of households in the Nielsen Homescan panel based on purchasing behavior. All entries are in percent unless otherwise indicated. RUCA is the Rural–Urban Commuting Area code (1-10, higher is more rural). County Democratic vote share is linearly interpolated for non-election years. Low access population is the percent of the population in a census tract that is low access to a supermarket, as measured in 2015.

Table C.6: Bottom-decile animal-product share — household & location characteristics by year

	All years	2004	2012	2019	2020
Household size	1.96	2.00	1.98	1.93	1.95
Income per capita	45,914	39,156	45,545	55,298	56,167
No college	27.8	27.2	28.7	25.6	25.5
Some college	31.6	34.2	31.8	30.2	30.0
College grad	26.5	24.4	25.7	28.1	28.1
Post-grad	14.1	14.1	13.8	16.0	16.5
Avg age of HH heads	53.56	52.77	53.31	54.44	53.96
Age < 35	10.8	9.2	11.2	11.8	12.0
Age 35-49	26.5	31.3	25.3	23.6	24.7
Age 50-64	40.3	39.7	42.7	36.9	37.4
Age 65+	21.6	18.8	19.9	26.8	25.1
Female HH head	36.7	35.0	35.9	39.1	39.8
Male HH head	31.6	30.4	31.6	30.5	30.1
Married HH heads	31.7	34.6	32.6	30.5	30.1
White	64.7	70.3	65.1	61.0	59.3
Black	16.8	16.3	17.0	17.6	17.9
Asian	3.6	1.9	3.2	4.9	5.0
Hispanic	11.4	8.8	10.9	12.7	13.8
Other	3.5	2.6	3.8	3.8	4.1
County Dem. vote share	52.7	50.8	52.7	53.4	53.8
RUCA (higher=rural)	1.96	2.01	2.02	1.85	1.86
Low access pop. (2015)	21.35	20.83	21.42	21.76	21.90
Ounces bought (Avg)	2752.89	2903.54	2763.44	2398.11	2630.34
Ounces meat (Avg)	85.87	97.20	87.27	64.80	72.80
Ounces milk (Avg)	32.87	48.92	31.88	16.21	17.97
Ounces animal products (Avg)	137.41	171.27	139.58	91.59	102.56
Bought PBMA	6.6	4.9	6.0	10.6	10.5
Bought plant-based milk	15.9	8.0	16.3	23.3	22.5
Ounces meat substitutes (Avg)	3.37	2.48	2.82	5.77	6.16
Ounces plant-based milk (Avg)	35.75	22.10	39.19	46.33	49.46

Notes: Characteristics of households in the Nielsen Homescan panel based on purchasing behavior. All entries are in percent unless otherwise indicated. RUCA is the Rural–Urban Commuting Area code (1-10, higher is more rural). County Democratic vote share is linearly interpolated for non-election years. Low access population is the percent of the population in a census tract that is low access to a supermarket, as measured in 2015.

Table C.7: No-animal-product consumers — household & location characteristics by year

	All years	2004	2012	2019	2020
Household size	1.48	1.43	1.48	1.57	1.57
Income per capita	57,177	50,783	55,632	64,278	62,660
No college	22.0	20.2	23.1	20.2	23.1
Some college	27.4	30.6	27.4	28.4	25.5
College grad	31.8	27.0	30.9	33.9	31.1
Post-grad	18.8	22.2	18.6	17.5	20.2
Avg age of HH heads	52.50	53.36	52.08	52.46	51.99
Age < 35	15.3	11.3	15.0	16.8	17.9
Age 35-49	24.9	25.5	26.3	24.5	24.9
Age 50-64	37.8	40.9	39.0	34.0	32.8
Age 65+	21.5	22.2	19.0	24.3	24.0
Female HH head	36.9	33.1	34.2	39.2	40.4
Male HH head	46.7	52.4	47.8	42.4	41.7
Married HH heads	16.4	14.5	18.0	18.4	17.9
White	63.8	69.2	64.1	60.9	59.5
Black	15.3	17.0	14.9	15.7	15.4
Asian	6.1	3.9	5.8	7.3	6.7
Hispanic	10.4	7.3	9.9	12.0	13.1
Other	4.5	2.6	5.2	4.1	5.3
County Dem. vote share	56.0	53.6	56.0	56.4	56.9
RUCA (higher=rural)	1.72	1.81	1.71	1.70	1.73
Low access pop. (2015)	19.84	19.46	19.57	20.29	20.51
Ounces bought (Avg)	1157.40	1228.37	1194.81	1124.55	1163.38
Ounces meat (Avg)	16.07	19.04	15.99	13.25	15.39
Ounces milk (Avg)	0.02	0.12	0.01	0.02	0.01
Ounces animal products (Avg)	0.00	0.00	0.00	0.00	0.00
Bought PBMA	11.1	7.5	10.5	14.7	12.9
Bought plant-based milk	17.5	10.2	17.9	21.5	18.9
Ounces meat substitutes (Avg)	5.99	5.09	5.19	7.28	7.92
Ounces plant-based milk (Avg)	42.03	25.67	48.82	46.06	41.82

Notes: Characteristics of households in the Nielsen Homescan panel based on purchasing behavior. All entries are in percent unless otherwise indicated. RUCA is the Rural–Urban Commuting Area code (1-10, higher is more rural). County Democratic vote share is linearly interpolated for non-election years. Low access population is the percent of the population in a census tract that is low access to a supermarket, as measured in 2015.

Milk Purchases

Table C.8: Top-decile milk share — household & location characteristics by year

	All years	2004	2012	2019	2020
Household size	2.42	2.43	2.44	2.44	2.45
Income per capita	42,819	35,190	42,375	51,654	54,494
No college	27.9	29.1	27.4	26.3	25.1
Some college	30.3	34.2	30.8	28.6	29.1
College grad	26.7	23.5	26.8	26.9	27.7
Post-grad	15.2	13.2	15.0	18.2	18.1
Avg age of HH heads	53.79	54.11	53.53	54.53	54.80
Age < 35	14.0	13.5	14.7	13.0	12.7
Age 35-49	27.6	30.9	25.8	26.6	26.5
Age 50-64	30.4	25.1	33.6	29.3	28.6
Age 65+	27.1	29.8	25.0	30.4	31.1
Female HH head	25.1	24.5	25.5	25.1	24.1
Male HH head	28.7	27.8	28.8	28.1	28.3
Married HH heads	46.2	47.7	45.7	46.8	47.6
White	80.1	84.8	80.4	77.0	76.1
Black	3.5	3.2	3.7	3.8	3.7
Asian	3.6	1.6	3.4	5.1	6.1
Hispanic	10.5	8.8	10.3	11.4	11.5
Other	2.2	1.6	2.1	2.7	2.5
County Dem. vote share	49.8	48.3	50.0	49.5	50.5
RUCA (higher=rural)	2.07	2.11	2.14	2.05	2.03
Low access pop. (2015)	22.80	22.37	22.90	23.00	23.01
Ounces bought (Avg)	2350.52	2552.99	2362.73	2126.90	2327.12
Ounces meat (Avg)	136.86	137.29	138.33	132.80	143.94
Ounces milk (Avg)	773.24	869.92	782.10	664.47	713.52
Ounces animal products (Avg)	1043.33	1139.41	1056.40	926.21	1001.68
Bought PBMA	2.1	1.9	2.0	2.5	3.3
Bought plant-based milk	4.9	2.1	4.5	7.9	8.1
Ounces meat substitutes (Avg)	0.68	0.65	0.61	0.76	1.12
Ounces plant-based milk (Avg)	7.34	4.08	6.52	10.73	13.44

Notes: Characteristics of households in the Nielsen Homescan panel based on purchasing behavior. All entries are in percent unless otherwise indicated. RUCA is the Rural–Urban Commuting Area code (1-10, higher is more rural). County Democratic vote share is linearly interpolated for non-election years. Low access population is the percent of the population in a census tract that is low access to a supermarket, as measured in 2015.

Table C.9: Bottom-decile milk share — household & location characteristics by year

	All years	2004	2012	2019	2020
Household size	1.91	1.84	1.92	1.95	1.98
Income per capita	46,532	38,851	44,825	54,691	56,502
No college	27.0	26.7	28.0	25.1	24.4
Some college	32.0	34.5	32.3	30.3	30.4
College grad	26.4	24.9	26.0	27.7	28.2
Post-grad	14.6	13.8	13.7	17.0	17.0
Avg age of HH heads	54.26	54.01	53.71	54.70	54.76
Age < 35	11.5	9.5	12.3	12.1	11.7
Age 35-49	24.5	28.4	24.1	23.5	24.0
Age 50-64	38.4	38.7	40.3	35.5	35.6
Age 65+	24.9	22.7	22.5	28.2	28.0
Female HH head	36.6	36.1	35.5	37.9	37.5
Male HH head	33.2	35.3	34.3	29.8	29.5
Married HH heads	30.2	28.6	30.2	32.3	33.0
White	68.1	73.8	68.6	66.2	64.6
Black	15.0	14.9	15.2	14.7	14.9
Asian	3.5	1.7	3.1	4.3	4.7
Hispanic	10.1	7.3	9.9	11.3	12.1
Other	3.2	2.4	3.2	3.6	3.7
County Dem. vote share	52.3	50.4	52.6	52.5	53.0
RUCA (higher=rural)	1.95	2.02	1.97	1.90	1.88
Low access pop. (2015)	21.82	20.97	21.92	22.11	22.32
Ounces bought (Avg)	1822.51	1873.51	1848.41	1723.26	1885.66
Ounces meat (Avg)	133.17	136.46	135.57	124.97	136.62
Ounces milk (Avg)	0.00	0.00	0.00	0.00	0.00
Ounces animal products (Avg)	223.12	226.99	227.72	209.92	230.95
Bought PBMA	5.3	4.2	5.0	7.0	7.6
Bought plant-based milk	16.8	7.5	15.6	22.0	22.2
Ounces meat substitutes (Avg)	2.29	2.00	2.09	3.09	3.59
Ounces plant-based milk (Avg)	32.96	19.35	31.69	38.67	42.77

Notes: Characteristics of households in the Nielsen Homescan panel based on purchasing behavior. All entries are in percent unless otherwise indicated. RUCA is the Rural–Urban Commuting Area code (1-10, higher is more rural). County Democratic vote share is linearly interpolated for non-election years. Low access population is the percent of the population in a census tract that is low access to a supermarket, as measured in 2015.

Table C.10: No-milk consumers — household & location characteristics by year

	All years	2004	2012	2019	2020
Household size	1.91	1.84	1.92	1.95	1.98
Income per capita	46,533	38,850	44,825	54,693	56,501
No college	27.0	26.7	28.0	25.1	24.4
Some college	32.0	34.5	32.3	30.3	30.4
College grad	26.4	24.9	26.0	27.7	28.2
Post-grad	14.6	13.8	13.7	17.0	17.0
Avg age of HH heads	54.26	54.01	53.71	54.70	54.76
Age < 35	11.5	9.5	12.3	12.1	11.7
Age 35-49	24.5	28.4	24.1	23.5	24.0
Age 50-64	38.4	38.7	40.3	35.5	35.6
Age 65+	24.9	22.7	22.5	28.2	28.0
Female HH head	36.6	36.1	35.5	37.9	37.5
Male HH head	33.2	35.3	34.3	29.8	29.5
Married HH heads	30.2	28.6	30.2	32.3	33.0
White	68.1	73.8	68.6	66.2	64.6
Black	15.0	14.9	15.2	14.7	14.9
Asian	3.5	1.7	3.1	4.3	4.7
Hispanic	10.1	7.3	9.9	11.3	12.1
Other	3.2	2.4	3.2	3.6	3.7
County Dem. vote share	52.3	50.4	52.6	52.5	53.0
RUCA (higher=rural)	1.95	2.02	1.97	1.90	1.88
Low access pop. (2015)	21.82	20.97	21.92	22.11	22.32
Ounces bought (Avg)	1822.34	1873.34	1848.35	1723.17	1885.60
Ounces meat (Avg)	133.16	136.45	135.56	124.97	136.62
Ounces milk (Avg)	0.00	0.00	0.00	0.00	0.00
Ounces animal products (Avg)	223.10	226.97	227.71	209.91	230.94
Bought PBMA	5.3	4.2	5.0	7.0	7.6
Bought plant-based milk	16.8	7.5	15.6	22.0	22.2
Ounces meat substitutes (Avg)	2.29	2.00	2.09	3.09	3.59
Ounces plant-based milk (Avg)	32.96	19.35	31.69	38.67	42.77

Notes: Characteristics of households in the Nielsen Homescan panel based on purchasing behavior. All entries are in percent unless otherwise indicated. RUCA is the Rural–Urban Commuting Area code (1-10, higher is more rural). County Democratic vote share is linearly interpolated for non-election years. Low access population is the percent of the population in a census tract that is low access to a supermarket, as measured in 2015.

Plant-Based Alternative Purchases

Table C.11: PBM adopters (any PBM) — household & location characteristics by year

	All years	2004	2012	2019	2020
Household size	2.50	2.44	2.46	2.51	2.52
Income per capita	48,037	40,760	45,747	55,450	57,397
No college	18.5	18.2	20.8	17.4	16.4
Some college	28.3	29.7	28.3	28.1	27.9
College grad	32.3	31.6	31.3	31.9	32.9
Post-grad	20.9	20.5	19.6	22.7	22.9
Avg age of HH heads	49.74	49.89	49.88	50.27	50.66
Age < 35	17.7	16.9	18.4	16.5	14.9
Age 35-49	32.8	33.2	30.8	33.3	33.6
Age 50-64	32.0	32.5	33.5	30.8	32.0
Age 65+	16.6	16.5	16.4	18.4	18.5
Female HH head	29.9	27.5	31.0	31.0	30.5
Male HH head	23.9	21.9	24.5	23.2	22.3
Married HH heads	46.2	50.7	44.6	45.8	47.3
White	70.7	82.1	70.4	65.2	63.0
Black	9.4	6.3	10.1	12.3	13.5
Asian	3.0	1.5	2.4	3.6	4.6
Hispanic	13.5	7.9	13.9	14.8	14.9
Other	3.5	2.2	3.1	4.1	4.0
County Dem. vote share	53.9	50.9	54.1	55.1	55.7
RUCA (higher=rural)	1.67	1.94	1.66	1.62	1.64
Low access pop. (2015)	22.00	21.20	21.71	22.20	22.20
Ounces bought (Avg)	2880.60	3096.00	2968.71	2577.95	2881.55
Ounces meat (Avg)	151.83	167.24	160.03	133.22	157.35
Ounces milk (Avg)	233.35	305.82	245.94	160.08	185.15
Ounces animal products (Avg)	535.69	630.97	569.22	416.73	488.98
Bought PBMA	100.0	100.0	100.0	100.0	100.0
Bought plant-based milk	31.5	15.9	30.1	41.6	41.4
Ounces meat substitutes (Avg)	36.01	34.42	35.18	38.66	40.46
Ounces plant-based milk (Avg)	66.13	39.62	65.49	80.14	86.60

Notes: Characteristics of households in the Nielsen Homescan panel based on purchasing behavior. All entries are in percent unless otherwise indicated. RUCA is the Rural–Urban Commuting Area code (1-10, higher is more rural). County Democratic vote share is linearly interpolated for non-election years. Low access population is the percent of the population in a census tract that is low access to a supermarket, as measured in 2015.

Table C.12: Plant-based milk adopters — household & location characteristics by year

	All years	2004	2012	2019	2020
Household size	2.60	2.50	2.59	2.64	2.67
Income per capita	47,041	38,552	42,951	52,931	56,152
No college	21.2	19.7	23.2	20.4	18.9
Some college	31.3	33.5	31.7	30.1	30.2
College grad	29.9	28.0	29.5	30.6	31.7
Post-grad	17.6	18.7	15.6	18.9	19.2
Avg age of HH heads	50.95	52.17	50.67	50.91	51.08
Age < 35	15.8	13.8	17.1	16.2	14.8
Age 35-49	31.1	30.6	30.0	31.8	32.3
Age 50-64	33.3	33.5	34.2	31.1	32.5
Age 65+	18.8	21.1	17.6	19.9	19.3
Female HH head	29.6	29.5	29.7	29.4	29.6
Male HH head	19.5	20.0	19.5	18.5	17.3
Married HH heads	50.8	50.5	50.8	52.0	53.1
White	63.8	68.9	63.5	63.5	61.7
Black	13.0	13.6	13.8	11.9	12.6
Asian	4.3	2.6	4.2	4.9	5.5
Hispanic	15.4	12.4	14.9	16.1	16.7
Other	3.5	2.5	3.6	3.6	3.6
County Dem. vote share	51.8	50.8	51.9	51.7	52.7
RUCA (higher=rural)	1.81	1.83	1.84	1.83	1.80
Low access pop. (2015)	22.58	21.44	22.70	22.93	22.89
Ounces bought (Avg)	2856.84	2931.07	2928.88	2717.31	3026.26
Ounces meat (Avg)	180.10	172.71	185.08	175.04	199.51
Ounces milk (Avg)	204.55	254.85	221.76	171.58	186.65
Ounces animal products (Avg)	530.71	566.34	555.70	486.35	540.36
Bought PBMA	10.8	11.6	10.6	12.2	13.5
Bought plant-based milk	100.0	100.0	100.0	100.0	100.0
Ounces meat substitutes (Avg)	4.75	5.24	4.53	5.49	6.45
Ounces plant-based milk (Avg)	154.22	159.98	158.35	148.08	156.73

Notes: Characteristics of households in the Nielsen Homescan panel based on purchasing behavior. All entries are in percent unless otherwise indicated. RUCA is the Rural–Urban Commuting Area code (1-10, higher is more rural). County Democratic vote share is linearly interpolated for non-election years. Low access population is the percent of the population in a census tract that is low access to a supermarket, as measured in 2015.

Table C.13: Meat — share (OLS stepwise + IV; w=PF; clustered by DMA)

	(1) Meat share (by weight)	(2) Meat share (by weight)	(3) Meat share (by weight)
2005	0.0008** (0.0003)	0.0007** (0.0003)	0.0005 (0.0004)
2006	0.0016*** (0.0004)	0.0009** (0.0004)	0.0018*** (0.0004)
2007	0.0020*** (0.0005)	0.0012** (0.0005)	0.0021*** (0.0004)
2008	0.0018** (0.0007)	0.0012* (0.0006)	0.0019*** (0.0006)
2009	0.0034*** (0.0006)	0.0022*** (0.0006)	0.0043*** (0.0006)
2010	0.0038*** (0.0007)	0.0023*** (0.0005)	0.0051*** (0.0007)
2011	0.0047*** (0.0008)	0.0032*** (0.0006)	0.0065*** (0.0009)
2012	0.0057*** (0.0010)	0.0036*** (0.0007)	0.0084*** (0.0011)
2013	0.0075*** (0.0011)	0.0048*** (0.0007)	0.0113*** (0.0014)
2014	0.0091*** (0.0012)	0.0059*** (0.0007)	0.0133*** (0.0015)
2015	0.0098*** (0.0015)	0.0061*** (0.0008)	0.0148*** (0.0018)
2016	0.0095*** (0.0015)	0.0055*** (0.0008)	0.0153*** (0.0021)
2017	0.0098*** (0.0020)	0.0050*** (0.0009)	0.0166*** (0.0025)
2018	0.0115*** (0.0021)	0.0059*** (0.0010)	0.0191*** (0.0028)
2019	0.0134*** (0.0022)	0.0073*** (0.0011)	0.0216*** (0.0029)
2020	0.0134*** (0.0026)	0.0070*** (0.0011)	0.0216*** (0.0028)
Month 2	-0.0008 (0.0007)	-0.0018*** (0.0002)	0.0003 (0.0006)
Month 3	-0.0042*** (0.0011)	-0.0053*** (0.0004)	-0.0035*** (0.0007)
Month 4	-0.0074*** (0.0014)	-0.0085*** (0.0005)	-0.0071*** (0.0009)
Month 5	-0.0074*** (0.0014)	-0.0076*** (0.0007)	-0.0092*** (0.0014)
Month 6	-0.0074*** (0.0016)	-0.0079*** (0.0007)	-0.0092*** (0.0014)
Month 7	-0.0073*** (0.0017)	-0.0078*** (0.0008)	-0.0094*** (0.0014)
Month 8	-0.0057*** (0.0016)	-0.0064*** (0.0007)	-0.0071*** (0.0012)

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	(1) Meat share (by weight)	(2) Meat share (by weight)	(3) Meat share (by weight)
Month 9	-0.0037*** (0.0010)	-0.0042*** (0.0004)	-0.0042*** (0.0009)
Month 10	-0.0025*** (0.0005)	-0.0030*** (0.0002)	-0.0018*** (0.0005)
Month 11	-0.0075*** (0.0004)	-0.0074*** (0.0003)	-0.0069*** (0.0005)
Month 12	-0.0063*** (0.0013)	-0.0083*** (0.0005)	-0.0031*** (0.0012)
lnp_meat	-0.0611*** (0.0145)	-0.0418*** (0.0050)	-0.0711*** (0.0062)
lnp_nonmeat	0.0211* (0.0112)	0.0402*** (0.0065)	-0.0280 (0.0175)
HH_Size	-0.0007*** (0.0001)	-0.0007*** (0.0001)	-0.0006*** (0.0001)
HH_Inc_10k	-0.0004*** (0.0001)	-0.0004*** (0.0000)	-0.0004*** (0.0001)
Some College	-0.0000 (0.0005)	-0.0004 (0.0005)	-0.0004 (0.0005)
Graduated College	-0.0028*** (0.0005)	-0.0030*** (0.0005)	-0.0030*** (0.0005)
Post-Graduate Studies	-0.0063*** (0.0006)	-0.0063*** (0.0006)	-0.0064*** (0.0006)
Black	0.0136*** (0.0010)	0.0141*** (0.0008)	0.0134*** (0.0009)
Asian	0.0072*** (0.0020)	0.0068*** (0.0018)	0.0077*** (0.0022)
Hispanic	-0.0008 (0.0007)	-0.0018** (0.0008)	-0.0008 (0.0009)
Other	0.0010 (0.0010)	0.0011 (0.0010)	0.0016 (0.0010)
avg_age	-0.0000 (0.0000)	-0.0000 (0.0000)	0.0000 (0.0000)
Female	0.0016*** (0.0003)	0.0017*** (0.0004)	0.0018*** (0.0004)
Male	0.0099*** (0.0006)	0.0100*** (0.0006)	0.0099*** (0.0006)
Pres Democratic vote share (observed or linear interp.)		0.0053* (0.0029)	0.0182** (0.0074)
ruca_num		-0.0005*** (0.0002)	-0.0003 (0.0002)
Child poverty rate, 2021		-0.0001 (0.0003)	-0.0000 (0.0003)
Deep child poverty rate, 2021		-0.0002	-0.0005

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	(1) Meat share (by weight)	(2) Meat share (by weight)	(3) Meat share (by weight)
Deep poverty rate, 2021		(0.0003) -0.0001	(0.0004) -0.0003
Poverty rate, 2021		(0.0005) 0.0006	(0.0006) 0.0001
Population, low ac- cess to store (pct), 2015		(0.0004) 0.0001	(0.0005) 0.0002
Population, low ac- cess to store (pct), 2019		(0.0001) -0.0002*	(0.0001) -0.0002*
Convenience stores/1,000 pop, 2016		(0.0001) 0.0063	(0.0001) 0.0134
Convenience stores/1,000 pop, 2020		(0.0091) -0.0115	(0.0117) -0.0200
Farmers' mar- kets/1,000 pop, 2013		(0.0104) -0.0330	(0.0128) 0.0624
Farmers' mar- kets/1,000 pop, 2018		(0.0569) -0.0448	(0.0866) -0.1176
Grocery stores/1,000 pop, 2016		(0.0558) -0.0087	(0.0844) -0.0256
Grocery stores/1,000 pop, 2020		(0.0135) -0.0066	(0.0196) 0.0228
Specialized food stores/1,000 pop, 2016		(0.0170) -0.0116	(0.0250) 0.0190
Specialized food stores/1,000 pop, 2020		(0.0276) -0.0544**	(0.0320) -0.0645**
Supercenters and club stores/1,000 pop, 2016		(0.0248) 0.2664***	(0.0296) 0.1061

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	(1) Meat share (by weight)	(2) Meat share (by weight)	(3) Meat share (by weight)
Supercenters and club stores/1,000 pop, 2020		(0.0593) -0.0193	(0.0962) -0.0586
Constant	0.0322 (0.0337)	(0.0378) 0.1103*** (0.0127)	(0.0532) -0.0963** (0.0447)
Observations	7760288	7760288	7760288
R^2	0.019	0.024	0.019
AIC	-2.02e+07	-2.02e+07	-2.02e+07
BIC	-2.02e+07	-2.02e+07	-2.02e+07
KP rk F			.
KP rk LM			30.3498
Hansen J			0.0000
Hansen J p			.

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.14: Meat — share (Fractional logit stepwise)

	(1) Meat share (by weight)	(2) Meat share (by weight)
2005	0.0127* (0.0052)	0.0114* (0.0052)
2006	0.0242*** (0.0060)	0.0134* (0.0057)
2007	0.0314*** (0.0079)	0.0190** (0.0073)
2008	0.0291** (0.0107)	0.0186 (0.0096)
2009	0.0526*** (0.0099)	0.0338*** (0.0086)
2010	0.0573*** (0.0115)	0.0353*** (0.0082)
2011	0.0713*** (0.0123)	0.0482*** (0.0093)
2012	0.0858*** (0.0156)	0.0547*** (0.0098)
2013	0.1137*** (0.0183)	0.0727*** (0.0107)
2014	0.1361*** (0.0205)	0.0894*** (0.0103)
2015	0.1460*** (0.0240)	0.0925*** (0.0114)
2016	0.1420*** (0.0244)	0.0834*** (0.0119)

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	(1) Meat share (by weight)	(2) Meat share (by weight)
2017	0.1475*** (0.0313)	0.0756*** (0.0137)
2018	0.1717*** (0.0343)	0.0897*** (0.0151)
2019	0.1991*** (0.0362)	0.1098*** (0.0159)
2020	0.1992*** (0.0415)	0.1045*** (0.0172)
Month 2	-0.0096 (0.0102)	-0.0235*** (0.0029)
Month 3	-0.0571*** (0.0150)	-0.0731*** (0.0048)
Month 4	-0.1050*** (0.0186)	-0.1210*** (0.0066)
Month 5	-0.1058*** (0.0201)	-0.1077*** (0.0092)
Month 6	-0.1066*** (0.0229)	-0.1122*** (0.0105)
Month 7	-0.1062*** (0.0242)	-0.1116*** (0.0113)
Month 8	-0.0796*** (0.0222)	-0.0888*** (0.0095)
Month 9	-0.0489*** (0.0136)	-0.0556*** (0.0057)
Month 10	-0.0342*** (0.0061)	-0.0412*** (0.0029)
Month 11	-0.1070*** (0.0060)	-0.1048*** (0.0036)
Month 12	-0.0881*** (0.0175)	-0.1174*** (0.0060)
lnp_meat	-0.9025*** (0.2268)	-0.6349*** (0.0754)
lnp_nonmeat	0.3085 (0.1623)	0.6025*** (0.0931)
HH_Size	-0.0101*** (0.0022)	-0.0107*** (0.0022)
HH_Inc_10k	-0.0060*** (0.0008)	-0.0059*** (0.0007)
Some College	-0.0001 (0.0076)	-0.0064 (0.0068)
Graduated College	-0.0408*** (0.0077)	-0.0439*** (0.0076)
Post-Graduate Studies	-0.0950*** (0.0089)	-0.0961*** (0.0087)
Black	0.1888*** (0.0121)	0.1965*** (0.0104)
Asian	0.1056*** (0.0289)	0.1000*** (0.0257)
Hispanic	-0.0130 (0.0114)	-0.0282* (0.0124)

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	(1) Meat share (by weight)	(2) Meat share (by weight)
Other	0.0144 (0.0144)	0.0168 (0.0149)
avg_age	-0.0001 (0.0002)	-0.0000 (0.0002)
Female	0.0251*** (0.0051)	0.0271*** (0.0057)
Male	0.1432*** (0.0080)	0.1436*** (0.0085)
Pres Democratic vote share (observed or linear interp.)		0.0825* (0.0420)
ruca_num		-0.0081** (0.0027)
Child poverty rate, 2021		-0.0013 (0.0040)
Deep child poverty rate, 2021		-0.0024 (0.0044)
Deep poverty rate, 2021		-0.0012 (0.0067)
Poverty rate, 2021		0.0084 (0.0058)
Population, low access to store (pct), 2015		0.0016 (0.0015)
Population, low access to store (pct), 2019		-0.0025 (0.0014)
Convenience stores/1,000 pop, 2016		0.1030 (0.1342)
Convenience stores/1,000 pop, 2020		-0.1835 (0.1548)
Farmers' markets/1,000 pop, 2013		-0.4758 (0.8493)
Farmers' markets/1,000 pop, 2018		-0.6870 (0.8423)
Grocery stores/1,000 pop, 2016		-0.1822 (0.2019)
Grocery stores/1,000 pop, 2020		-0.0601 (0.2582)
Specialized food stores/1,000 pop, 2016		-0.2177 (0.4312)
Specialized food stores/1,000 pop, 2020		-0.8269* (0.3707)

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	(1) Meat share (by weight)	(2) Meat share (by weight)
Supercenters and club stores/1,000 pop, 2016		3.8876*** (0.8855)
Supercenters and club stores/1,000 pop, 2020		-0.2810 (0.5702)
Constant	-3.1647*** (0.5111)	-2.0008*** (0.1832)
Observations	7760288	7760288
R^2		
AIC	8.15e+09	8.14e+09
BIC	8.15e+09	8.14e+09

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.15: Meat — avoid (OLS stepwise + IV; w=PF; clustered by DMA)

	(1) No meat this month (weight-based)	(2) No meat this month (weight-based)	(3) No meat this month (weight-based)
2005	-0.0006 (0.0011)	-0.0005 (0.0010)	-0.0003 (0.0010)
2006	-0.0000 (0.0014)	0.0018 (0.0011)	0.0018 (0.0011)
2007	0.0002 (0.0014)	0.0017 (0.0011)	0.0016 (0.0012)
2008	0.0015 (0.0014)	0.0017 (0.0013)	0.0010 (0.0013)
2009	-0.0011 (0.0018)	0.0014 (0.0014)	0.0006 (0.0018)
2010	-0.0032* (0.0017)	0.0002 (0.0013)	-0.0008 (0.0017)
2011	-0.0021 (0.0017)	0.0013 (0.0015)	-0.0001 (0.0020)
2012	-0.0010 (0.0023)	0.0044*** (0.0016)	0.0027 (0.0025)
2013	-0.0028 (0.0027)	0.0050*** (0.0018)	0.0031 (0.0029)
2014	-0.0057* (0.0030)	0.0036** (0.0017)	0.0018 (0.0029)
2015	-0.0074* (0.0038)	0.0034* (0.0017)	0.0014 (0.0037)
2016	-0.0067* (0.0035)	0.0052*** (0.0018)	0.0027 (0.0040)
2017	-0.0082* (0.0042)	0.0065*** (0.0022)	0.0039 (0.0046)
2018	-0.0104**	0.0063***	0.0034

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	(1) No meat this month (weight-based)	(2) No meat this month (weight-based)	(3) No meat this month (weight-based)
2019	(0.0050) -0.0116** (0.0046)	(0.0023) 0.0063** (0.0028)	(0.0050) 0.0032 (0.0054)
2020	-0.0166*** (0.0057)	0.0023 (0.0025)	-0.0008 (0.0055)
Month 2	-0.0016 (0.0020)	0.0016*** (0.0006)	0.0015 (0.0010)
Month 3	-0.0010 (0.0028)	0.0031*** (0.0007)	0.0038*** (0.0011)
Month 4	0.0078** (0.0032)	0.0122*** (0.0009)	0.0133*** (0.0012)
Month 5	0.0102*** (0.0028)	0.0120*** (0.0011)	0.0143*** (0.0015)
Month 6	0.0117*** (0.0033)	0.0145*** (0.0012)	0.0171*** (0.0017)
Month 7	0.0111*** (0.0035)	0.0141*** (0.0013)	0.0170*** (0.0019)
Month 8	0.0075** (0.0033)	0.0112*** (0.0013)	0.0136*** (0.0018)
Month 9	0.0066*** (0.0020)	0.0089*** (0.0009)	0.0101*** (0.0011)
Month 10	0.0048*** (0.0009)	0.0064*** (0.0007)	0.0062*** (0.0007)
Month 11	0.0068*** (0.0011)	0.0057*** (0.0007)	0.0047*** (0.0008)
Month 12	0.0046* (0.0025)	0.0106*** (0.0007)	0.0094*** (0.0020)
oz_bought_1k	-0.0153*** (0.0008)	-0.0151*** (0.0007)	-0.0151*** (0.0007)
lnp_meat	0.1055*** (0.0394)	0.0336*** (0.0082)	0.0204 (0.0174)
lnp_nonmeat	0.0358*** (0.0133)	-0.0137 (0.0104)	0.0169 (0.0287)
HH_Size	-0.0116*** (0.0006)	-0.0116*** (0.0006)	-0.0117*** (0.0006)
HH_Inc_10k	0.0019*** (0.0002)	0.0019*** (0.0003)	0.0019*** (0.0003)
Some College	-0.0004 (0.0013)	0.0004 (0.0011)	0.0003 (0.0011)
Graduated College	0.0102*** (0.0015)	0.0103*** (0.0015)	0.0103*** (0.0015)
Post-Graduate Studies	0.0262*** (0.0025)	0.0260*** (0.0025)	0.0260*** (0.0025)
Black	-0.0155*** (0.0015)	-0.0198*** (0.0025)	-0.0196*** (0.0024)
Asian	0.0405*** (0.0068)	0.0373*** (0.0065)	0.0370*** (0.0065)
Hispanic	0.0014	-0.0009	-0.0010

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	(1) No meat this month (weight-based)	(2) No meat this month (weight-based)	(3) No meat this month (weight-based)
Other	(0.0017) 0.0129*** (0.0032)	(0.0023) 0.0098*** (0.0029)	(0.0025) 0.0097*** (0.0029)
avg_age	-0.0003*** (0.0001)	-0.0004*** (0.0001)	-0.0004*** (0.0001)
Female	0.0193*** (0.0010)	0.0177*** (0.0011)	0.0177*** (0.0012)
Male	0.0249*** (0.0022)	0.0230*** (0.0019)	0.0230*** (0.0019)
Pres Democratic vote share (observed or linear interp.)		0.0121**	0.0083
ruca_num		(0.0061) 0.0018** (0.0007)	(0.0086) 0.0017** (0.0007)
Child poverty rate, 2021		-0.0000	0.0000
Deep child poverty rate, 2021		(0.0005) 0.0003	(0.0005) 0.0003
Deep poverty rate, 2021		(0.0006) 0.0009	(0.0006) 0.0011
Poverty rate, 2021		(0.0011) -0.0006 (0.0009)	(0.0012) -0.0006 (0.0009)
Population, low ac- cess to store (pct), 2015		-0.0003	-0.0003
Population, low ac- cess to store (pct), 2019		(0.0002) 0.0002	(0.0002) 0.0003
Convenience stores/1,000 pop, 2016		(0.0002) -0.0351**	(0.0002) -0.0372**
Convenience stores/1,000 pop, 2020		(0.0177) 0.0149	(0.0186) 0.0177
Farmers' mar- kets/1,000 pop, 2013		(0.0174) 0.1119	(0.0180) 0.0782
		(0.0883)	(0.0971)

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	(1) No meat this month (weight-based)	(2) No meat this month (weight-based)	(3) No meat this month (weight-based)
Farmers' mar- kets/1,000 pop, 2018		-0.1662*	-0.1515*
		(0.0885)	(0.0907)
Grocery stores/1,000 pop, 2016		0.1178***	0.1226**
		(0.0442)	(0.0485)
Grocery stores/1,000 pop, 2020		-0.0945	-0.1015
		(0.0608)	(0.0677)
Specialized food stores/1,000 pop, 2016		0.1284	0.1198
		(0.0951)	(0.0908)
Specialized food stores/1,000 pop, 2020		0.0517	0.0560
		(0.0675)	(0.0665)
Supercenters and club stores/1,000 pop, 2016		-0.3741***	-0.3601***
		(0.0959)	(0.1174)
Supercenters and club stores/1,000 pop, 2020		0.0386	0.0422
		(0.0483)	(0.0569)
Constant	0.3651*** (0.0746)	0.1266*** (0.0210)	0.1794** (0.0827)
Observations	7760422	7760422	7760422
R^2	0.042	0.045	0.045
AIC	3.18e+05	2.95e+05	2.95e+05
BIC	3.19e+05	2.96e+05	2.96e+05
KP rk F			.
KP rk LM			30.0947
Hansen J			0.0000
Hansen J p			.

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.16: Animal — share (OLS stepwise + IV; w=PF; clustered by DMA)

	(1) Animal-product share (by weight)	(2) Animal-product share (by weight)	(3) Animal-product share (by weight)
2005	-0.0004 (0.0008)	-0.0002 (0.0008)	0.0029 (0.0019)

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	(1) Animal-product share (by weight)	(2) Animal-product share (by weight)	(3) Animal-product share (by weight)
2006	-0.0046*** (0.0009)	-0.0044*** (0.0009)	-0.0010 (0.0018)
2007	0.0009 (0.0009)	0.0001 (0.0009)	-0.0072** (0.0035)
2008	0.0010 (0.0010)	-0.0000 (0.0010)	-0.0112** (0.0047)
2009	-0.0049*** (0.0012)	-0.0053*** (0.0011)	-0.0086** (0.0037)
2010	-0.0025* (0.0013)	-0.0035*** (0.0011)	-0.0141** (0.0063)
2011	0.0009 (0.0015)	-0.0009 (0.0013)	-0.0212** (0.0098)
2012	-0.0003 (0.0017)	-0.0024* (0.0013)	-0.0282** (0.0123)
2013	0.0019 (0.0019)	-0.0010 (0.0014)	-0.0380** (0.0171)
2014	0.0054** (0.0024)	0.0016 (0.0016)	-0.0477** (0.0216)
2015	0.0069** (0.0029)	0.0028 (0.0019)	-0.0509** (0.0240)
2016	0.0048* (0.0027)	0.0005 (0.0017)	-0.0557** (0.0257)
2017	0.0028 (0.0032)	-0.0021 (0.0019)	-0.0667** (0.0296)
2018	0.0019 (0.0037)	-0.0037 (0.0023)	-0.0772** (0.0337)
2019	0.0028 (0.0037)	-0.0033 (0.0022)	-0.0843** (0.0368)
2020	0.0048 (0.0040)	-0.0019 (0.0023)	-0.0896** (0.0395)
Month 2	-0.0009 (0.0007)	-0.0012** (0.0006)	-0.0064** (0.0027)
Month 3	-0.0051*** (0.0008)	-0.0053*** (0.0007)	-0.0077*** (0.0009)
Month 4	-0.0049*** (0.0009)	-0.0049*** (0.0008)	-0.0050*** (0.0007)
Month 5	-0.0016 (0.0011)	-0.0014 (0.0009)	0.0030 (0.0044)
Month 6	0.0009 (0.0011)	0.0010 (0.0009)	0.0048 (0.0043)
Month 7	0.0021* (0.0011)	0.0022*** (0.0007)	0.0065 (0.0048)
Month 8	0.0026** (0.0011)	0.0026*** (0.0008)	0.0048 (0.0034)
Month 9	0.0022** (0.0009)	0.0020*** (0.0007)	0.0002 (0.0009)
Month 10	-0.0036*** (0.0008)	-0.0039*** (0.0007)	-0.0089*** (0.0023)
Month 11	-0.0075***	-0.0080***	-0.0140***

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	(1) Animal-product share (by weight)	(2) Animal-product share (by weight)	(3) Animal-product share (by weight)
Month 12	(0.0010) -0.0025 (0.0017)	(0.0009) -0.0038*** (0.0012)	(0.0026) -0.0231** (0.0095)
lnp_animal	-0.1409*** (0.0120)	-0.1200*** (0.0064)	0.1672 (0.1144)
lnp_nonan	0.0965*** (0.0123)	0.1028*** (0.0080)	0.2172*** (0.0836)
HH_Size	0.0041*** (0.0005)	0.0041*** (0.0005)	0.0036*** (0.0006)
HH_Inc_10k	-0.0009*** (0.0001)	-0.0009*** (0.0001)	-0.0011*** (0.0001)
Some College	0.0016 (0.0010)	0.0009 (0.0010)	0.0007 (0.0010)
Graduated College	0.0059*** (0.0012)	0.0052*** (0.0011)	0.0053*** (0.0012)
Post-Graduate Studies	0.0110*** (0.0015)	0.0106*** (0.0015)	0.0110*** (0.0016)
Black	-0.0471*** (0.0012)	-0.0448*** (0.0013)	-0.0460*** (0.0020)
Asian	-0.0044 (0.0037)	-0.0050 (0.0036)	-0.0131** (0.0055)
Hispanic	-0.0132*** (0.0020)	-0.0135*** (0.0020)	-0.0222*** (0.0045)
Other	-0.0223*** (0.0035)	-0.0219*** (0.0034)	-0.0261*** (0.0044)
avg_age	0.0004*** (0.0000)	0.0004*** (0.0000)	0.0003*** (0.0000)
Female	-0.0088*** (0.0011)	-0.0084*** (0.0011)	-0.0093*** (0.0011)
Male	0.0062*** (0.0014)	0.0065*** (0.0014)	0.0062*** (0.0014)
Pres Democratic vote share (observed or linear interp.)		0.0005	-0.0259
ruca_num		(0.0063) -0.0017*** (0.0005)	(0.0267) -0.0031*** (0.0010)
Child poverty rate, 2021		-0.0010*	-0.0031*
Deep child poverty rate, 2021		(0.0005) -0.0005	(0.0018) 0.0027
Deep poverty rate, 2021		(0.0007) 0.0004	(0.0020) -0.0012
Poverty rate, 2021		(0.0011) 0.0017** (0.0008)	(0.0029) 0.0052* (0.0032)

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	(1) Animal-product share (by weight)	(2) Animal-product share (by weight)	(3) Animal-product share (by weight)
Population, low access to store (pct), 2015		0.0001 (0.0002)	-0.0005 (0.0006)
Population, low access to store (pct), 2019		-0.0001 (0.0002)	0.0006 (0.0006)
Convenience stores/1,000 pop, 2016		0.0205 (0.0178)	-0.0054 (0.0431)
Convenience stores/1,000 pop, 2020		-0.0390** (0.0186)	-0.0293 (0.0411)
Farmers' markets/1,000 pop, 2013		0.0227 (0.1119)	-0.1792 (0.3180)
Farmers' markets/1,000 pop, 2018		-0.0470 (0.1104)	0.4208 (0.3638)
Grocery stores/1,000 pop, 2016		0.0084 (0.0290)	0.0969 (0.0981)
Grocery stores/1,000 pop, 2020		-0.0232 (0.0330)	-0.1690 (0.1309)
Specialized food stores/1,000 pop, 2016		-0.0001 (0.0499)	-0.1735 (0.1277)
Specialized food stores/1,000 pop, 2020		-0.0448 (0.0462)	0.0393 (0.1069)
Supercenters and club stores/1,000 pop, 2016		0.3328*** (0.0955)	1.4389** (0.6004)
Supercenters and club stores/1,000 pop, 2020		0.0751 (0.0690)	0.1971 (0.1805)
Constant	0.1509***	0.2146***	1.0853**

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	(1) Animal-product share (by weight)	(2) Animal-product share (by weight)	(3) Animal-product share (by weight)
	(0.0382)	(0.0246)	(0.4345)
Observations	7760288	7760288	7760288
R^2	0.032	0.034	-0.004
AIC	-9.07e+06	-9.08e+06	-8.79e+06
BIC	-9.07e+06	-9.08e+06	-8.79e+06
KP rk F			.
KP rk LM			7.3344
Hansen J			0.0000
Hansen J p			.

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.17: Animal Products — share (Fractional logit stepwise)

	(1) Animal-product share (by weight)	(2) Animal-product share (by weight)
2005	-0.0026 (0.0046)	-0.0015 (0.0046)
2006	-0.0256*** (0.0048)	-0.0246*** (0.0047)
2007	0.0051 (0.0048)	0.0008 (0.0048)
2008	0.0059 (0.0056)	-0.0000 (0.0056)
2009	-0.0265*** (0.0069)	-0.0289*** (0.0063)
2010	-0.0133 (0.0073)	-0.0186** (0.0061)
2011	0.0053 (0.0084)	-0.0044 (0.0071)
2012	-0.0012 (0.0094)	-0.0129 (0.0072)
2013	0.0102 (0.0105)	-0.0058 (0.0079)
2014	0.0293* (0.0131)	0.0083 (0.0086)
2015	0.0381* (0.0159)	0.0153 (0.0102)
2016	0.0260 (0.0152)	0.0024 (0.0095)
2017	0.0145 (0.0175)	-0.0127 (0.0105)
2018	0.0086 (0.0203)	-0.0222 (0.0126)
2019	0.0135	-0.0205

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	(1) Animal-product share (by weight)	(2) Animal-product share (by weight)
2020	(0.0202) 0.0240 (0.0224)	(0.0117) -0.0131 (0.0129)
Month 2	-0.0050 (0.0039)	-0.0067* (0.0032)
Month 3	-0.0287*** (0.0042)	-0.0296*** (0.0037)
Month 4	-0.0274*** (0.0047)	-0.0276*** (0.0042)
Month 5	-0.0090 (0.0061)	-0.0081 (0.0047)
Month 6	0.0048 (0.0062)	0.0053 (0.0046)
Month 7	0.0113 (0.0058)	0.0118** (0.0038)
Month 8	0.0142* (0.0061)	0.0141** (0.0046)
Month 9	0.0123* (0.0049)	0.0111** (0.0038)
Month 10	-0.0200*** (0.0044)	-0.0218*** (0.0037)
Month 11	-0.0422*** (0.0055)	-0.0444*** (0.0045)
Month 12	-0.0137 (0.0091)	-0.0209*** (0.0064)
lnp_animal	-0.7762*** (0.0660)	-0.6593*** (0.0353)
lnp_nonan	0.5335*** (0.0678)	0.5655*** (0.0438)
HH_Size	0.0228*** (0.0026)	0.0228*** (0.0026)
HH_Inc_10k	-0.0050*** (0.0007)	-0.0051*** (0.0007)
Some College	0.0088 (0.0054)	0.0047 (0.0053)
Graduated College	0.0327*** (0.0065)	0.0290*** (0.0063)
Post-Graduate Studies	0.0614*** (0.0082)	0.0588*** (0.0082)
Black	-0.2810*** (0.0074)	-0.2679*** (0.0079)
Asian	-0.0240 (0.0204)	-0.0274 (0.0201)
Hispanic	-0.0737*** (0.0113)	-0.0753*** (0.0112)
Other	-0.1263*** (0.0210)	-0.1240*** (0.0202)
avg_age	0.0020***	0.0021***

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	(1) Animal-product share (by weight)	(2) Animal-product share (by weight)
Female	(0.0002) -0.0501*** (0.0058)	(0.0002) -0.0483*** (0.0061)
Male	0.0343*** (0.0074)	0.0364*** (0.0075)
Pres Democratic vote share (observed or linear interp.)		0.0043
ruca_num		(0.0350) -0.0095*** (0.0026)
Child poverty rate, 2021		-0.0053
Deep child poverty rate, 2021		(0.0031) -0.0027
Deep poverty rate, 2021		(0.0038) 0.0021
Poverty rate, 2021		(0.0058) 0.0090* (0.0045)
Population, low ac- cess to store (pct), 2015		0.0002
Population, low ac- cess to store (pct), 2019		(0.0013) -0.0003
Convenience stores/1,000 pop, 2016		(0.0012) 0.1225
Convenience stores/1,000 pop, 2020		(0.0989) -0.2242*
Farmers' mar- kets/1,000 pop, 2013		(0.1042) 0.1663
Farmers' mar- kets/1,000 pop, 2018		(0.6142) -0.2832
Grocery stores/1,000 pop, 2016		(0.6086) 0.0314

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	(1) Animal-product share (by weight)	(2) Animal-product share (by weight)
Grocery stores/1,000 pop, 2020		(0.1635) -0.1224
Specialized food stores/1,000 pop, 2016		(0.1865) -0.0122
Specialized food stores/1,000 pop, 2020		(0.2743) -0.2487
Supercenters and club stores/1,000 pop, 2016		(0.2540) 1.7224***
Supercenters and club stores/1,000 pop, 2020		(0.5222) 0.4291
Constant	-1.6423*** (0.2163)	-1.2901*** (0.1365)
Observations	7760288	7760288
R^2		
AIC	1.69e+10	1.69e+10
BIC	1.69e+10	1.69e+10

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.18: Animal — avoid (OLS stepwise + IV; w=PF; clustered by DMA)

	(1) No anml prod this month (weight-based)	(2) No anml prod this month (weight-based)	(3) No anml prod this month (weight-based)
2005	0.0002 (0.0003)	0.0000 (0.0003)	-0.0004 (0.0004)
2006	0.0004 (0.0005)	0.0004 (0.0005)	0.0000 (0.0005)
2007	0.0002 (0.0004)	0.0003 (0.0004)	0.0012* (0.0007)
2008	0.0010* (0.0005)	0.0011** (0.0006)	0.0025** (0.0010)
2009	0.0012** (0.0005)	0.0014** (0.0006)	0.0019** (0.0008)
2010	0.0005	0.0010	0.0023*

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	(1) No anml prod this month (weight-based)	(2) No anml prod this month (weight-based)	(3) No anml prod this month (weight-based)
2011	(0.0006) 0.0005	(0.0006) 0.0013	(0.0013) 0.0037**
2012	(0.0006) 0.0015**	(0.0008) 0.0025***	(0.0019) 0.0057**
2013	(0.0007) 0.0018***	(0.0008) 0.0031***	(0.0023) 0.0076**
2014	(0.0006) 0.0011**	(0.0008) 0.0028***	(0.0030) 0.0087**
2015	(0.0006) 0.0003	(0.0007) 0.0022***	(0.0036) 0.0087**
2016	(0.0006) 0.0005	(0.0006) 0.0026***	(0.0038) 0.0094**
2017	(0.0007) 0.0012*	(0.0006) 0.0036***	(0.0041) 0.0115**
2018	(0.0007) 0.0016*	(0.0007) 0.0043***	(0.0048) 0.0132**
2019	(0.0009) 0.0035***	(0.0008) 0.0064***	(0.0053) 0.0162***
2020	(0.0008) 0.0020**	(0.0010) 0.0050***	(0.0059) 0.0156**
Month 2	(0.0009) -0.0003	(0.0009) -0.0000	(0.0063) 0.0006
Month 3	(0.0002) 0.0003*	(0.0002) 0.0003**	(0.0004) 0.0006***
Month 4	(0.0002) 0.0008***	(0.0001) 0.0007***	(0.0002) 0.0007***
Month 5	(0.0002) 0.0015***	(0.0002) 0.0009***	(0.0003) 0.0003
Month 6	(0.0003) 0.0013***	(0.0003) 0.0008**	(0.0007) 0.0002
Month 7	(0.0004) 0.0012***	(0.0003) 0.0006*	(0.0008) -0.0001
Month 8	(0.0003) 0.0011***	(0.0003) 0.0007*	(0.0009) 0.0003
Month 9	(0.0003) 0.0005*	(0.0003) 0.0004	(0.0006) 0.0005
Month 10	(0.0003) 0.0009***	(0.0003) 0.0011***	(0.0004) 0.0017***
Month 11	(0.0002) 0.0003	(0.0002) 0.0005**	(0.0004) 0.0012***
Month 12	(0.0003) 0.0002	(0.0002) 0.0010***	(0.0004) 0.0033**
oz_bought_1k	(0.0003) -0.0027***	(0.0002) -0.0027***	(0.0015) -0.0027***
lnp_animal	(0.0002) 0.0120***	(0.0002) 0.0051**	(0.0002) -0.0287
lnp_nonan	(0.0042) 0.0073**	(0.0023) -0.0016	(0.0177) -0.0173

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	(1) No anml prod this month (weight-based)	(2) No anml prod this month (weight-based)	(3) No anml prod this month (weight-based)
HH_Size	(0.0035) -0.0026***	(0.0029) -0.0026***	(0.0134) -0.0025***
HH_Inc_10k	(0.0002) 0.0005***	(0.0002) 0.0005***	(0.0002) 0.0005***
Some College	(0.0001) -0.0009	(0.0001) -0.0008	(0.0001) -0.0008
Graduated Col- lege	(0.0006) 0.0004	(0.0006) 0.0004	(0.0006) 0.0004
Post-Graduate Studies	(0.0007) 0.0009	(0.0007) 0.0008	(0.0007) 0.0007
Black	(0.0007) 0.0038***	(0.0007) 0.0027***	(0.0007) 0.0029***
Asian	(0.0007) 0.0078***	(0.0006) 0.0067***	(0.0006) 0.0077***
Hispanic	(0.0016) 0.0017***	(0.0016) 0.0006	(0.0018) 0.0016*
Other	(0.0005) 0.0087***	(0.0006) 0.0079***	(0.0009) 0.0084***
avg_age	(0.0025) -0.0002***	(0.0022) -0.0002***	(0.0022) -0.0002***
Female	(0.0000) 0.0036***	(0.0000) 0.0032***	(0.0000) 0.0032***
Male	(0.0005) 0.0090***	(0.0005) 0.0084***	(0.0005) 0.0084***
Pres Demo- cratic vote share (ob- served or linear interp.)	(0.0010)	(0.0009) 0.0069***	(0.0009) 0.0104**
ruca_num		(0.0026) 0.0006*	(0.0051) 0.0007**
Child poverty rate, 2021		(0.0003) 0.0000	(0.0004) 0.0002
Deep child poverty rate, 2021		(0.0002) -0.0000	(0.0002) -0.0004
Deep poverty rate, 2021		(0.0002) -0.0005	(0.0003) -0.0003
Poverty rate, 2021		(0.0004) 0.0004	(0.0004) -0.0001
		(0.0003)	(0.0004)

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	(1) No anml prod this month (weight-based)	(2) No anml prod this month (weight-based)	(3) No anml prod this month (weight-based)
Population, low access to store (pct), 2015		-0.0000	0.0000
		(0.0001)	(0.0001)
Population, low access to store (pct), 2019		-0.0000	-0.0001
		(0.0001)	(0.0001)
Convenience stores/1,000 pop, 2016		-0.0119**	-0.0087
		(0.0057)	(0.0077)
Convenience stores/1,000 pop, 2020		0.0041	0.0027
		(0.0050)	(0.0069)
Farmers' mar- kets/1,000 pop, 2013		-0.0236	0.0033
		(0.0312)	(0.0560)
Farmers' mar- kets/1,000 pop, 2018		-0.0068	-0.0635
		(0.0314)	(0.0614)
Grocery stores/1,000 pop, 2016		0.0120	0.0012
		(0.0102)	(0.0131)
Grocery stores/1,000 pop, 2020		-0.0107	0.0071
		(0.0130)	(0.0168)
Specialized food stores/1,000 pop, 2016		0.0295	0.0506*
		(0.0181)	(0.0262)
Specialized food stores/1,000 pop, 2020		-0.0089	-0.0190
		(0.0167)	(0.0216)
Supercenters and club stores/1,000 pop, 2016		0.0266	-0.1049
		(0.0280)	(0.0911)

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	(1) No anml prod this month (weight-based)	(2) No anml prod this month (weight-based)	(3) No anml prod this month (weight-based)
Supercenters and club stores/1,000 pop, 2020		-0.0222	-0.0375
Constant	0.0680*** (0.0126)	(0.0188) 0.0300*** (0.0063)	(0.0269) -0.0776 (0.0665)
Observations	7760422	7760422	7760422
R^2	0.012	0.013	0.012
AIC	-1.39e+07	-1.39e+07	-1.39e+07
BIC	-1.39e+07	-1.39e+07	-1.39e+07
KP rk F			.
KP rk LM			7.3275
Hansen J			0.0000
Hansen J p			.

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.8.2 Time Trends

Meat

Table C.19: Group-trend regressions (linear), Part 1: level effects

	(1) Share Meat (oz)	(2) Top 10%	(3) Bottom 10%	(4) No Meat
t (Year)	0.0007*** (0.0001)	-0.0000 (0.0003)	-0.0012*** (0.0003)	-0.0004* (0.0002)
Income Q2	-0.0009* (0.0005)	-0.0070*** (0.0024)	0.0032 (0.0021)	0.0012 (0.0016)
Income Q3	-0.0026*** (0.0007)	-0.0143*** (0.0032)	0.0050** (0.0023)	0.0006 (0.0016)
Income Q4 (highest)	-0.0032*** (0.0008)	-0.0167*** (0.0031)	0.0245*** (0.0030)	0.0153*** (0.0023)
Some College	0.0001 (0.0006)	-0.0002 (0.0025)	0.0026 (0.0019)	0.0016 (0.0015)
Graduated College	-0.0034*** (0.0006)	-0.0132*** (0.0024)	0.0160*** (0.0027)	0.0092*** (0.0021)
Post-Graduate Stud- ies	-0.0062*** (0.0008)	-0.0226*** (0.0028)	0.0386*** (0.0041)	0.0252*** (0.0033)
Black	0.0147*** (0.0012)	0.0528*** (0.0056)	-0.0295*** (0.0036)	-0.0154*** (0.0030)

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	(1) Share Meat (oz)	(2) Top 10%	(3) Bottom 10%	(4) No Meat
Asian	0.0062*** (0.0018)	0.0250*** (0.0072)	0.0225*** (0.0080)	0.0231*** (0.0064)
Hispanic	-0.0021 (0.0014)	-0.0093*** (0.0035)	-0.0017 (0.0045)	-0.0053 (0.0034)
Other	0.0012 (0.0016)	0.0095 (0.0068)	0.0102** (0.0050)	0.0077* (0.0039)
Female	0.0030*** (0.0004)	-0.0014 (0.0017)	0.0270*** (0.0020)	0.0165*** (0.0014)
Male	0.0126*** (0.0008)	0.0402*** (0.0030)	0.0304*** (0.0028)	0.0277*** (0.0024)
Boomers (1946–64)	-0.0003 (0.0011)	0.0094** (0.0039)	-0.0074** (0.0034)	-0.0047* (0.0027)
Gen X (1965–80)	0.0010 (0.0010)	0.0104*** (0.0036)	-0.0146*** (0.0038)	-0.0046 (0.0029)
Millennials (1981–96), Gen Z (1997–)	0.0040** (0.0016)	0.0025 (0.0061)	-0.0092 (0.0059)	-0.0017 (0.0048)
lnp_meat	-0.0378*** (0.0021)	-0.1223*** (0.0090)	0.0293*** (0.0068)	0.0082 (0.0050)
lnp_nonmeat	0.0380*** (0.0024)	0.0789*** (0.0095)	-0.0748*** (0.0088)	-0.0357*** (0.0060)
oz_bought_1k		-0.0256*** (0.0006)	-0.0134*** (0.0006)	-0.0168*** (0.0008)
Constant	0.0999*** (0.0057)	0.1843*** (0.0242)	-0.0156 (0.0226)	0.0167 (0.0164)
Observations	9984436	9984589	9984589	9984589
Adjusted R^2	0.027	0.040	0.028	0.040

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.20: Group-trend regressions (linear), Part 2: interaction effects

	(1) Share Meat (oz)	(2) Top 10%	(3) Bottom 10%	(4) No Meat
Q2 $\times$ t	-0.0000 (0.0001)	-0.0002 (0.0002)	-0.0003 (0.0002)	-0.0002 (0.0002)
Q3 $\times$ t	0.0001 (0.0001)	0.0002 (0.0003)	-0.0001 (0.0002)	0.0001 (0.0002)
Q4 (highest) $\times$ t	-0.0001 (0.0001)	-0.0006** (0.0003)	-0.0006** (0.0002)	-0.0002 (0.0002)
Some College $\times$ t	-0.0001 (0.0001)	-0.0004** (0.0002)	-0.0001 (0.0002)	-0.0001 (0.0002)
Graduated College $\times$ t	0.0000 (0.0001)	0.0001 (0.0002)	-0.0001 (0.0002)	0.0002 (0.0002)
Post-Graduate Studies $\times$ t	0.0000 (0.0001)	0.0001 (0.0003)	-0.0004 (0.0003)	0.0002 (0.0002)
Black $\times$ t	-0.0002** (0.0001)	-0.0011** (0.0004)	0.0006** (0.0003)	-0.0000 (0.0002)
Asian $\times$ t	-0.0001 (0.0002)	-0.0003 (0.0006)	0.0017*** (0.0006)	0.0017*** (0.0006)
Hispanic $\times$ t	-0.0000 (0.0001)	0.0000 (0.0003)	0.0006 (0.0004)	0.0005 (0.0003)
Other $\times$ t	-0.0001 (0.0001)	-0.0002 (0.0006)	0.0001 (0.0005)	0.0002 (0.0004)
Female $\times$ t	-0.0001*** (0.0000)	0.0001 (0.0002)	0.0013*** (0.0002)	0.0015*** (0.0002)
Male $\times$ t	-0.0003*** (0.0001)	-0.0008*** (0.0003)	0.0014*** (0.0003)	0.0013*** (0.0002)
Boomers (1946–64) $\times$ t	-0.0001 (0.0001)	-0.0004 (0.0003)	0.0007** (0.0003)	0.0005** (0.0002)
Gen X (1965–80) $\times$ t	-0.0002* (0.0001)	-0.0000 (0.0003)	0.0007* (0.0003)	0.0002 (0.0003)
Millennials (1981–96), Gen Z (1997–) $\times$ t	-0.0003** (0.0001)	0.0004 (0.0004)	0.0012*** (0.0004)	0.0009** (0.0003)
Observations	9984436	9984589	9984589	9984589
Adjusted R^2	0.027	0.040	0.028	0.040
Standard errors in parentheses				
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$				

Animal Products

Table C.21: Group-trend regressions (linear) Part 1: level effects)

	(1) Share Animl Prod (oz)	(2) Top 10%	(3) Bottom 10%	(4) No Anml Prod
t (Year)	0.0001 (0.0002)	0.0012*** (0.0003)	-0.0011*** (0.0004)	-0.0002** (0.0001)
Income Q2	0.0002 (0.0014)	-0.0064** (0.0026)	0.0017 (0.0023)	-0.0004 (0.0006)
Income Q3	-0.0054*** (0.0017)	-0.0154*** (0.0032)	0.0097*** (0.0027)	-0.0017** (0.0007)
Income Q4 (highest)	-0.0096*** (0.0019)	-0.0226*** (0.0035)	0.0266*** (0.0035)	0.0011 (0.0008)
Some College	0.0031** (0.0014)	0.0055** (0.0027)	-0.0003 (0.0023)	-0.0001 (0.0005)
Graduated College	0.0081*** (0.0015)	0.0146*** (0.0028)	0.0044* (0.0025)	0.0006 (0.0007)
Post-Graduate Studies	0.0106*** (0.0024)	0.0211*** (0.0048)	0.0104*** (0.0037)	0.0030*** (0.0011)
Black	-0.0424*** (0.0018)	-0.0591*** (0.0030)	0.0575*** (0.0047)	0.0017* (0.0010)
Asian	-0.0117** (0.0052)	-0.0017 (0.0086)	0.0566*** (0.0105)	0.0058** (0.0027)
Hispanic	-0.0120*** (0.0028)	-0.0159*** (0.0044)	0.0126*** (0.0034)	-0.0010 (0.0008)
Other	-0.0202*** (0.0051)	-0.0108 (0.0086)	0.0520*** (0.0133)	0.0041 (0.0034)
Female	-0.0087*** (0.0014)	-0.0171*** (0.0021)	0.0513*** (0.0033)	0.0000 (0.0004)
Male	0.0035* (0.0019)	0.0146*** (0.0033)	0.0613*** (0.0041)	0.0056*** (0.0009)
Boomers (1946–64)	-0.0287*** (0.0016)	-0.0317*** (0.0028)	0.0193*** (0.0025)	0.0026*** (0.0006)
Gen X (1965–80)	-0.0106*** (0.0017)	-0.0135*** (0.0034)	-0.0087*** (0.0026)	0.0031*** (0.0007)
Millennials (1981–96), Gen Z (1997–)	-0.0108*** (0.0035)	-0.0286*** (0.0062)	0.0030 (0.0051)	0.0009 (0.0019)
lnp_animal	-0.0761*** (0.0038)	-0.1143*** (0.0085)	0.0376*** (0.0065)	-0.0039* (0.0020)
lnp_nonan	0.0900*** (0.0043)	0.0720*** (0.0085)	-0.1045*** (0.0079)	-0.0035* (0.0020)
oz_bought_1k		-0.0221*** (0.0004)	0.0035*** (0.0003)	-0.0030*** (0.0002)
Constant	0.3166*** (0.0144)	0.1312*** (0.0289)	-0.1330*** (0.0244)	-0.0062 (0.0064)
Observations	9984436	9984589	9984589	9984589
Adjusted R^2	0.040	0.037	0.022	0.011
Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$				

Table C.22: Group-trend regressions (linear), Part 2: interaction effects

	(1) Share Anml Prod (oz)	(2) Top 10%	(3) Bottom 10%	(4) No Anml Prod
Q2 $\times$ t	-0.0002* (0.0001)	-0.0002 (0.0002)	0.0004 (0.0003)	-0.0001 (0.0001)
Q3 $\times$ t	-0.0000 (0.0001)	0.0001 (0.0003)	0.0002 (0.0003)	0.0000 (0.0001)
Q4 (highest) $\times$ t	0.0000 (0.0002)	0.0001 (0.0003)	-0.0003 (0.0003)	0.0000 (0.0001)
Some College $\times$ t	-0.0000 (0.0001)	-0.0001 (0.0002)	-0.0000 (0.0002)	-0.0000 (0.0001)
Graduated College $\times$ t	-0.0001 (0.0001)	-0.0004 (0.0003)	0.0002 (0.0003)	0.0001 (0.0001)
Post-Graduate Studies $\times$ t	0.0002 (0.0002)	0.0000 (0.0004)	-0.0004 (0.0004)	-0.0000 (0.0001)
Black $\times$ t	-0.0003* (0.0002)	-0.0001 (0.0002)	0.0003 (0.0004)	0.0002 (0.0001)
Asian $\times$ t	0.0005 (0.0004)	0.0004 (0.0007)	-0.0013* (0.0007)	0.0001 (0.0002)
Hispanic $\times$ t	-0.0002 (0.0002)	-0.0003 (0.0003)	0.0007** (0.0003)	0.0001 (0.0001)
Other $\times$ t	-0.0001 (0.0004)	-0.0011 (0.0007)	-0.0010 (0.0009)	0.0003 (0.0002)
Female $\times$ t	-0.0005*** (0.0001)	-0.0004* (0.0002)	0.0009*** (0.0002)	0.0007*** (0.0000)
Male $\times$ t	-0.0002 (0.0002)	0.0000 (0.0003)	0.0001 (0.0003)	0.0007*** (0.0001)
Boomers (1946–64) $\times$ t	0.0003 (0.0002)	0.0004 (0.0003)	0.0003 (0.0003)	0.0001* (0.0001)
Gen X (1965–80) $\times$ t	-0.0012*** (0.0002)	-0.0010*** (0.0004)	0.0018*** (0.0003)	0.0002*** (0.0001)
Millennials (1981–96), Gen Z (1997–) $\times$ t	-0.0003 (0.0003)	0.0010* (0.0005)	0.0011*** (0.0004)	0.0007*** (0.0002)
Observations	9984436	9984589	9984589	9984589
Adjusted R^2	0.040	0.037	0.022	0.011
Standard errors in parentheses				
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$				

Plant-Based Alternatives

Table C.23: Animal — avoid (OLS stepwise + IV; w=PF; clustered by DMA)

	(1) Buy PBMA (Any)	(2) Buy PBMA (New)	(3) Buy PBMA (Old)	(4) Buy Milk Alt.
t (Year)	-0.0007*** (0.0003)	0.0005 (0.0006)	-0.0007*** (0.0002)	0.0044*** (0.0004)
Income Q2	0.0005 (0.0015)	-0.0015 (0.0067)	0.0006 (0.0015)	-0.0011 (0.0019)
Income Q3	0.0027 (0.0019)	-0.0043 (0.0075)	0.0030 (0.0019)	0.0001 (0.0027)
Income Q4 (highest)	0.0026 (0.0021)	-0.0096 (0.0071)	0.0032 (0.0021)	-0.0019 (0.0033)
Some College	0.0040** (0.0016)	-0.0034 (0.0052)	0.0042** (0.0017)	0.0053** (0.0026)
Graduated College	0.0178*** (0.0018)	-0.0192*** (0.0073)	0.0182*** (0.0018)	0.0133*** (0.0029)
Post-Graduate Studies	0.0282*** (0.0024)	-0.0280*** (0.0095)	0.0292*** (0.0024)	0.0328*** (0.0037)
Black	-0.0156*** (0.0016)	-0.0313*** (0.0076)	-0.0153*** (0.0017)	0.0286*** (0.0037)
Asian	-0.0118** (0.0054)	-0.0140 (0.0124)	-0.0112** (0.0055)	0.0498*** (0.0092)
Hispanic	-0.0048 (0.0036)	-0.0171* (0.0088)	-0.0043 (0.0036)	0.0128*** (0.0048)
Other	0.0032 (0.0053)	-0.0071 (0.0176)	0.0039 (0.0053)	0.0307*** (0.0091)
Female	0.0043*** (0.0015)	-0.0019 (0.0059)	0.0048*** (0.0015)	0.0077*** (0.0020)
Male	0.0010 (0.0019)	-0.0017 (0.0071)	0.0012 (0.0019)	0.0005 (0.0024)
Boomers (1946–64)	0.0021 (0.0019)	-0.0048 (0.0054)	0.0024 (0.0019)	-0.0026 (0.0020)
Gen X (1965–80)	0.0079*** (0.0022)	-0.0159*** (0.0061)	0.0088*** (0.0022)	-0.0092*** (0.0026)
Millennials (1981–96), Gen Z (1997–)	0.0092* (0.0055)	-0.0128 (0.0087)	0.0126** (0.0055)	0.0074 (0.0063)
lnp_pbm_any	0.0001 (0.0010)			
lnp_nonpbm_any	0.0286*** (0.0081)			
oz_bought_1k	0.0014*** (0.0002)	0.0001 (0.0001)	0.0014*** (0.0002)	0.0028*** (0.0003)
lnp_pbm_new		-0.0005 (0.0006)		
lnp_nonpbm_new		0.0011 (0.0061)		

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	(1) Buy PBMA (Any)	(2) Buy PBMA (New)	(3) Buy PBMA (Old)	(4) Buy Milk Alt. ()
lnp_pbm_old			-0.0036*** (0.0009)	
lnp_nonpbm_old			0.0247*** (0.0076)	
lnp_milkalt				0.0024 (0.0031)
lnp_nonmilkalt				0.0285** (0.0132)
Constant	0.0777*** (0.0182)	-0.0068 (0.0181)	0.0653*** (0.0171)	0.0833*** (0.0314)
Observations	9707716	1574600	9663720	9943190
Adjusted R^2	0.010	0.005	0.010	0.039

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.24: Group-trend regressions (linear), Part 2: interaction effects

	(1) Buy PBMA (Any)	(2) Buy PBMA (New)	(3) Buy PBMA (Old)	(4) Buy Milk Alt
Q2 $\times$ t	0.0001 (0.0002)	0.0001 (0.0005)	0.0001 (0.0002)	0.0010*** (0.0002)
Q3 $\times$ t	0.0000 (0.0002)	0.0004 (0.0005)	-0.0000 (0.0002)	0.0012*** (0.0003)
Q4 (highest) $\times$ t	0.0001 (0.0003)	0.0008* (0.0005)	-0.0000 (0.0003)	0.0013*** (0.0004)
Some College $\times$ t	0.0003* (0.0002)	0.0003 (0.0004)	0.0003 (0.0002)	0.0015*** (0.0003)
Graduated College $\times$ t	0.0000 (0.0002)	0.0015*** (0.0005)	-0.0000 (0.0002)	0.0023*** (0.0003)
Post-Graduate Studies $\times$ t	0.0002 (0.0002)	0.0022*** (0.0007)	0.0000 (0.0002)	0.0016*** (0.0004)
Black $\times$ t	0.0013*** (0.0002)	0.0023*** (0.0005)	0.0012*** (0.0002)	0.0004 (0.0004)
Asian $\times$ t	0.0001 (0.0004)	0.0008 (0.0009)	-0.0000 (0.0004)	-0.0011 (0.0007)
Hispanic $\times$ t	0.0008*** (0.0003)	0.0012* (0.0006)	0.0007*** (0.0003)	0.0019*** (0.0005)
Other $\times$ t	0.0005 (0.0005)	0.0005 (0.0012)	0.0004 (0.0005)	0.0005 (0.0008)
Female $\times$ t	0.0004** (0.0002)	0.0002 (0.0004)	0.0003* (0.0002)	-0.0009*** (0.0002)
Male $\times$ t	0.0002 (0.0002)	0.0003 (0.0005)	0.0001 (0.0002)	-0.0029*** (0.0003)
Boomers (1946–64) $\times$ t	0.0003* (0.0002)	0.0005 (0.0004)	0.0003 (0.0002)	0.0010*** (0.0003)
Gen X (1965–80) $\times$ t	0.0009*** (0.0002)	0.0015*** (0.0004)	0.0007*** (0.0002)	0.0036*** (0.0004)
Millennials (1981–96), Gen Z (1997–) $\times$ t	0.0015*** (0.0005)	0.0014** (0.0006)	0.0011** (0.0005)	0.0045*** (0.0006)
Observations	9707716	1574600	9663720	9943190
Adjusted R^2	0.010	0.005	0.010	0.039
Standard errors in parentheses				
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$				

B.8.3 Additional Tables

Table C.25: Average grocery purchases by category and demographic group (ounces)

	Shellfish	Fish	Chicken	Beef	Pork	Any Meat	Meat Alternatives	Animal Product	N
<i>Age</i>									
Overall	4.69	9.55	77.38	41.91	52.81	189.26	2.08	546.24	50349
Cohort $\geq$ 1980	4.42	8.91	83.29	44	53.27	191.26	2.77	603.39	5119
Cohort $<$ 1980	4.72	9.63	76.71	41.68	52.76	189.03	2	539.77	45230
<i>Education</i>									
Overall	4.69	9.55	77.38	41.91	52.81	189.26	2.08	546.24	50349
No College	4.11	9.42	79.84	50.84	61.57	203.63	1.2	574.85	8877
Some College	4.7	9.9	79.88	46.41	57.77	199.65	1.74	557	14033
College Grad	4.99	9.61	77.87	39.6	50.48	186.79	2.29	544.16	17630
Post-Grad Study	4.65	9.1	70.69	31.55	42	165.83	2.96	508.69	9809
<i>Race</i>									
Overall	4.69	9.55	77.38	41.91	52.81	189.26	2.08	546.24	50349
White	4.27	8.89	78.29	43.07	53.73	190.48	1.88	573.3	38774
Black	6.57	13.2	71.34	36.06	53.95	191.38	3.11	374.61	5185
Asian	7.23	11.21	72.13	31.01	35.74	162.25	2.08	478.9	1672
Hispanic	5.09	10.24	77.01	41.93	48.6	183.97	2.62	544.04	3435
Other	5.19	11.02	82.05	44.77	53.95	193.26	2.24	515.66	1283
<i>Income</i>									
Overall	4.69	9.55	77.38	41.91	52.81	189.26	2.08	546.24	50349
1st Quartile	4.51	10.69	86.38	54.56	64.27	217.25	1.77	622.31	11481
2nd Quartile	4.53	9.65	78.07	43.65	54.69	192.77	1.96	556.34	15216
3rd Quartile	4.73	8.95	72.27	35.81	47.03	173.97	2.23	495.91	15350
4th Quartile	5.14	8.93	73.12	32.54	44.23	172.4	2.43	515.58	8302

Notes: Rows report demographic groups. Columns report average January 2020 grocery purchases, measured in ounces, for the listed categories. N reports the number of households in each group.

Table C.26: Shares of grocery purchase weight by category and demographic group

	Shellfish	Fish	Chicken	Beef	Pork	Any Meat	Meat Alternatives	Animal Product	N
<i>Age</i>									
Overall	0.23	0.46	3.33	1.73	2.29	8.28	0.11	23.05	50349
Cohort $\geq$ 1980	0.22	0.4	3.46	1.69	2.15	8.05	0.16	23.82	5119
Cohort $<$ 1980	0.23	0.46	3.32	1.74	2.3	8.31	0.11	22.97	45230
<i>Education</i>									
Overall	0.23	0.46	3.33	1.73	2.29	8.28	0.11	23.05	50349
No College	0.19	0.4	3.24	1.98	2.51	8.39	0.06	23.04	8877
Some College	0.22	0.46	3.32	1.87	2.41	8.43	0.09	22.86	14033
College Grad	0.25	0.47	3.4	1.66	2.23	8.3	0.12	23.13	17630
Post-Grad Study	0.25	0.48	3.31	1.44	2.01	7.94	0.17	23.21	9809
<i>Race</i>									
Overall	0.23	0.46	3.33	1.73	2.29	8.28	0.11	23.05	50349
White	0.21	0.42	3.33	1.77	2.28	8.21	0.1	23.95	38774
Black	0.34	0.68	3.33	1.61	2.66	9.2	0.19	17.58	5185
Asian	0.41	0.6	3.74	1.47	1.88	8.42	0.14	23.07	1672
Hispanic	0.23	0.46	3.18	1.6	1.98	7.64	0.14	21.91	3435
Other	0.22	0.52	3.42	1.76	2.2	8.25	0.11	21.26	1283
<i>Income</i>									
Overall	0.23	0.46	3.33	1.73	2.29	8.28	0.11	23.05	50349
1st Quartile	0.19	0.44	3.25	1.98	2.44	8.33	0.09	23.19	11481
2nd Quartile	0.21	0.44	3.29	1.78	2.33	8.26	0.1	23.22	15216
3rd Quartile	0.25	0.49	3.44	1.64	2.26	8.4	0.13	22.78	15350
4th Quartile	0.26	0.45	3.33	1.45	2.04	8.04	0.13	23.07	8302

Notes: Rows report demographic groups. Columns report the average January 2020 share of grocery purchase weight in the listed categories. N reports the number of households in each group.

Table C.27: Average plant-based alternative purchases by category and demographic group (ounces)

	Heritage Meat Alternative	Beyond/Impossible	Tofu/Seitan	N
<i>Age</i>				
Overall	1.83	0.22	0.53	50349
Cohort $\geq$ 1980	2.52	0.2	0.81	5119
Cohort $<$ 1980	1.75	0.22	0.5	45230
<i>Education</i>				
Overall	1.83	0.22	0.53	50349
No College	1.07	0.12	0.23	8877
Some College	1.53	0.19	0.35	14033
College Grad	2	0.25	0.64	17630
Post-Grad Study	2.62	0.3	0.85	9809
<i>Race</i>				
Overall	1.83	0.22	0.53	50349
White	1.67	0.2	0.36	38774
Black	2.75	0.34	0.47	5185
Asian	1.67	0.28	4.44	1672
Hispanic	2.28	0.27	0.51	3435
Other	1.93	0.26	0.68	1283
<i>Income</i>				
Overall	1.83	0.22	0.53	50349
1st Quartile	1.61	0.14	0.44	11481
2nd Quartile	1.77	0.17	0.47	15216
3rd Quartile	1.92	0.29	0.49	15350
4th Quartile	2.06	0.31	0.83	8302

Notes: Rows report demographic groups. Columns report average January 2020 purchases, measured in ounces, for the listed plant-based categories. N reports the number of households in each group.

Table C.28: Shares of grocery purchase weight in plant-based categories, by demographic group

	Heritage Meat Alternative	Beyond/Impossible	Tofu/Seitan	N
<i>Age</i>				
Overall	0.1	0.01	0.03	50349
Cohort $\geq$ 1980	0.14	0.02	0.05	5119
Cohort $<$ 1980	0.09	0.01	0.03	45230
<i>Education</i>				
Overall	0.1	0.01	0.03	50349
No College	0.05	0	0.01	8877
Some College	0.08	0.01	0.02	14033
College Grad	0.11	0.02	0.04	17630
Post-Grad Study	0.14	0.02	0.06	9809
<i>Race</i>				
Overall	0.1	0.01	0.03	50349
White	0.09	0.01	0.02	38774
Black	0.17	0.02	0.03	5185
Asian	0.1	0.03	0.29	1672
Hispanic	0.11	0.02	0.03	3435
Other	0.09	0.01	0.03	1283
<i>Income</i>				
Overall	0.1	0.01	0.03	50349
1st Quartile	0.08	0.01	0.02	11481
2nd Quartile	0.09	0.01	0.03	15216
3rd Quartile	0.11	0.02	0.03	15350
4th Quartile	0.11	0.02	0.05	8302

Notes: Rows report demographic groups. Columns report the average January 2020 share of grocery purchase weight in the listed plant-based categories. N reports the number of households in each group.