Demand Estimation of Oatmeal

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Abstract

This paper estimates consumer demand for oatmeal using Dominick's supermarket scanner data and applies a structural discrete-choice framework to evaluate pricing counterfactuals. Employing a Berry (1994) logit model with rich product and store–week fixed effects, I recover price elasticities, examine substitution patterns, and quantify revenue and consumer-welfare effects under alternative pricing and packaging strategies. The estimates imply an average own-price elasticity of approximately -1.75, with instant oatmeal exhibiting notably higher price sensitivity than regular varieties. Counterfactual simulations show that modest, category-wide price increases raise revenue with relatively small welfare losses, while targeted discounts—especially for high-elasticity products—generate substantial consumer-welfare gains at the cost of large revenue declines. These results highlight the central tradeoff between profitability and consumer welfare and underscore the importance of accounting for product heterogeneity and substitution when designing category-level pricing policies.

1 Introduction

This note examines consumer demand for oatmeal and evaluates market counterfactuals to estimate price elasticities and assess consumer welfare, with a focus on how consumers respond to changes in prices and product attributes. Oatmeal provides a useful case study: it is a differentiated packaged good with substantial variation across brands and formats, and demand likely shifts both seasonally and across consumer types. Simple correlations between prices and quantities can be misleading in such markets due to endogenous pricing and other unobserved factors, including quality differences and promotional activity. To address these issues, I adopt a structural demand framework that recovers underlying preference parameters and enables welfare analysis under a set of simulated pricing and packaging scenarios, including promotional interventions.

The analysis uses scanner data from Dominick's Finer Foods, provided by the University of Chicago Booth School of Business Kilts Center.[1] The data cover more than seven years of weekly observations from roughly 100 stores in the Chicago metropolitan area and include over 3,500 Universal Product Codes (UPCs), each representing a distinct brand–size–variety combination. For each UPC, the dataset records quantities sold, prices, profits, and product characteristics. Store-level demographic variables derived from the 1990 U.S. Census are also available, along with weekly customer counts, which define market size at the store–week level. After merging these components and applying sample restrictions, the resulting panel contains 752,069 store–week–UPC observations.

Market shares are calculated as the quantity of each UPC sold divided by the total number of customers visiting a given store in a given week. I estimate a logit demand model in which the dependent variable is the log of a product's market share relative to an outside option, defined as non-purchase of oatmeal in that store–week. Two specifications are considered: a baseline model and one including a full set of economically significant covariates. Standard

[1] I thank the Kilts Center at the University of Chicago Booth School of Business for granting public access to this dataset.

errors are clustered at the store level, and revenue-weighted prices are used to mitigate measurement error from low-volume transactions, ensuring the effective price reflects the marginal unit sold. The results indicate a strong negative relationship between price and market share, implying substantial consumer responsiveness to price changes. The implied own-price elasticity for an average product is approximately -1.75, with instant oatmeal exhibiting higher price sensitivity than regular oatmeal.

This paper contributes to the empirical analysis of differentiated product markets by combining detailed evidence on demand with methodological and counterfactual analysis within the oatmeal category. Using high-frequency scanner data, it documents systematic differences in price sensitivity and substitution patterns between instant and regular varieties, with clear implications for category management. Methodologically, it demonstrates that economically plausible demand elasticities can be recovered within a Berry (1994) logit framework using high-dimensional fixed effects, even without explicit cost instruments or complete promotional data. Building on these estimates, the paper quantifies the revenue and consumer-welfare effects of alternative pricing and packaging strategies, illustrating the tradeoffs between profitability and consumer surplus.

The remainder of the paper is organized as follows. Section 2 describes the methodology, including the data, construction of market shares, and demand estimation framework. Section 3 presents the main results, including price elasticities, and evaluates counterfactual pricing and packaging scenarios. Section 4 concludes with a summary of the findings.

2 Methodology

2.1 Data

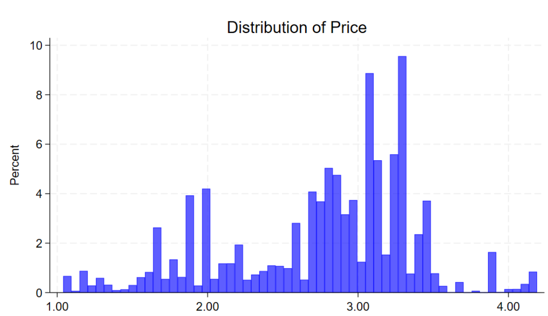
The analysis draws on scanner data from Dominick's Finer Foods, spanning over seven years of weekly observations from the late 1980s through the mid-1990s (dom, 2024). Each observation corresponds to a store–week–UPC combination, where a UPC identifies a unique brand–

size–variety product. Dominick's operated roughly 100 stores in the Chicago metropolitan area, so the data are geographically concentrated. In this study, I focus specifically on oatmeal products as classified by Dominick's.

To ensure the estimation sample reflects economically meaningful transactions, I impose several restrictions. Observations with zero quantity are excluded because the Berry inversion requires strictly positive shares. Extreme prices are trimmed by retaining only values within the 1st and 99th percentiles of the revenue-weighted price distribution, which mitigates the influence of outliers. The quantity distribution exhibits substantial right skewness, with some store-week-UPC observations recording sales exceeding 10,000 units. These high-volume observations reflect legitimate promotional events or high-traffic periods rather than data errors, and are retained in the estimation sample as they represent economically meaningful variation in demand. Moreover, to reduce sparsity and ensure the reliable identification of substitution patterns, only products sold in at least half of store–weeks are retained. After applying these filters, the final sample contains 752,069 store–week–UPC observations.

Observed product characteristics include package size (in ounces), an indicator for instant labeling, and a brand identifier. Figure 1 displays the distribution of prices across all observations, which range from \$1.04 to \$4.19 with a mean of \$2.76. This variation, both across brands and package sizes and over time within stores, provides the identifying variation necessary for demand estimation.

Figure 1: Histogram of Prices



In addition to product-level scanner data, the dataset contains store-level demographic information derived from the 1990 U.S. Census, capturing income, age composition, education, household size, and ethnicity. Because these characteristics are time-invariant, they are absorbed by store fixed effects in the baseline specification and are only interacted with time-varying covariates in the more elaborate specification to explore heterogeneity in price sensitivity.

Market size is proxied using store–week customer counts, representing the total number of shoppers visiting each store in a given week. Product-level market shares are then calculated by dividing units sold of each UPC by the corresponding store–week customer count, treating all store visitors as potential oatmeal buyers. Observations missing prices, quantities, or market shares are excluded. The dependent variable for the logit demand estimation is the log of each product's market share relative to the outside option of not purchasing oatmeal in a given week.

2.2 Estimation Method and Model

Consumer demand for oatmeal is estimated using the discrete-choice framework of Berry (1994). Consumers select among a finite set of differentiated products, including an outside option, and observed market shares arise from aggregating individual utility-maximizing choices. The key object of interest is the product-level mean utility, capturing the average valuation of each product after accounting for price and observed characteristics.

Market shares s_{jst} are defined as units sold of product j in store s during week t divided by the store–week customer count M_{st}. The outside option share is then

$$s_{0st} = 1 - \sum_{j \in \mathcal{J}_{st}} s_{jst},$$

where $\mathcal{J}_{st}$ denotes the set of products available in store s during week t. Utility for consumer i from product j is

$$u_{ijst} = \delta_{jst} + \varepsilon_{ijst},$$

with ε_{ijst} assumed to be independently and identically distributed Type I Extreme Value, yielding multinomial logit choice probabilities. Thus, mean utility decomposes as

$$\delta_{jst} = \mathbf{X}_{jst}\beta - \alpha p_{jst} + \xi_{jst},$$

where $\mathbf{X}_{jst}$ contains observed product characteristics, p_{jst} is the revenue-weighted price, and ξ_{jst} captures unobserved demand shocks, including unmeasured quality and promotional effects. Package size enters the utility specification directly, allowing counterfactual scenarios to capture consumer responses to changes in product size holding price constant. The Berry inversion recovers mean utility from observed shares:

$$\delta_{jst} = \log(s_{jst}) - \log(s_{0st}),$$

which, substituted into the mean utility equation, yields the estimating specification:

$$\log(s_{jst}) - \log(s_{0st}) = \mathbf{X}_{jst}\beta - \alpha p_{jst} + \xi_{jst}. \tag{1}$$

Identification of α is achieved through high-dimensional fixed effects: product fixed effects absorb time-invariant quality differences across UPCs, while store–week fixed effects control for common shocks affecting all products in a store-week, such as seasonal demand patterns and other store-week–specific shocks, including local competition and promotional intensity. After conditioning on these controls, remaining variation comes from within-product price changes over time, plausibly reflecting cost-driven adjustments or idiosyncratic promotions rather than systematic responses to product-specific demand shocks.

Own-price elasticities follow from the logit structure:

$$\varepsilon_{jst}^{\text{own}} = -\alpha\, p_{jst}\,(1 - s_{jst}),$$

incorporating substitution to both the outside option and other products. Consumer welfare changes under counterfactual scenarios are computed using the standard log-sum formula from discrete-choice theory, which aggregates utility changes across all products and the outside option.

Estimation is implemented in Stata using REGHDFE, which efficiently absorbs high-dimensional fixed effects via iterative demeaning, with standard errors clustered at the store level to account for within-store correlation in demand shocks over time.

2.3 Limitations and Identification

Interpreting the estimated demand requires acknowledging several limitations inherent to the data and model. To clarify sources of identifying variation, the unobserved demand component is decomposed as

$$\xi_{jst} = \lambda_{st} + \mu_j + \eta_{jst},$$

where λ_{st} captures market-level shocks common to all products in a store-week, μ_j represents time-invariant product attributes, and η_{jst} denotes residual idiosyncratic shocks. Store–week fixed effects absorb λ_{st}, and UPC fixed effects absorb μ_j, leaving identifying variation to within-product price changes over time.

While this controls-as-instruments strategy substantially mitigates price endogeneity, residual correlation between prices and unobserved demand shocks may remain. These within-product price shifts may reflect temporary discounts or other short-run pricing responses, such as inventory adjustments or idiosyncratic sales fluctuations. Promotional activity is imperfectly measured in the scanner data, raising the possibility that the estimated price coefficient partially captures endogenous promotional behavior rather than purely exogenous variation. Promotions may coincide with unobserved demand shocks, coupons or loyalty discounts may be misrecorded, and retailers may adjust multiple UPCs simultaneously, potentially correlating price with η_{jst}. Revenue-weighted prices and the absorption of store–week-level promotional intensity help reduce this concern, but it cannot be fully eliminated without access to retailer cost data.

Beyond endogeneity, the logit specification imposes the independence of irrelevant alternatives (IIA) assumption, which implies proportional substitution across products regardless of similarity. Consequently, substitution toward close competitors may be understated, while substitution toward dissimilar products could be overstated. More flexible specifications, such as nested logit or random-coefficients models, would allow richer correlation structures, but nested logit requires credible nesting definitions that can be arbitrary in a category with multiple overlapping similarity dimensions, and random-coefficients models require cost-side instruments or sufficient within-group price variation. The model is also static and abstracts from intertemporal considerations. Consumers may stockpile oatmeal during promotions or shift purchases across weeks, potentially reinforcing brand preferences over time. Such dynamics, including dynamic considerations such as habit formation or state dependence, are not captured in a single-period logit framework.

Finally, the analysis is limited to a single product category in a single geographic market during a specific historical period. Dominick's operated exclusively in the Chicago metropolitan area in the late 1980s and early 1990s, so estimated elasticities may differ in other regions or under contemporary retail conditions. Market size is proxied by store–week customer counts, which treat all visitors as potential oatmeal buyers, potentially overstating the outside option and biasing elasticity estimates downward.

2.4 Model Fit

The estimated demand model is evaluated by comparing predicted mean utilities with observed market shares and assessing the plausibility of behavioral responses. Figure 2 plots observed Berry logits, $\ln(s_{jst}) - \ln(s_{0st})$, against model-fitted values. The fitted relationship passes through the center of the observed distribution without systematic bias, and modest dispersion reflects idiosyncratic variation expected in discrete-choice settings.

Figure 2: Actual vs. Fitted Berry Logit Values

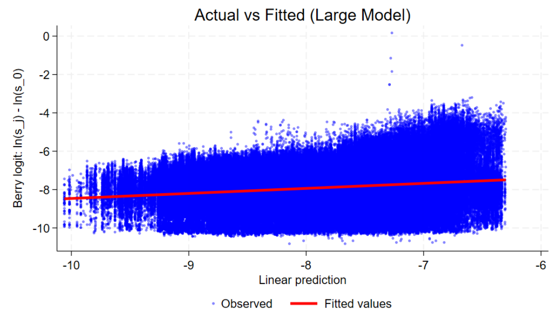
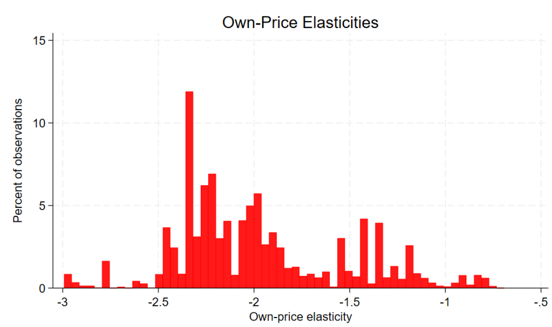


Figure 3 shows the distribution of own-price elasticities implied by the model. Most mass lies between approximately -1.5 and -2.5, concentrated near -2. The distribution avoids implausible outcomes such as positive elasticities, and the thin left tail indicates few products exhibit extreme sensitivity, suggesting that elasticities are not driven by outliers. Overall, these diagnostics confirm that the model rationalizes observed purchasing behavior and generates economically coherent price responses.

Figure 3: Distribution of Own–Price Elasticities



3 Discussion

3.1 Initial Estimation Results

Table 2 in the Appendix presents estimates from the Berry logit regression of product market shares relative to the outside option on revenue-weighted prices at the store-week-UPC level.

The coefficient on price is negative and highly statistically significant in both specifications, indicating that higher prices reduce the likelihood that a consumer purchases a given oatmeal product. In the naive model, which includes only store–week and UPC fixed effects, the estimated coefficient is -0.8645. The more comprehensive specification, which additionally controls for interactions between product characteristics and time-varying market conditions, yields a coefficient of -0.6608. This means that a one-unit increase in price reduces the log-odds of purchase by 0.6608, holding all else constant. The attenuation toward zero in the large model occurs because the additional covariates absorb variation in demand that was previously attributed to price, separating true price sensitivity from correlated demand factors such as quality differences and promotional timing.

Using the estimated coefficient from the richer specification and the average price and market share of the top 50 UPCs —\$2.76 and 0.043, respectively—the implied own-price elasticity of demand is approximately -1.75. This indicates that a one percent increase in price reduces quantity demanded by roughly 1.75 percent, placing oatmeal in the elastic portion of the demand curve. The rationale for focusing on the top 50 UPCs is straightforward. As Figure 12 shows, only a small number of UPCs account for a substantial portion of market share, while the remainder contribute very little, thereby lowering the overall average. To obtain a more meaningful and representative measure of market share, I therefore restrict the analysis to the top 50 UPCs.

Importantly, the elasticity varies meaningfully across product types. As shown in Figure 9 and discussed further in Section 4, instant oatmeal exhibits substantially higher price sensitivity than regular oatmeal, with median elasticities near -2.04 compared to -1.84 for regular varieties. This heterogeneity reflects differences in the competitive environment: instant products face closer substitutes from ready-to-eat cereals and breakfast bars, whereas regular oatmeal competes primarily within a narrower set of hot breakfast options. These patterns motivate the counterfactual analysis that follows, which exploits variation in elasticities to evaluate targeted pricing strategies.

3.2 Notes on Counterfactuals

I consider five counterfactual pricing and packaging scenarios designed to capture realistic retailer decision problems. Scenario 1 applies a uniform 10% price increase to all products, representing a category-wide margin improvement strategy. Scenario 2 raises prices by 15% for the top 20 products by market share, reflecting a premium-targeting approach that exploits high-share UPCs' perceived inelasticity. Scenario 3 increases package size by 15% for smaller products without altering prices, effectively reducing the price per ounce and testing consumer responsiveness to value-per-unit changes. Scenario 4 reduces prices by 25% for products with the highest estimated price elasticities, simulating an aggressive promotional strategy aimed at elastic segments. Scenario 5 applies a 25% price reduction to products labeled "INST" in their descriptions, targeting the instant oatmeal subcategory specifically. In all cases, product characteristics other than the targeted price or size adjustment are held fixed, and the analysis abstracts from potential supply-side constraints or competitor responses.

To simulate demand responses, I exploit the invertibility of the logit model to trace how changes in prices or product attributes propagate through the choice set and reallocate demand across products and to the outside option. The baseline for each counterfactual is defined at the store–week–UPC level using observed prices, quantities, and revenues from the estimation sample. For each scenario, I construct a counterfactual mean utility $\delta_{jst}^{\mathrm{CF}}$ by modifying the relevant component of δ_{jst} according to the scenario-specific policy rule. For price changes, this involves updating the price term $-\alpha p_{jst}$ to $-\alpha p_{jst}^{\mathrm{CF}}$. For size changes, the modification adjusts the package size component of $\mathbf{X}_{jst}$, effectively lowering the implicit price per ounce and allowing consumers to substitute toward larger package sizes. Counterfactual market shares are computed by applying the logit formula to the modified utilities:

$$s_{jst}^{\mathrm{CF}} = \frac{\exp(\delta_{jst}^{\mathrm{CF}})}{\sum_{k \in \mathcal{J}_{st}} \exp(\delta_{kst}^{\mathrm{CF}})},$$

where $\mathcal{J}_{st}$ denotes the set of products available in market (s, t). Counterfactual quantities follow directly from the implied choice probabilities:

$$Q_{jst}^{\mathrm{CF}} = s_{jst}^{\mathrm{CF}} \cdot M_{st}.$$

Revenue under each scenario is computed as $R_{jst}^{\mathrm{CF}} = P_{jst}^{\mathrm{CF}} \times Q_{jst}^{\mathrm{CF}}$, where P_{jst}^{CF} denotes the counterfactual price. Changes in quantities and revenues are measured relative to their baseline counterparts. Consumer welfare is evaluated using the standard log-sum formula from discrete-choice theory, which aggregates utility changes across all available products. The change in expected consumer surplus, expressed in dollar-equivalent units, is given by

$$\Delta \mathrm{CS}_{st} = \frac{1}{|\bar{\alpha}|} \left[\ln\left(\sum_{k \in \mathcal{J}_{st}} \exp(\delta_{kst}^{\mathrm{CF}}) \right) - \ln\left(\sum_{k \in \mathcal{J}_{st}} \exp(\delta_{kst}) \right) \right],$$

where $\bar{\alpha} < 0$ denotes the estimated price coefficient. This expression measures the compensating variation required to make consumers indifferent between the baseline and counterfactual choice sets. Welfare changes are aggregated across store–weeks to obtain total consumer surplus effects for each scenario, enabling comparison of the distributional consequences of alternative pricing strategies.

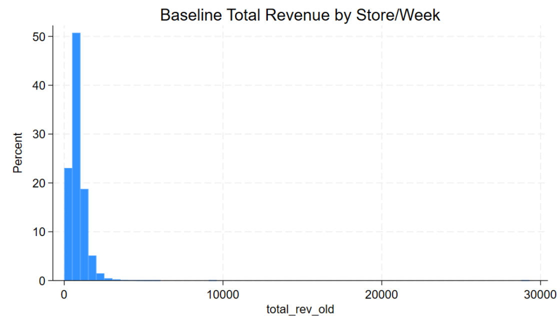
For each counterfactual, I report market-level aggregates for total revenue and consumer welfare and omit product-level results for brevity. All simulations preserve the internal consistency of the logit model by ensuring that counterfactual market shares sum to one within each store–week and that the outside option absorbs any residual probability mass.

3.3 Counterfactual Revenue Effects

Baseline total revenue exhibits substantial cross-sectional variation (Figure 4). The distribution is strongly right-skewed: most store–weeks generate oatmeal revenue below $2,000, while a small fraction exceed $5,000.

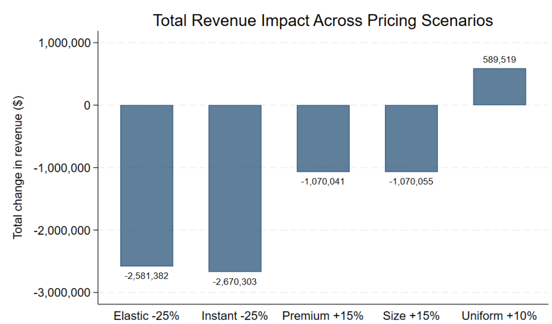
Figure 5 reports revenue changes relative to baseline across the five scenarios. By con-

Figure 4: Baseline Total Revenue



struction, these comparisons isolate demand-side effects, holding market size and assortment composition fixed. The uniform 10% price increase raises total revenue by approximately \$589,519, which is consistent with the estimated category-level elasticity.

Figure 5: Revenue Comparison across Scenarios



All other interventions reduce revenue. Increasing prices by 15% on the top 20 products lowers revenue by roughly \$1,070,041, and the package-size expansion yields a nearly identical decline of \$1,070,055. In the first case, the revenue loss reflects the disproportionate exposure of the category to a small set of high-share UPCs. In the second, increasing package sizes without adjusting prices effectively lowers unit prices and shifts demand toward the expanded sizes, altering the category mix in a revenue-unfavorable direction.

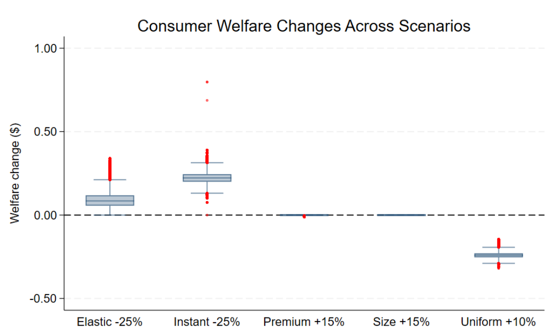
The deepest revenue losses arise under the targeted discount scenarios. Reducing prices by 25% for high-elasticity products and for instant oatmeal decreases revenue by \$2,581,382 and \$2,670,303, respectively. Although these discounts expand category volume, the implied margin compression dominates: the additional sales induced by lower prices do not offset the per-unit revenue reduction at the category level.

Taken together, the revenue results draw a clear distinction between modest, broad-based adjustments as opposed to narrowly targeted interventions. The former produces a stable, positive revenue response in aggregate, whereas targeted changes—whether increases on high-share items, implicit unit-price cuts via package expansion, or deep discounts—expose the category to sharper and less forgiving shifts in demand across products.

3.4 Distribution of Welfare Changes and Revenue–Welfare Trade-off

Figure 6 displays the distribution of consumer welfare changes, measured in dollars per consumer per week. The discount scenarios generate welfare gains for most consumers and exhibit substantial right skewness, indicating that benefits are concentrated among consumers most exposed to the discounted set. The instant oatmeal discount produces the largest effects, with a median gain of approximately \$0.20 per consumer per week and a long right tail extending beyond \$0.70. The elasticity-targeted discount yields a median gain of roughly \$0.10.

Figure 6: Welfare Comparison across Scenarios



By contrast, price increases and package-size expansion generate welfare changes clustered tightly around zero. The uniform 10% price increase produces small but systematic welfare losses, with a median decline of approximately \$0.25 per consumer per week. While modest in magnitude, these losses are diffuse, reflecting that the policy affects essentially all category shoppers. The targeted 15% increase on the top 20 products yields a near-zero median and modest negative skew, consistent with concentrated impacts among consumers with strong preferences for the high-share items. Because market size includes all store visitors, welfare changes represent the average effect across all potential consumers, not just oatmeal purchasers.

To connect consumer surplus changes to firm outcomes, Figures 7 and 8 plot changes in consumer welfare against changes in total revenue for the elasticity-based discount scenario at the store–week level. Observations are sorted by welfare change and divided into 20 equal-sized bins (ventiles). Each point represents mean revenue and welfare changes within a bin.

Figure 7: Revenue–Welfare Tradeoff for the Elastic Scenario

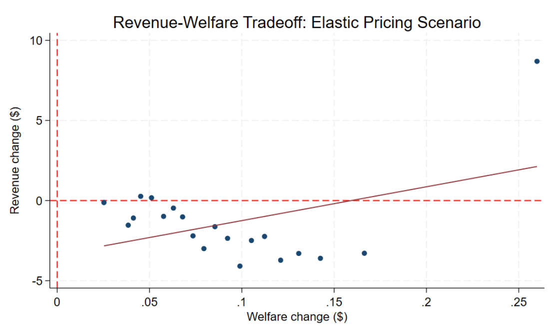
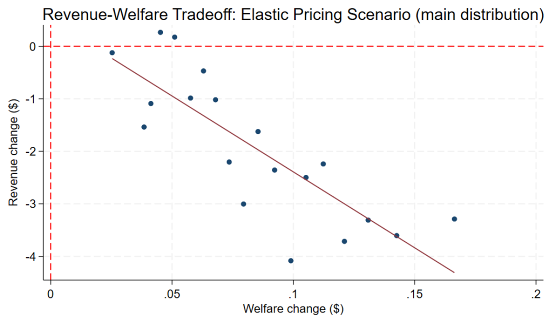


Figure 7 displays the full distribution across 20 bins. The fitted line suggests an upward-sloping pattern, but this appearance is driven almost entirely by the extreme right tail. The rightmost point represents store-weeks in the top 5% of welfare changes, where an outlier observation with welfare gains exceeding \$0.25 and revenue gains near \$9 pulls the apparent relationship upward and dominates the scale of the entire plot.

When attention is restricted to the main body of the welfare distribution, a fundamentally different pattern emerges. Figure 8 excludes observations above the 95th percentile of welfare changes and re-bins the remaining data into 19 equal-sized bins where each point represents mean revenue and welfare changes within a bin. The fitted line shows a clear negative relationship.

Figure 8: Revenue–Welfare Tradeoff for the Elastic Scenario (Main Distribution)



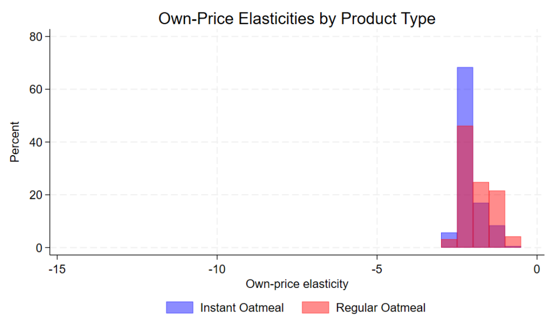
Across these 19 bins, higher average welfare gains are systematically associated with larger average revenue losses. The fitted linear relationship shows a negative slope, indicating that typical welfare improvements come at the cost of reduced revenue. While the binned scatter absorbs within-bin variation, the consistent downward pattern across the full range of typical welfare changes reveals a genuine tradeoff: incremental welfare improvements tend to reduce revenue for the vast majority of store-week outcomes. The fact that this negative relationship only becomes visible once the extreme tail is removed underscores that the tradeoff is systematic across the main distribution rather than driven by averaging over heterogeneous effects. The sensitivity to these outliers suggests caution when interpreting aggregate welfare-revenue relationships without examining the full distribution.

The welfare evidence therefore illustrates a central policy tension. Interventions that deliver meaningful improvements in consumer surplus in this category tend, on average, to reduce firm revenue; conversely, policies that reliably increase revenue impose welfare losses spread across consumers. The practical implication is not that one objective dominates, but that revenue and welfare move in systematically different directions under the pricing scenarios considered. Policy evaluation therefore necessarily depends on how the analyst weighs these competing objectives and on the importance assigned to the distributional incidence of gains and losses across consumers.

3.5 Heterogeneity and Substitution Patterns

The revenue–welfare patterns above are shaped by heterogeneity in demand sensitivity and by how consumers reallocate purchases across the assortment. Figure 9 shows systematic differences in own-price elasticities across product types: instant oatmeal is considerably more price-elastic than regular oatmeal, with median elasticities near -2.04 versus -1.84. This distinction is consistent with a wider set of close substitutes for instant products, whereas regular oatmeal buyers tend to face a narrower comparison set and exhibit greater persistence in purchases.

Figure 9: Own-price Elasticities by Product Type



Substitution under discounting also exhibits a clear direction. In the elasticity-targeted discount scenario, quantity gains concentrate in the lowest price quartile while higher-priced quartiles lose volume (Figure 10), indicating systematic down-trading. Total units increase by approximately 600,000, but the mix shifts toward cheaper products, compressing average margins despite higher category volume. The UPC-level decomposition reinforces this pattern: Figure 11 shows gains concentrated among lower-priced products and losses among higher-priced premium UPCs.

Finally, the oatmeal category is highly concentrated, which amplifies the consequences of targeted interventions. A small number of high-share UPCs account for a large share of category volume (Figure 12), so price changes applied narrowly to these items can generate large revenue swings even when average elasticities appear moderate. This concentration

Figure 10: Net Quantity Change by Price Quartile in Elastic Scenario

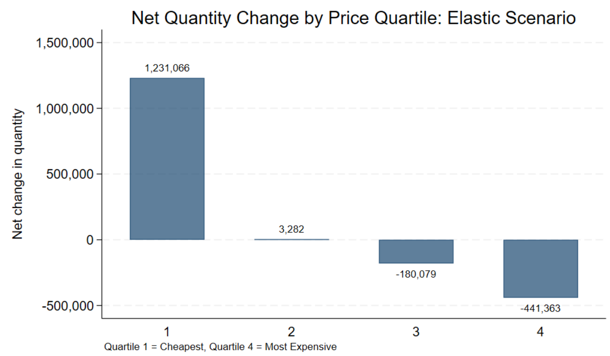
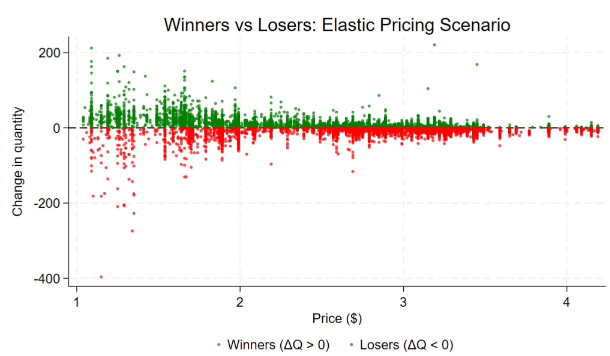


Figure 11: UPC-level Winners and Losers in Elastic Scenario



helps rationalize why the premium-targeted price increase reduces revenue: the policy loads the quantity response onto the products that matter most for category totals.

Figure 12: Price-Share Relationship

4 Insights and Conclusion

The counterfactuals deliver a consistent message about pricing in differentiated packaged goods: outcomes hinge not only on average demand sensitivity, but also on how interventions reshape the composition of demand within the assortment. In this setting, modest category-wide price increases are the most reliable way to raise revenue, precisely because they avoid concentrating the adjustment on a small set of high-exposure products and limit sharp shifts in the product mix. By contrast, narrowly targeted changes—whether increases on a small set of high-share UPCs or deep discounts on price-sensitive segments—are more likely to trigger large reallocations of purchases across products and to erode revenue through mix and margin effects.

Several practical implications follow. First, for revenue-oriented objectives, modest and broadly applied price increases (on the order of 5–10%) are a comparatively robust instrument. Second, deep discounts on price-sensitive items can generate meaningful consumer surplus gains, but they do so at substantial revenue cost, and these costs are amplified when discounts induce down-trading toward lower-revenue products. Third, the concentration of the oatmeal category implies that pricing on a small set of high-share UPCs warrants particular caution: small miscalibrations can have outsized aggregate effects. Fourth, package-size expansions without accompanying price adjustments should be treated as implicit unit-price reductions and evaluated accordingly.

More broadly, the analysis highlights why pricing policy cannot be assessed solely through average elasticities. Product heterogeneity and substitution patterns, especially given the concentration of sales within the category jointly determine whether a given intervention expands the category or reshuffles demand within it. For both managers and policymakers, the relevant question is therefore not just whether consumers respond to prices, but where that response comes from and how it redistributes purchases across the assortment, profits, and consumer surplus.

5 Appendix: Summary Statistics and Regression Results

Table 1: Summary Statistics for Key Variables

Variable	Mean	SD	Min	Max
Berry logit: $\ln(s_j) - \ln(s_0)$	-7.92	0.97	-10.82	0.17
Price	2.76	0.62	1.04	4.19
price_wmean	2.76	0.62	1.04	4.19
size_oz	18.51	8.55	5.00	42.00
instant	0.34	0.47	0.00	1.00
income	10.62	0.29	9.87	11.24
age9	0.14	0.02	0.05	0.19
age60	0.17	0.06	0.06	0.31
educ	0.23	0.11	0.05	0.53
ethnic	0.16	0.19	0.02	1.00
quantity	10.62	21.53	1.00	10816.00
rev	807.52	447.08	2.75	29199.62
share	.001	0.00	0.00	0.41
Observations	752,069			

Notes: Summary statistics are calculated at the store-week-UPC level.

Table 2: Regression Results: Berry Logit

	Naive Model (1)	**Large Model** (2)
Dependent variable:	Berry logit: $\ln(s_j) - \ln(s_0)$	
Mean price per store-week-UPC	-0.8645***	-0.6608***
	(0.0073)	(0.0367)
Observations	752,067	727,432
R-squared	0.2658	0.6337

Notes: Standard errors are in parentheses. All regressions include store × week and UPC fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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