

Large Firms, Consumer Heterogeneity and the Profit Share

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ONLINE APPENDIX

A1. Model Derivations

COMPLEMENTS AND SUBSTITUTES.

Consider the demand for a product i by firm f in a segment n and product group g . For ease of notation, let us focus on a single product group and a single segment, so that the only subscripts left are product i and firm f :

$$(A1) \quad q_{if} = zwP^{\sigma-1}z_f^{\sigma-1}P_f^{\eta-\sigma}z_{if}^{\eta-1}p_{if}^{-\eta},$$

Let us now consider the cross-price elasticity of demand for product i with respect to the price of product j produced by the same firm:

$$\begin{aligned} \frac{d \ln q_{if}}{d \ln p_{jf}} &= (\sigma - 1) \frac{d \ln P}{d \ln P_f} \frac{d \ln P_f}{d \ln p_{jf}} + (\eta - \sigma) \frac{d \ln P_f}{d \ln p_{jf}} = \\ &= \frac{d \ln P_f}{d \ln p_{jf}} \left((\sigma - 1) \frac{d \ln P}{d \ln P_f} + \eta - \sigma \right) = \\ &= s_{jf} ((\sigma - 1)s_f + \eta - \sigma) \end{aligned}$$

The elasticity is positive and the two products are substitutes if:

$$(A2) \quad \eta > \sigma - (\sigma - 1)s_f$$

If $\eta > \sigma$ then the products within all firms are positive. If $\eta < \sigma$, then whether or not products within a firm are complements or substitutes depends on the market share of the firm. If $s_f > \frac{\sigma-\eta}{\sigma-1}$, then products are substitutes and, vice versa, products are complements if $s_f < \frac{\sigma-\eta}{\sigma-1}$.

PROFITS

Revenues for a firm f from UPC i in segment n are given by:

$$L_n p_{ifn} q_{ifn} = z_g L_n w_n P_n^{\sigma-1} z_f^{\sigma-1} P_{fn}^{\eta-\sigma} z_{ifn}^{\eta-1} p_{if}^{1-\eta} = z_g L_n w_n \left(\frac{P_{fn}}{z_f P_n} \right)^{1-\sigma} \left(\frac{p_{if}}{z_{ifn} P_{fn}} \right)^{1-\eta},$$

where z_g denotes the demand shifter for good g , but for convenience, we omit the subscript g on all other variables and parameters. Summing over the varieties sold to segment n yields the following segment-specific revenues:

$$\sum_{i \in I_f} L_n p_{ifn} q_{ifn} = z_g L_n w_n \left(\frac{P_{fn}}{z_f P_n} \right)^{1-\sigma} \sum_{i \in I_f} \left(\frac{p_{if}}{z_{ifn} P_{fn}} \right)^{1-\eta} = z_g L_n w_n \left(\frac{P_{fn}}{z_f P_n} \right)^{1-\sigma}.$$

Let $Lw^N L_n w_n$ denote total income of all consumers, and $\alpha_n = L_n w_n / \sum_{n=1}^N L_n w_n$ denote the share of income for consumers in segment n . Firm f total revenues R_f are given by:

$$(A3) \quad R_f = \sum_{n=1}^N \sum_{i \in I_f} L_n p_{ifn} q_{ifn} = z_g Lw \sum_{n=1}^N \alpha_n z_f^{\sigma-1} \left(\frac{P_{fn}}{P_n} \right)^{1-\sigma}.$$

We also keep track of the total variable costs of a firm, which are:

$$TC_f = \sum_{n=1}^N \sum_{i \in I_f} L_n c_{if} q_{ifn} = z_g z_f^{\sigma-1} Lw \sum_{n=1}^N \alpha_n P_n^{\sigma-1} P_{fn}^{\eta-\sigma} \sum_{i \in I_f} z_{ifn}^{\eta-1} c_{if} p_{if}^{-\eta}.$$

FIRST ORDER CONDITION

To simplify the derivations of the first-order condition, let us consider the derivative of revenues with respect to prices p_{if} . In Bertrand competition, firms take into account the effects of changing prices both on the firm and segment-specific price index P_{fn} , and on the product group and segment-specific price index P_n :

$$\frac{\partial R_f}{\partial p_{if}} = z_g Lw \sum_{n=1}^N \alpha_n z_f^{\sigma-1} \left(\frac{P_{fn}}{P_n} \right)^{1-\sigma} (1-\sigma) \left[\frac{\partial P_{fn}}{\partial p_{if}} \frac{1}{P_{fn}} - \frac{\partial P_n}{\partial P_{fn}} \frac{P_{fn}}{P_n} \frac{\partial P_{fn}}{\partial p_{if}} \frac{1}{P_{fn}} \right].$$

Using the definitions of market shares in (7) and (8), we obtain:

$$\frac{\partial R_f}{\partial p_{if}} = z_g Lw \sum_{n=1}^N \alpha_n s_{fn} (1 - \sigma) \left[\frac{s_{ifn}}{p_{if}} - \frac{s_{ifn}}{p_{if}} s_{fn} \right] = (1 - \sigma) \frac{z_g Lw}{p_{if}} \sum_{n=1}^N \alpha_n s_{fn} s_{ifn} (1 - s_{fn}).$$

Taking the derivative of total costs with respect to p_{if} yields:

$$\begin{aligned} \frac{\partial TC_f}{\partial p_{if}} &= z_g z_f^{\sigma-1} Lw \sum_{n=1}^N \alpha_n P_n^{\sigma-1} P_{fn}^{\eta-\sigma} \left[(\sigma - 1) \frac{s_{ifn}}{p_{if}} s_{fn} + (\eta - \sigma) \frac{s_{ifn}}{p_{if}} \right] \sum_{i \in I_f} z_{ifn}^{\eta-1} c_{if} p_{if}^{-\eta} \\ &\quad + z_g z_f^{\sigma-1} Lw \sum_{n=1}^N \alpha_n P_n^{\sigma-1} P_{fn}^{\eta-\sigma} z_{ifn}^{\eta-1} (-\eta) c_{if} p_{if}^{-\eta-1} \\ &= z_g Lw \sum_{n=1}^N \alpha_n \left(\frac{P_{fn}}{z_f P_n} \right)^{1-\sigma} P_{fn}^{\eta-1} \left[(\sigma - 1) \frac{s_{ifn}}{p_{if}} s_{fn} + (\eta - \sigma) \frac{s_{ifn}}{p_{if}} \right] \sum_{i \in I_f} z_{ifn}^{\eta-1} c_{if} p_{if}^{-\eta} \\ &\quad + z_g Lw \sum_{n=1}^N \alpha_n \left(\frac{P_{fn}}{z_f P_n} \right)^{1-\sigma} P_{fn}^{\eta-1} z_{ifn}^{\eta-1} (-\eta) c_{if} p_{if}^{-\eta-1}. \end{aligned}$$

Using the definitions of market shares, we obtain:

$$\begin{aligned} \frac{\partial TC_f}{\partial p_{if}} &= \frac{z_g Lw}{p_{if}} \sum_{n=1}^N \alpha_n s_{fn} [(\sigma - 1) s_{ifn} s_{fn} + (\eta - \sigma) s_{ifn}] \frac{\sum_{i \in I_f} z_{ifn}^{\eta-1} c_{if} p_{if}^{-\eta}}{\sum_{i \in I_f} z_{ifn}^{\eta-1} p_{if}^{1-\eta}} + \\ &\quad - \eta \frac{z_g Lw}{p_{if}} \sum_{n=1}^N \alpha_n s_{fn} \frac{s_{ifn}}{p_{if}} c_{if}. \end{aligned}$$

Using the definition of market shares of UPC within a firm, we can rewrite the term above as:

$$\frac{\sum_{i \in I_f} z_{ifn}^{\eta-1} c_{if} p_{if}^{-\eta}}{\sum_{i \in I_f} z_{ifn}^{\eta-1} p_{if}^{1-\eta}} = \frac{\sum_{i \in I_f} s_{ifn} \frac{c_{if}}{p_{if}}}{\sum_{i \in I_f} s_{ifn}} = \sum_{i \in I_f} s_{ifn} \frac{c_{if}}{p_{if}}.$$

It follows that the derivative of the firm total costs is equal to:

$$\frac{\partial TC_f}{\partial p_{if}} = \frac{z_g L w}{p_{if}} \left[\sum_{n=1}^N \alpha_n s_{fn} s_{ifn} [(\sigma - 1)s_{fn} + (\eta - \sigma)] \sum_{i \in I_f} s_{ifn} \frac{c_{if}}{p_{if}} - \eta \sum_{n=1}^N \alpha_n s_{fn} s_{ifn} \frac{c_{if}}{p_{if}} \right].$$

We, therefore, obtain the following first-order condition:

$$\begin{aligned} \frac{\partial R_f}{\partial p_{if}} &= \frac{\partial TC_f}{\partial p_{if}} \implies \\ (\sigma - 1) \sum_{n=1}^N \alpha_n s_{fn} s_{ifn} (1 - s_{fn}) &= \eta \sum_{n=1}^N \alpha_n s_{fn} s_{ifn} \frac{c_{if}}{p_{if}} \\ &\quad - \sum_{n=1}^N \alpha_n s_{fn} s_{ifn} [(\sigma - 1)s_{fn} + (\eta - \sigma)] \sum_{i \in I_f} s_{ifn} \frac{c_{if}}{p_{if}}. \end{aligned}$$

It is convenient to rewrite the equation as a function of markups $\mu_{if} = p_{if}/c_{if}$:

$$(\sigma - 1) \sum_{n=1}^N \alpha_n s_{fn} s_{ifn} (1 - s_{fn}) = \frac{\eta}{\mu_{if}} \sum_{n=1}^N \alpha_n s_{fn} s_{ifn} - \sum_{n=1}^N \alpha_n s_{fn} s_{ifn} [(\sigma - 1)s_{fn} + (\eta - \sigma)] \sum_{i \in I_f} \frac{s_{ifn}}{\mu_{if}}$$

Notice that $\sum_{n=1}^N \alpha_n s_{fn} s_{ifn} = s_{if}$ equals the market share of UPC i of firm f within the product group. We divide both sides of the equation by $\sum_{n=1}^N \alpha_n s_{fn} s_{ifn}$, to obtain the expression (10) shown in the main text.

PROOF OF PROPOSITION 1

Proposition 1 is stated for all product groups $g = 1, \dots, G$, but in this proof we drop the subscript g . Jensen's inequality states that $\sum_{n=1}^N \alpha_n s_{fn}^2 \geq \left(\sum_{n=1}^N \alpha_n s_{fn} \right)^2$, and this inequality holds as equality if and only if $s_{fn} = s_{fm} \forall m, n$. So the inequality is strict if $s_{fn} \neq s_{fm}$ for some firm f and segments $m \neq n$. Let us consider the ratio s_{fn}/s_{fm} from (5) and (7), using the fact that the firm shifter z_f (appearing as z_{fg} in (5)) cancels because s_{fn} and s_{fm} are for the same firm f :

$$(A4) \quad \frac{s_{fn}}{s_{fm}} = \left(\frac{P_{fn}/P_n}{P_{fm}/P_m} \right)^{1-\sigma} = \left(\frac{z_{ifm} P_m}{z_{ifn} P_n} \right)^{1-\sigma},$$

where the second equality follows from (6) and using the assumption of a single product firm in the *HetC* model, so that $I_{fn} = \{i\}$. We need to show that $s_{fn} \neq s_{fm}$ for two consumer segments m and n and some firm f to ensure that Jensen's inequality holds strictly.

Suppose to the contrary that $s_{fn} = s_{fm}$ in (A4), which implies that $P_m/P_n = z_{ifn}/z_{ifm}$. Then we make use $z_{jf'm}/z_{jf'n} \neq z_{ifm}/z_{ifn}$ from Definition 1, to conclude that

$$1 \neq \left(\frac{z_{jf'm}}{z_{jf'n}} \frac{z_{ifn}}{z_{ifm}} \right)^{1-\sigma} = \left(\frac{z_{jf'm}}{z_{jf'n}} \frac{P_m}{P_n} \right)^{1-\sigma} = \frac{s_{f'n}}{s_{f'm}},$$

where the second equality follows from our assumption that $s_{fn} = s_{fm}$, which implies that $P_m/P_n = z_{ifn}/z_{ifm}$, and the third equality follows by computing $s_{f'n}/s_{f'm}$ just like in (A4). So we find that $s_{f'n} \neq s_{f'm}$, which guarantees that Jensen's inequality holds strictly.

DEMAND ELASTICITIES AND MARKUPS

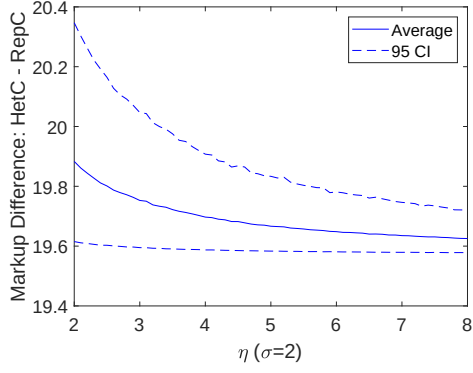
Figure A.1 plots the percentage point difference in markups between the *HetC* model and the *RepC* model. We consider a numerical exercise with four segments with the following expenditure shares $\alpha = [0.5, 0.2, 0.2, 0.1]$ and a firm with the following firm-segment market share across segments: $s_{fn} = [0.4, 0.05, 0.1, 0.2]$. We fixed these values to minimize the number of simulations needed to in the exercise. The firm sells five products, whose market shares in each segment are drawn from a uniform distribution. In particular, for each product we draw a value from the uniform distribution $\tilde{u}_{ifn}$ and normalize it so that the draws yield the market share of the items within a firm-segment ($s_{ifn} = \tilde{u}_{ifn} / \sum_i \tilde{u}_{ifn}$). For each value of σ and η shown in the figure, we draw the market share of the firm's products 1000 times and compute the percentage point difference between μ_{HetC} and μ_{RepC} . Across realizations, we compute the average difference and the 5th and 95th percentiles, which we plot in the figures. Higher demand elasticities are associated with lower markups and the relationship is steeper for the elasticity across-firm (σ) than within-firm (η).

CANNIBALIZATION RATE

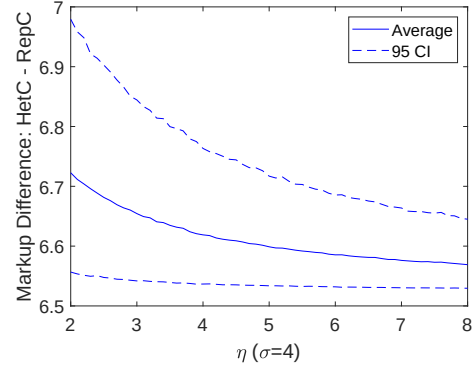
In a slight abuse of notation (because we omit the subscript f), let $\bar{I} \equiv |I_f|$ denote the number of items in the set I_f , and suppose that we rank these items by decreasing demand. Following Hottman, Redding and Weinstein (2016), we can compute the cannibalization rate defined as the elasticity

Figure A.1. : Markups and Demand Elasticities

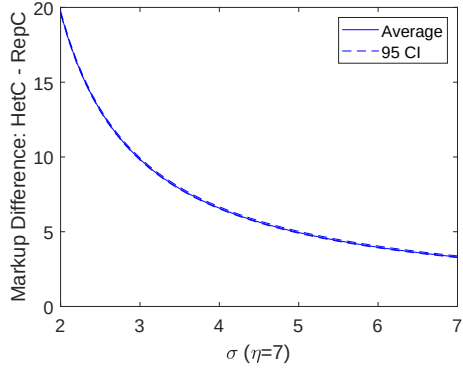
(a) Within-Firm Elasticity η



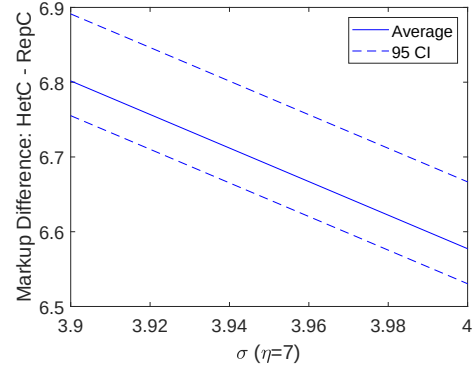
(b) Within-Firm Elasticity η



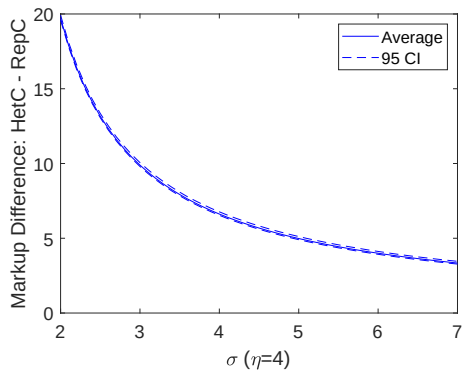
(c) Across-Firm Elasticity σ



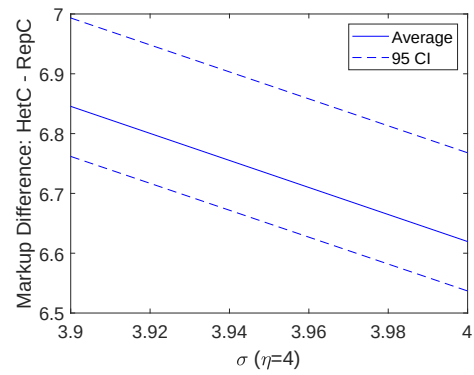
(d) Across-Firm Elasticity σ (Zoom)



(e) Across-Firm Elasticity σ



(f) Across-Firm Elasticity σ (Zoom)



of demand for the last UPC, $q_{\bar{I}fn}$, with respect to the number of UPCs $\bar{I}$. Such an elasticity can be derived analytically, assuming that the number of products is large enough to be approximated by a continuum, so that:

$$\frac{\partial P_{fn}}{\partial \bar{I}} \approx \frac{P_{fn} s_{\bar{I}fn}}{1 - \eta}.$$

As a result, we can compute the cannibalization rate as follows:

$$\begin{aligned} \frac{\partial q_{\bar{I}fn}}{\partial \bar{I}} &= (\sigma - 1) \frac{q_{\bar{I}fn}}{P_n} \frac{\partial P_n}{\partial P_{fn}} \frac{\partial P_{fn}}{\partial \bar{I}} + (\eta - \sigma) \frac{q_{\bar{I}fn}}{P_n} \frac{\partial P_{fn}}{\partial \bar{I}} \\ &= (\sigma - 1) \frac{q_{\bar{I}fn}}{P_{fn}} \frac{\partial P_n}{\partial P_{fn}} \frac{P_{fn} s_{\bar{I}fn}}{1 - \eta} + (\eta - \sigma) \frac{q_{\bar{I}fn}}{P_n} \frac{P_{fn} s_{\bar{I}fn}}{1 - \eta} \\ &= (\sigma - 1) \frac{q_{\bar{I}fn} s_{fn} s_{\bar{I}fn}}{1 - \eta} + (\eta - \sigma) \frac{q_{\bar{I}fn} s_{\bar{I}fn}}{1 - \eta}, \end{aligned}$$

with which we can obtain the cannibalization rate by segment:

$$(A5) \quad \frac{\partial q_{\bar{I}fn}}{\partial \bar{I}} \frac{\bar{I}}{q_{\bar{I}fn}} = - \left(\frac{\sigma - 1}{\eta - 1} s_{fn} + \frac{\sigma - \eta}{\eta - 1} \right) s_{\bar{I}fn} \bar{I}.$$

Thus, expanding the scope reduces the demand for an individual UPC from a segment and such a reduction is proportional to the market share of the firm in the niche (s_{fn}), the market share of the UPC in the segment-firm ($s_{\bar{I}fn}$), and the number of UPCs ($\bar{I}$). The difference in demand elasticities within and across firms generates part of the cannibalization effects: when a firm introduces a new variety, the new variety cannibalizes the sales of the firm's existing varieties *and* the sales of other firms. The magnitude of the own-cannibalization effects depends on the firm market size and on the substitutability within-firm relative to across-firm. Following Hottman, Redding and Weinstein (2016), let us define the cannibalization rate as (A5) evaluated at a particular product that has a market share in the segment equal to the average market share, so that $s_{\bar{I}fn} \bar{I} = 1$ and $s_{\bar{I}fn} = 1/\bar{I}$.

To account for the fact that introducing a new UPC cannibalizes demand across other segments, we compute an average cannibalization rate across segments where we use segment size (α_n) as weights:

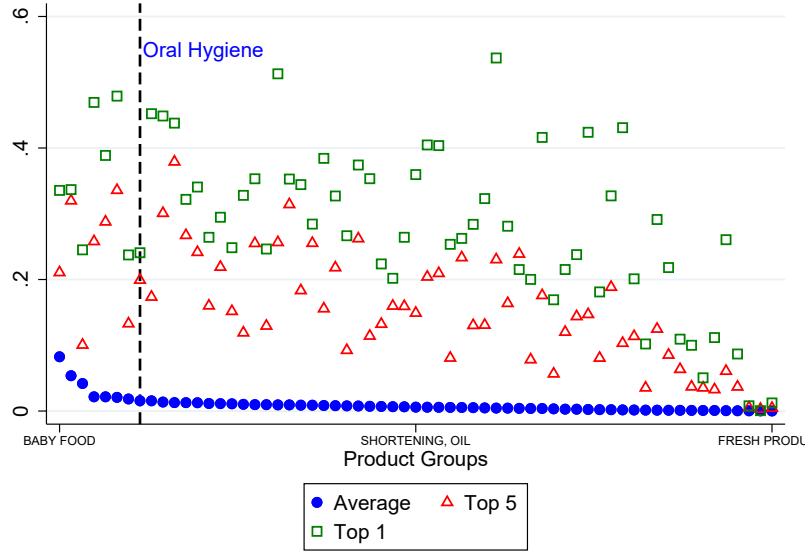
$$(A6) \quad \sum_{n=1}^N \alpha_n \frac{\partial q_{\bar{I}fn}}{\partial \bar{I}} \frac{\bar{I}}{q_{\bar{I}fn}} = - \left(\frac{\sigma - 1}{\eta - 1} \sum_{n=1}^N \alpha_n s_{fn} + \frac{\sigma - \eta}{\eta - 1} \right),$$

which has the convenient property of being identical to the formula in

Hottman, Redding and Weinstein (2016), since $\sum_{n=1}^N \alpha_n s_{fn}$ is the market share of the firm. Although the average cannibalization rate is independent of consumer heterogeneity, the rate is heterogeneous across segments, which could be a crucial factor for firms deciding to introduce new products.

We compute the cannibalization rate by segment and the average cannibalization rate for firms defined in equations (A5) and (A6). Then, for each firm, we compute the difference between the maximum cannibalization rate and its minimum, across segments. In Figure A.2, we report the average difference by product group and the difference for the top one and five firms. For instance, in the oral hygiene case, the difference between the maximum and minimum cannibalization rate is 0.02, which suggests minimal differences across segments. However, when we consider the top five firms and the top one firm, the rate jumps to 0.2 and 0.24. As shown in the picture, considering the largest firms, the heterogeneity across segments for cannibalization rate is sizable.

Figure A.2. : Max-Min Difference of Cannibalization Rates across Segments



A2. Consumer Segments

Table A.1 reports the number of consumer types by product group using our clustering methodology of section III.A for 2012. Table A.2 reports the

percentage point difference in markups between the *HetC* and the *RepC* models across product groups.

In Table A.3, we provide summary statistics for the demographic heterogeneity across segments. In particular, for each demographic group described in the rows, we compute its share in each segment and product group. Then, we compute the coefficient of variation (defined as the ratio between standard deviation and average), average, standard deviation, difference between maximum and minimum value, maximum, and minimum of such a share across segments within a product group. We then average across years and across product groups. Take the row “Young”. The coefficient of variation for young households is 0.13. Young households constitute on average 31% of a segment and the standard deviation across segments is, on average, 0.04, and the coefficient of variation is 10.8. The segment that is typically most represented by young households has a share of 36%, while the segment that is typically underrepresented by young households has a share of 27%. On average, the difference between the most “Young” segment and the least “Young” segment is 9 percentage points.

Figures A.3 and A.4 plot the distribution across product groups of a few quantitatively relevant demographic characteristics. Figures A.5 and A.6 show the changes over time of these demographic characteristics.

A3. Geographic Distribution of Consumer Segments

Let $Popsh_{n|c}$ and $Popsh_g$ be the population share of consumers of type n in location c and at the national level, respectively. Under the null hypothesis that consumers of type n is independently uniformly distributed across regions $c = 1, \dots, C$, the Bayesian rule suggests that:

$$(A7) \quad H_0 : \quad Popsh_{n|c} = \frac{Popsh_n \times Popsh_c}{Popsh_c} = Popsh_n$$

where $Popsh_n$ is the population share of group n at the national level, and $Popsh_c$ is the population of consumers in region c as a share of national total. Rejection of (A7) may raise the concern that consumers are concentrated in particular regions and firms may practice price discrimination across segments by setting different prices in different locations, which is inconsistent with the model and empirical specifications. In each year and product group, we test equation (A7) by consumer segment, where we consider consumer segments are based upon their taste. Since the number of certain types of consumers is somewhat sparse at the county level, we consider a region as a state.

Table A.1—: Number of Customer Types by Product Group (2012)

	Number of Consumer Types
Baby Food	4
Baking Supplies	4
Batteries And Flashlights	3
Beer	3
Bread And Baked Goods	6
Breakfast Food	2
Butter And Margarine	4
Candy	3
Cereal	4
Cheese	2
Coffee	6
Condiments, Gravies, And Sauces	2
Cookies	3
Cosmetics	7
Cot Cheese, Sour Cream, Toppings	4
Cough And Cold Remedies	7
Crackers	5
Deodorant	7
Detergents	2
Disposable Diapers	3
Dressings/Salads/Prep Foods-Deli	4
Eggs	6
First Aid	7
Fresh Meat	6
Fresh Produce	2
Hair Care	3
Household Cleaners	5
Household Supplies	5
Ice Cream, Novelties	7
Jams, Jellies, Spreads	3
Juice, Drinks - Canned, Bottled	7
Kitchen Gadgets	3
Laundry Supplies	7
Liquor	4
Medications/Remedies/Health Aids	2
Milk	6
Nuts	7
Oral Hygiene	7
Packaged Meats-Deli	4
Packaged Milk And Modifiers	2
Paper Products	6
Pet Care	6
Pet Food	5
Pizza/Snacks/Hors D'oeuvres-Frzn	7
Prepared Food-Dry Mixes	7
Prepared Food-Ready-To-Serve	4
Prepared Foods-Frozen	4
Salad Dressings, Mayo, Toppings	2
Shaving Needs	2
Shortening, Oil	4
Snacks	2
Soft Drinks-Non-Carbonated	7
Soup	3
Spices, Seasoning, Extracts	2
Tea	7
Tobacco & Accessories	7
Unprep Meat/Poultry/Seafood-Frzn	2
Vegetables - Canned	5
Vegetables-Frozen	7
Vitamins	2
Wine	2
Wrapping Materials And Bags	6
Yogurt	3

Table A.2—: Percentage Point Difference between *HetC* and *RepC* Markup Formula

	Average	Top 5 Firms	Top 1 Firm
Eggs	128.5	223.7	230.7
Butter And Margarine	83.1	97.8	165.6
Fresh Meat	65.8	114.5	259.2
Tobacco & Accessories	64.2	84.8	119.3
Vegetables-Frozen	56.4	75.9	106.7
Shaving Needs	53.6	56.6	89.1
Cereal	52.9	55.1	74.8
Disposable Diapers	49.8	49.9	55.0
Deodorant	47.3	50.5	53.5
Soup	42.4	48.4	62.5
Milk	42.2	78.4	131.0
Beer	40.6	52.4	63.7
Crackers	39.4	46.3	45.5
Coffee	37.3	50.8	76.2
Pizza/Snacks/Hors D'oeuvres-Frzn	35.0	43.4	46.9
Yogurt	34.1	38.0	57.0
Jams, Jellies, Spreads	33.4	42.1	59.0
Pet Food	31.9	38.1	62.4
Packaged Milk And Modifiers	27.3	33.0	49.0
Wrapping Materials And Bags	25.4	28.4	26.1
Paper Products	25.2	28.6	35.6
Oral Hygiene	25.2	34.0	37.5
Detergents	23.5	26.1	44.9
Cot Cheese, Sour Cream, Toppings	22.0	38.9	76.0
First Aid	19.7	33.3	46.6
Juice, Drinks - Canned, Bottled	19.4	33.1	21.5
Nuts	18.3	25.9	34.4
Shortening, Oil	18.3	31.5	59.1
Laundry Supplies	18.0	23.4	32.9
Breakfast Food	17.3	22.5	38.0
Prepared Food-Dry Mixes	16.2	22.8	27.3
Tea	14.7	24.0	41.7
Soft Drinks-Non-Carbonated	14.1	24.8	45.7
Batteries And Flashlights	14.0	15.5	21.4
Household Cleaners	13.2	20.7	32.9
Baby Food	12.7	13.6	24.0
Vegetables - Canned	11.4	17.2	31.5
Cosmetics	11.3	15.1	17.4
Household Supplies	10.9	20.4	31.4
Pet Care	10.2	19.8	38.6
Prepared Food-Ready-To-Serve	9.9	17.1	24.1
Ice Cream, Novelties	8.9	14.4	16.9
Cough And Cold Remedies	8.7	12.5	26.4
Prepared Foods-Frozen	7.6	12.9	21.1
Bread And Baked Goods	7.4	11.3	15.3
Hair Care	7.1	10.0	18.8
Snacks	6.6	10.8	15.8
Spices, Seasoning, Extracts	6.6	10.1	13.6
Baking Supplies	4.6	8.3	16.3
Candy	3.7	5.6	9.3
Liquor	3.5	6.5	18.8
Kitchen Gadgets	3.1	7.1	18.2
Dressings/Salads/Prep Foods-Deli	2.6	5.6	8.5
Salad Dressings, Mayo, Toppings	1.5	1.9	4.3
Cheese	1.2	2.3	5.1
Packaged Meats-Deli	1.1	2.1	4.3
Cookies	0.9	1.7	2.8
Condiments, Gravies, And Sauces	0.6	1.2	2.6
Wine	0.6	1.6	2.7
Vitamins	0.3	0.6	0.8
Medications/Remedies/Health Aids	0.1	0.0	0.0
Unprep Meat/Poultry/Seafood-Frzn	0.0	0.0	0.0
Fresh Produce	0.0	0.0	0.0

Figure A.3. : Segment Demographic Characteristics: Heterogeneity Across Product Groups (Max-Min Difference)

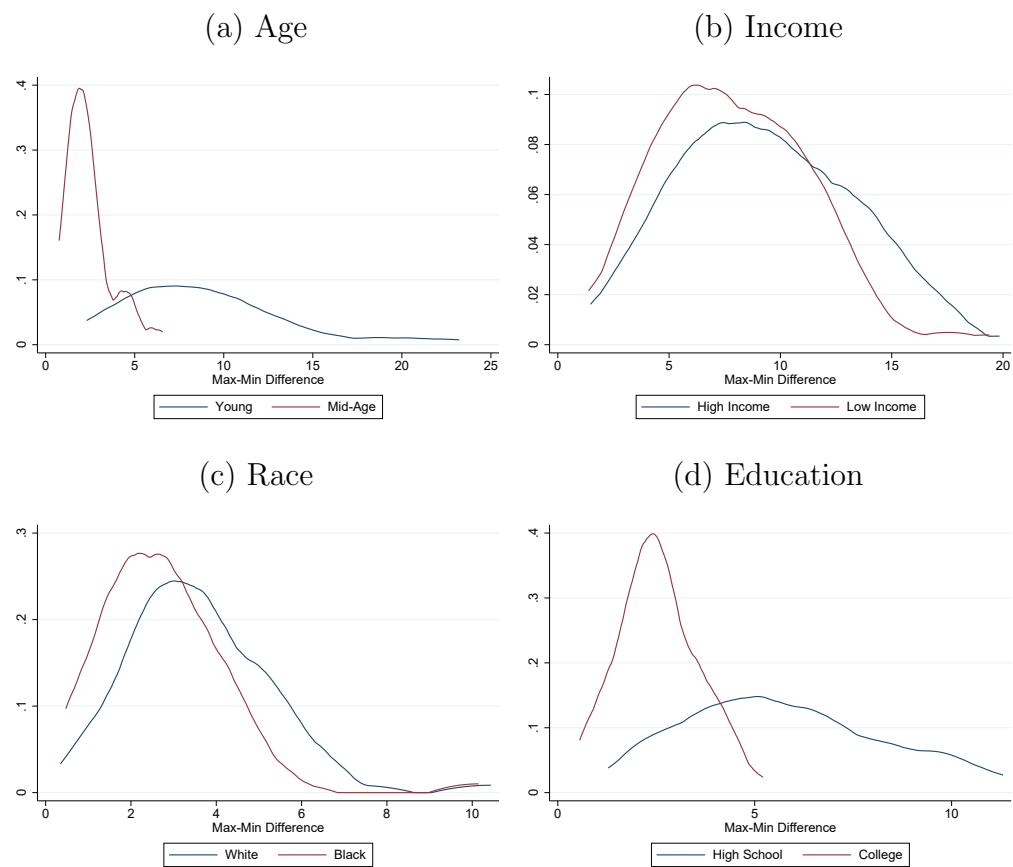


Figure A.4. : Segment Demographic Characteristics: Heterogeneity Across Product Groups (Coefficient of Variation)

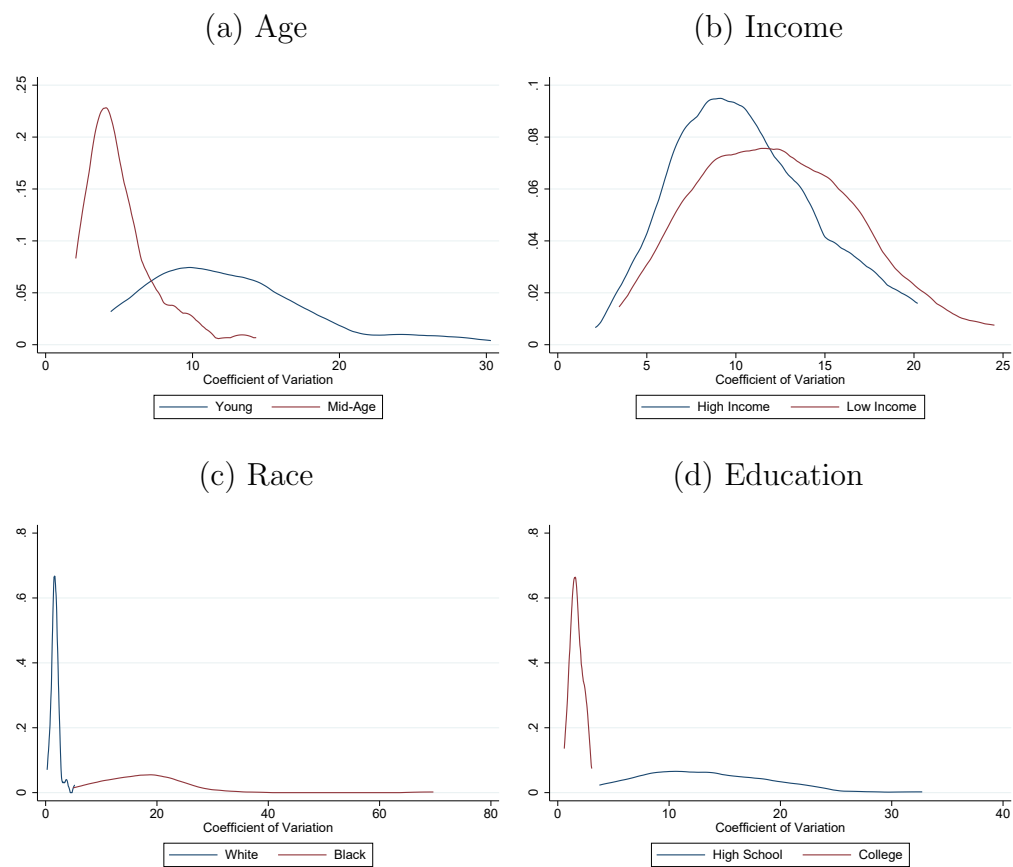


Figure A.5. : Segment Demographic Characteristics: Changes over Time (Max-Min Difference)

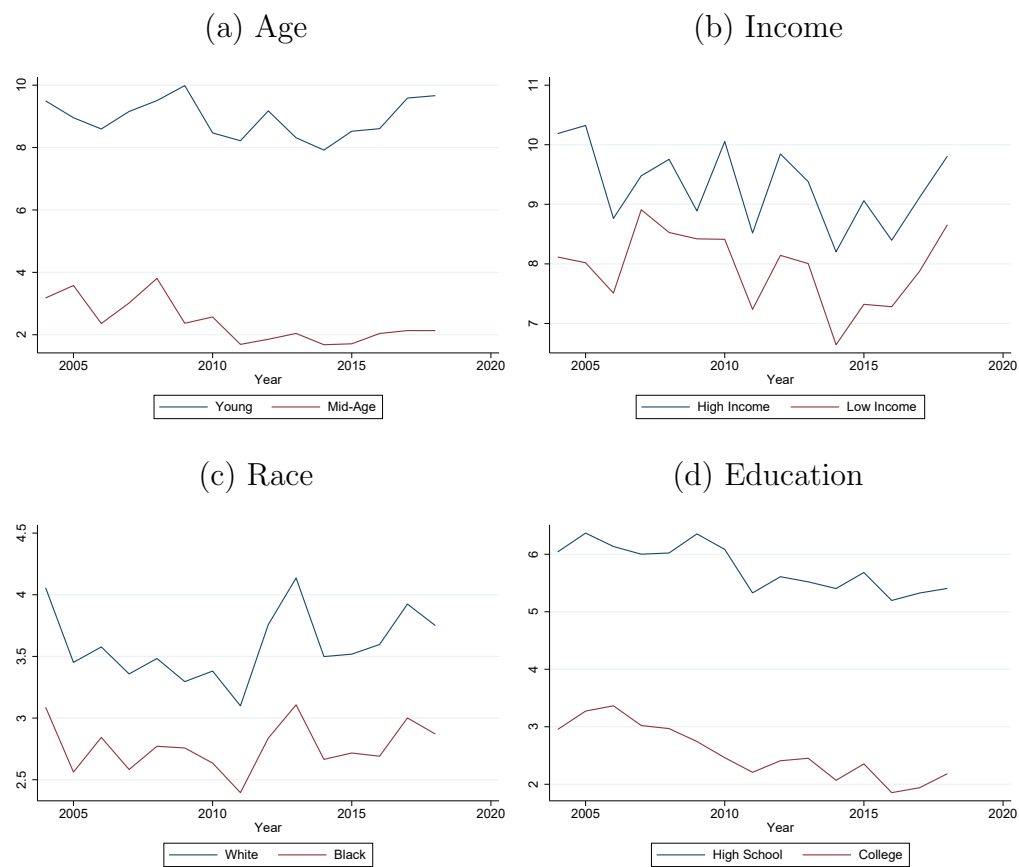


Figure A.6. : Segment Demographic Characteristics: Changes over Time (Coefficient of Variation)

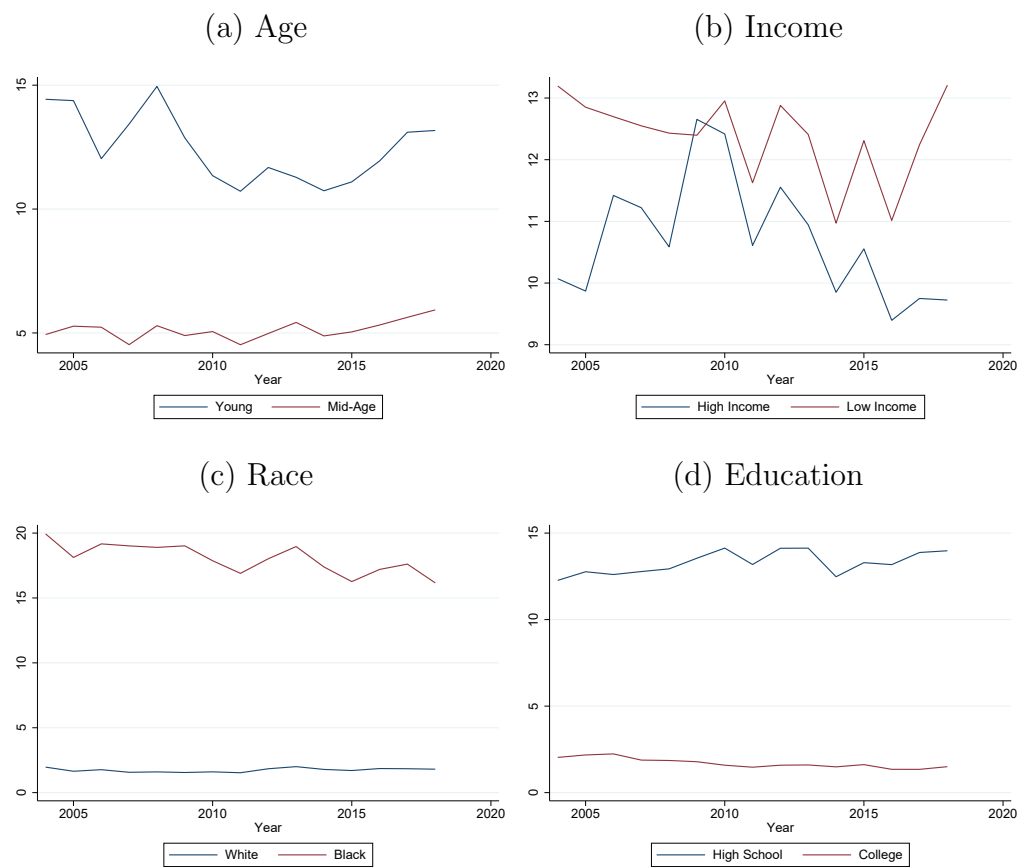


Table A.3—: Demographic Characteristics: Summary Statistics

	Coeff. Var.	Mean	Std. Dev.	Max-Min Diff.	Max	Min
Young	0.13	0.31	0.04	0.09	0.36	0.27
Mid-Age	0.05	0.21	0.01	0.02	0.22	0.20
High-Income	0.11	0.38	0.04	0.09	0.43	0.34
Low-Income	0.12	0.28	0.03	0.08	0.32	0.24
With Kid	0.01	0.93	0.01	0.02	0.94	0.92
Single	0.05	0.65	0.03	0.07	0.68	0.61
White	0.02	0.90	0.02	0.04	0.92	0.88
Black	0.18	0.07	0.01	0.03	0.08	0.05
High School	0.13	0.19	0.03	0.06	0.22	0.16
College	0.02	0.64	0.01	0.03	0.65	0.63

The table reports the coefficient of variation, average, standard deviation, max-min difference, maximum, and minimum across years and product groups of the share of households that belong to the demographic groups reported in the first column. All values are multiplied by 100. Notice that for ease of exposition, we have simplified the list of demographic characteristics. In particular, we only show the results for a subset of characteristics. For age, households are divided into Young, Mid-Age, and Old. For income, households are divided into high-income, middle-income, and low-income.

Panel A of Table A.4 reports the results for testing the random distribution of consumer segments across space. The last column shows low rejection rates (i.e., less than 14%) through all years, suggesting that the probability that certain types of consumers are clustered in some states is low. Table A.5 lists product groups where our null hypothesis has been rejected in the test. To rule out the possibility that our results are not driven by some outlier states, especially those with the least represented states in the consumer survey, we repeat the exercise and drop the lowest represented states with the lowest number of consumers. This set of results is provided in panel B of Table A.4, and product groups where our null hypothesis has been rejected in the test are provided in Table A.6.

Table A.4—: Test for Geographic Distribution of Consumer Segments

Year	Average # of Segments / Group	Number of Tests	Number of Rejections	Rejection %
Panel A: All States				
2004	4.31	276	51	18.48%
2005	4.36	279	38	13.62%
2006	4.22	270	38	14.07%
2007	4.30	275	33	12.00%
2008	4.56	292	36	12.33%
2009	4.53	290	35	12.07%
2010	4.45	285	33	11.58%
2011	4.13	264	41	15.53%
2012	4.41	282	32	11.35%
2013	4.30	275	42	15.27%
2014	4.06	260	45	17.31%
2015	4.27	273	33	12.09%
2016	3.92	251	36	14.34%
2017	4.05	259	39	15.06%
2018	4.25	272	39	14.34%
Panel B: Drop the Bottom Five States with Lowest Number of Consumers				
2004	3.08	197	27	13.71%
2005	3.30	211	24	11.37%
2006	3.17	203	24	11.82%
2007	3.25	208	17	8.17%
2008	3.25	208	15	7.21%
2009	3.50	224	12	5.36%
2010	3.02	193	12	6.22%
2011	3.48	223	11	4.93%
2012	3.34	214	20	9.35%
2013	3.31	212	19	8.96%
2014	4.06	260	24	9.23%
2015	4.27	273	21	7.69%
2016	3.92	251	21	8.37%
2017	4.05	259	25	9.65%
2018	4.25	272	24	8.82%

Note: The table reports statistics tests for the null hypothesis displayed in (A7), which is conducted for each of the 64 product groups by year independently, and the third column reports the total number of tests. The fourth and fifth columns report the number of rejections and the percentage rate.

Table A.5—: Product Group with Rejections (2004-2018)

Group Description	Number of Rejections
DEODORANT	28
COT CHEESE, SOUR CREAM, TOPPINGS	27
WINE	27
PREPARED FOOD-READY-TO-SERVE	22
ICE CREAM, NOVELTIES	21
COSMETICS	20
FRESH PRODUCE	18
COUGH AND COLD REMEDIES	18
YOGURT	16
CRACKERS	15
SOFT DRINKS-NON-CARBONATED	14
CEREAL	13
BAKING SUPPLIES	13
DRESSINGS/SALADS/PREP FOODS-DELI	13
PIZZA/SNACKS/HORS D'OEUVRES-FRZN	13
BATTERIES AND FLASHLIGHTS	12
SHAVING NEEDS	12
ORAL HYGIENE	12
PREPARED FOODS-FROZEN	11
VEGETABLES - CANNED	11
DISPOSABLE DIAPERS	11
SHORTENING, OIL	11
MILK	10
HAIR CARE	10
CONDIMENTS, GRAVIES, AND SAUCES	9
SNACKS	9
JUICE, DRINKS - CANNED, BOTTLED	9
FRESH MEAT	9
PACKAGED MILK AND MODIFIERS	9
MEDICATIONS/REMEDIES/HEALTH AIDS	9
NUTS	8
PAPER PRODUCTS	8
TOBACCO & ACCESSORIES	8
EGGS	8
BREAD AND BAKED GOODS	8
BEER	7
HOUSEHOLD CLEANERS	7
BREAKFAST FOOD	7
BABY FOOD	7
LIQUOR	6
ELECTRONICS, RECORDS, TAPES	6
COOKIES	6
BUTTER AND MARGARINE	6
WRAPPING MATERIALS AND BAGS	5
PREPARED FOOD-DRY MIXES	5
UNPREP MEAT/POULTRY/SEAFOOD-FRZN	5
VEGETABLES-FROZEN	5
FIRST AID	4
SPICES, SEASONING, EXTRACTS	3
CANDY	3
KITCHEN GADGETS	3
HOUSEHOLD SUPPLIES	2
SOUP	2
LAUNDRY SUPPLIES	2
PET FOOD	2
PACKAGED MEATS-DELI	2
TEA	1
DETERGENTS	1
JAMS, JELLIES, SPREADS	1
SALAD DRESSINGS, MAYO, TOPPINGS	1

Table A.6—: Robustness: Drop the Bottom Five States with Lowest Number of Consumers (2004-2018)

Group Description	Number of Rejections
WINE	32
FRESH MEAT	20
MEDICATIONS/REMEDIES/HEALTH AIDS	17
DEODORANT	15
BATTERIES AND FLASHLIGHTS	14
FRESH PRODUCE	12
PACKAGED MILK AND MODIFIERS	10
HAIR CARE	10
COUGH AND COLD REMEDIES	9
EGGS	8
DISPOSABLE DIAPERS	8
VITAMINS	7
OFT DRINKS-NON-CARBONATED	7
FIRST AID	7
PET FOOD	6
ICE CREAM, NOVELTIES	6
COT CHEESE, SOUR CREAM, TOPPINGS	6
PIZZA/SNACKS/HORS D'OEUVRES-FRZN	6
DETERGENTS	6
SHORTENING, OIL	5
JAMS, JELLIES, SPREADS	5
LIQUOR	5
PREPARED FOOD-READY-TO-SERVE	4
UNPREP MEAT/POULTRY/SEAFOOD-FRZN	4
BREAKFAST FOOD	4
COSMETICS	4
DRESSINGS/SALADS/PREP FOODS-DELI	4
CRACKERS	4
TOBACCO & ACCESSORIES	4
BEER	4
PAPER PRODUCTS	4
KITCHEN GADGETS	4
VEGETABLES - CANNED	3
YOGURT	3
BAKING SUPPLIES	3
CEREAL	3
ELECTRONICS, RECORDS, TAPES	3
VEGETABLES-FROZEN	2
CANDY	2
LAUNDRY SUPPLIES	2
CONDIMENTS, GRAVIES, AND SAUCES	2
JUICE, DRINKS - CANNED, BOTTLED	2
SNACKS	1
BABY FOOD	1
NUTS	1
COFFEE	1
COOKIES	1
PREPARED FOODS-FROZEN	1
BUTTER AND MARGARINE	1
SPICES, SEASONING, EXTRACTS	1
TEA	1
BREAD AND BAKED GOODS	1

A4. Robustness Checks of Clustering Algorithm

We provide an example of how we compute the probability that a consumer is classified into a segment where the majority of consumers had also appeared in a given segment in the baseline case. Suppose we would like to categorize 12 consumers into several groups based on different criteria. Table A.7 provides the baseline and alternative classification results, with the headline indicating the segment name. For instance, according to the baseline classification, segment A comprises consumers indexed as 1, 2, 3, and 4. In the alternative method, segment α consists of consumers indexed as 2, 3, 4, 5, 7, and 12.

Table A.7—: Procedure Example

Baseline Classification				
Segment:	A	B	C	D
	1	5	8	10
	2	6	9	11
	3	7		12
	4			
Alternative Classification				
Segment:	α	β	γ	
	2	1	9	
	3	6	10	
	4	8	11	
	5			
	7			
	12			

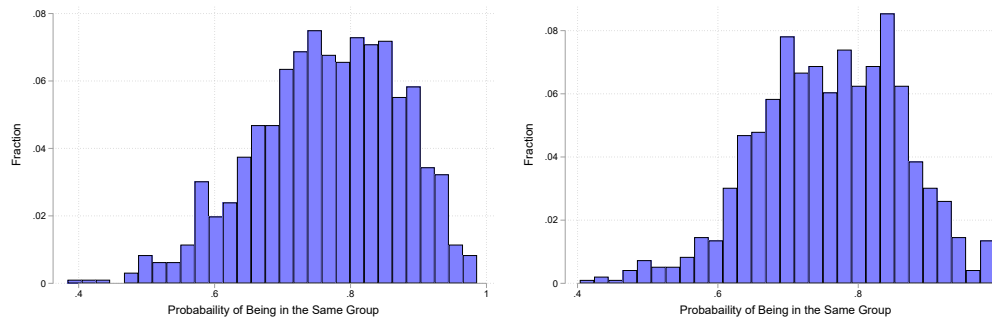
As segment A and α are hardly comparable (due to the nature of the classification algorithm), it is difficult to tell whether consumers (who used to be) in segment A are classified in the same segment under the new criteria. To resolve this ambiguity, we consider that a consumer is classified into the “same segment” as before if the new segment (where the consumer is in the new criteria) comprises the majority of segment members belonging to her/his old segment. In the above example, consumer 1 is in segment β , while the majority of her/his group members belong to segment α (i.e., 2, 3, 4). So, we think consumer 1 is not classified into the “same segment” in baseline criteria (i.e., segment A). In contrast, consumers 2, 3, and 4 are considered to remain in the same group, as the majority of her/his segment members stay with her/him.

In this way, seven consumers are classified into the “same segment” as

before, and they are consumers 2, 3, 4, 5, 7, 10, 11. The rest are classified into different segments: consumers 1, 6, 8, 9, 12. Suppose members of a specific segment in the baseline criteria are evenly distributed in new segments. In that case, we consider all these consumers are not in the same segment as before, corresponding to consumers 8 and 9 in the above example. The probability that a consumer is classified into a segment consisting of most consumers who had been put into the same segment based on the baseline criteria is thus $7/12 = 0.58$. We compute such a probability for each year and product category, and their distribution is reported in Figure A.7.

Figure A.7. : Probability of being Classified into the Same Group

(a) Share of UPC Number by Brand (b) Brand Indicator Variable

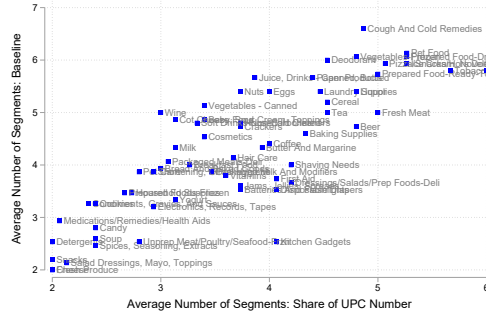


A5. Profit Share

Figure A.9 reports the market share of the top 1, 5, and 10 firms in each product group in 2012. Figure A.10 reports the profit share computed in the three models and the difference across models holding constant the expenditure shares for each product group at its 2004 level. As a result, the profit share predicted by the model with small firms is constant. In Figure A.11, we replicate dropping a few outlier product groups that experience a drastic drop in the profit share after 2010. The product groups are baby food; condiments, gravies, and sauces; unprepared meat/poultry/seafood frozen; dressings/salads/prepared foods - deli; fresh produce; vitamins. Figure A.12 shows the result using alternative clustering criteria as discussed in section III.B.

Figure A.8. : Average Number of Segments by Product Group Comparision (2004 - 2018)

(a) Baseline & Share of UPC Number by Brand



(b) Baseline & Brand Indicator

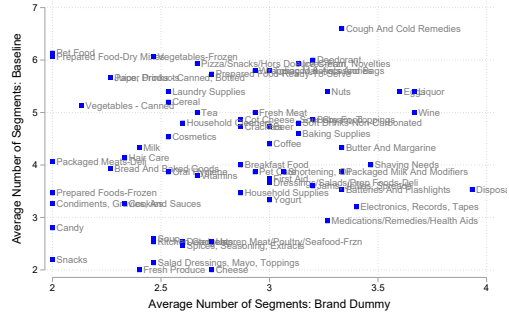
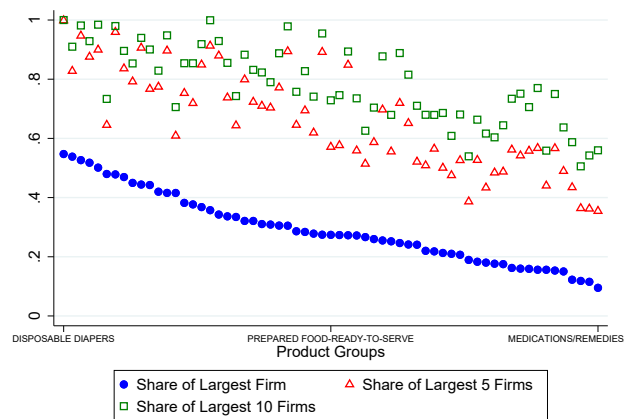


Figure A.13 plots the average number of firms per product group and the average number of products per firm (per product group) from 2004 to 2018. These changes in the number of firms and in their scope can contribute to the decline in profits after 2010 for the *RepC* model, in particular, where consumer heterogeneity does not play a role.

Figure A.9. : Market Share of the Largest Firms by Product Group



The figure plots the market share of the largest firm, largest 5 firms, and largest 10 firms across product groups.

Figure A.10. : Profit Share Over Time - Constant Expenditure Shares

(a) Aggregate Profit Share Across Models (b) Percentage Point Difference Across Models

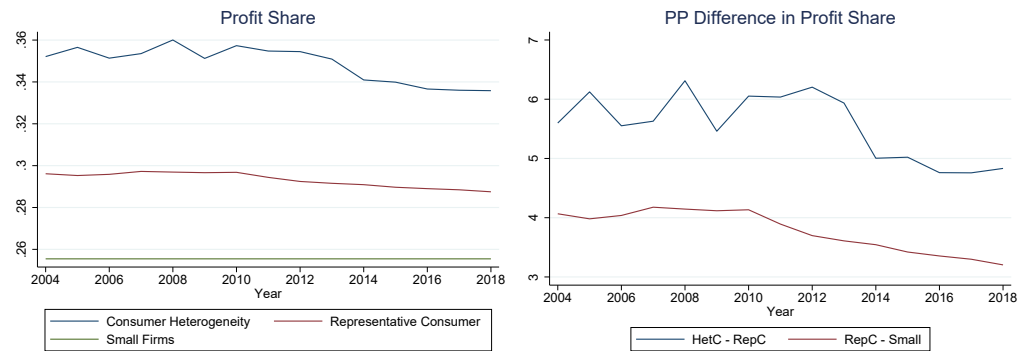


Figure A.11. : Profit Share Over Time - Drop Outliers

(a) Aggregate Profit Share Across Models (b) Percentage Point Difference Across Models

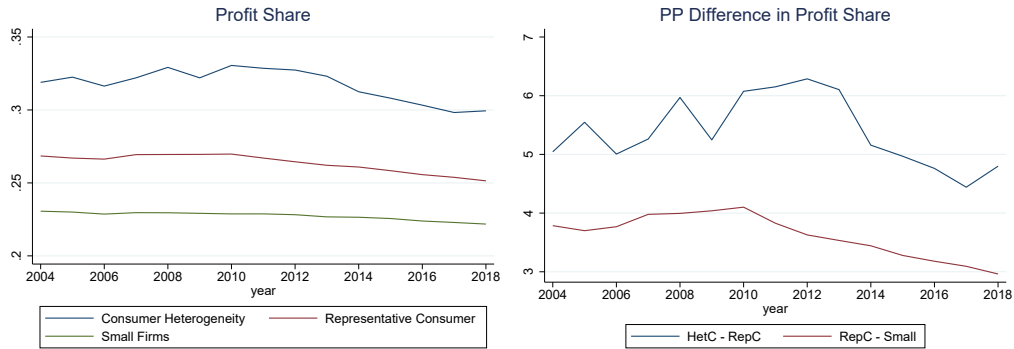


Figure A.12. : Profit Share Over Time - Alternative Clustering Criteria

(a) Share of UPC Number by Brand (b) Brand Indicator

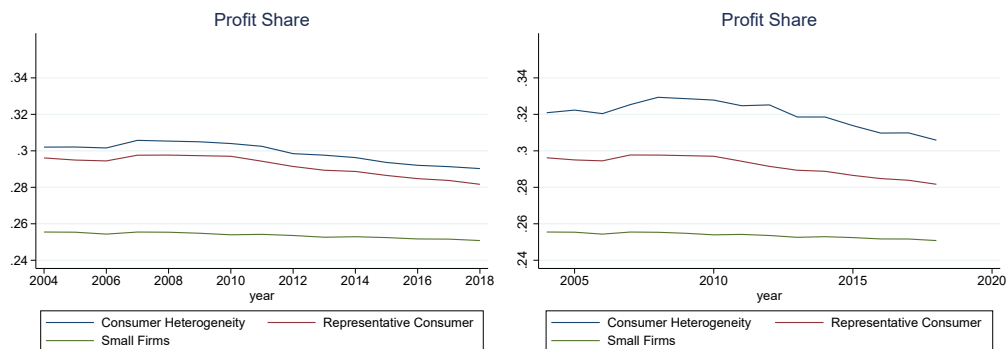
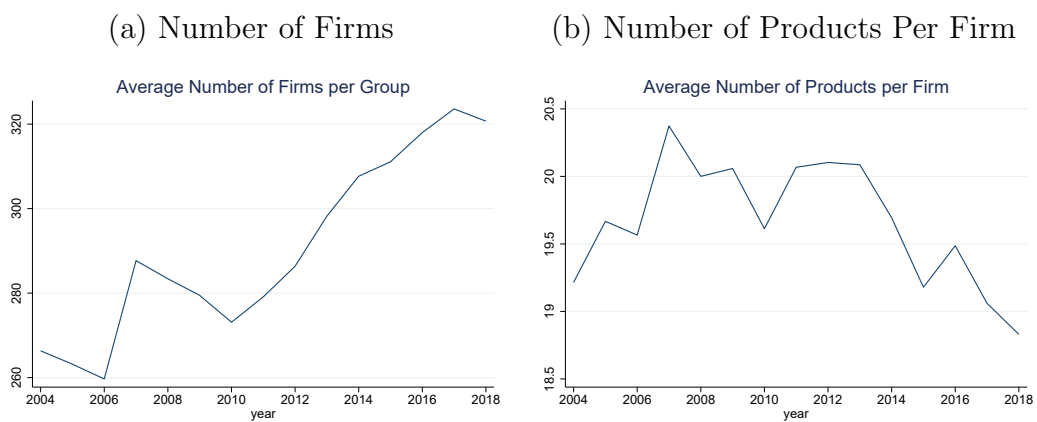


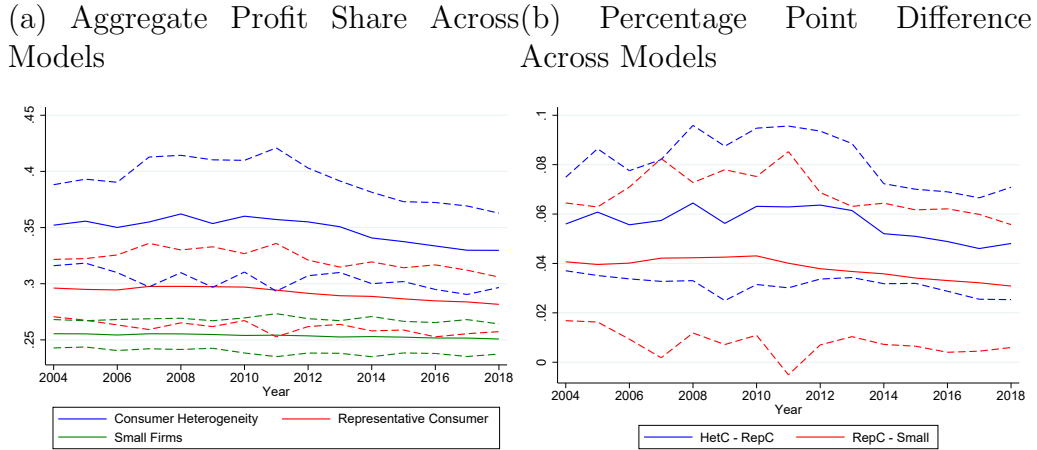
Figure A.13. : Number of Firms and Number of Products Per Firm



A6. Profit Share with Confidence Interval

Figure A.14 reports the 95% confidence intervals for the profit share computed in the three models and the difference across models holding constant the expenditure shares for each product group at its 2004 level. Robust standard errors are calculated using bootstrapping. Firms are sampled 30 times randomly within strata based on size and product categories, where a bootstrapped sample has the same sample size as the raw data.¹ We recompute their market shares, then markups and profit shares. Panel (b) shows the difference in the profit shares between the *HetC* and *RepC* models and between the *RepC* and small firm models (with 0.1 on the vertical axis representing a 10 percentage point difference, for example). The profit shares of the *HetC* and *RepC* models are significantly different in all years, and likewise for the *RepC* and small firm models except in 2011.

Figure A.14. : Profit Share with 95% Confidence Interval



A7. Robustness

For robustness, we also divide consumers into segments based on geography and distribution channel. In the next paragraphs, we describe how we divide consumers into segments according to the two dimensions.

¹In each product category, we divide firms into 20 size categories, with firm size measured as total sales each year.

Geography. We consider the division by state, using the home scanner data to divide consumers according to the states in which they reside.

Distribution Channel. We consider the division by retail chain. We assign consumers to a retail chain according to the store belonging to the chain in which they conduct the majority of their purchases. That is, both for the geographical and the distribution channel criteria, the demand from each segment n consists of the average demand of consumers in each geographical area or retail chain when we use the home scanner data.

In Figures A.15, A.16, A.17, and A.18 we use the two criteria described in this section along with consumer type to divide consumers in segments. Hence, one segment is a geography-retail chain-type triplet. Figure A.15 confirms the results of Figure A.20, since we find a positive correlation between sales and the common component of the demand shifter (panel (a)) and a negative correlation between the common component of the demand shifter and the variance of the segment-specific component (panel (b)). In Figure A.16, we plot the coefficient of a regression of IP_{fg} on firm sales (panel (a)) and scope (panel (b)). The results are in line with those shown in Figure A.21, in which consumers are divided in segments only by their type. In Figure A.17, we confirm the results of Figure A.22 as we find a positive correlation between EP_{fg} and firm sales (panel (a)) and scope (panel (b)). The results indicate that larger firms use their products to target different segments, defined at the state-retail chain-type level. Finally, Figure A.18 replicates the results shown in section A.A8. The figure shows the distribution of the coefficients of a univariate regression of B_{fgn} , which is defined in (A8), on the average household expenditures and expenditure share of each segment.

A8. Firm Strategy to Target Segments

While in the main text we document the strategies firms follow to deal with consumer heterogeneity over time, in this section, we consider the year 2012 and examine the heterogeneity across product groups and across firms. In Figure A.19, we plot the results from the variance decomposition discussed in section V.A across product groups. In particular, for each product group, we report how much of the variance of the demand shifter is explained by the segment-specific component.

Panel (a) of Figure A.20 reports the coefficients obtained by regressing UPC log sales on the estimated UPC taste parameter in logs common across

Figure A.15. : Demand Shifters and Segments

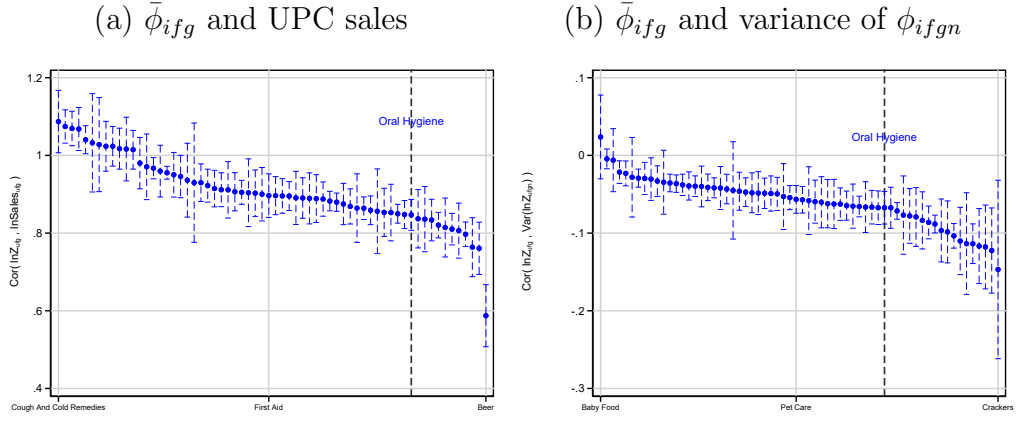


Figure A.16. : Intensiveness of Personalization and Firm Characteristics

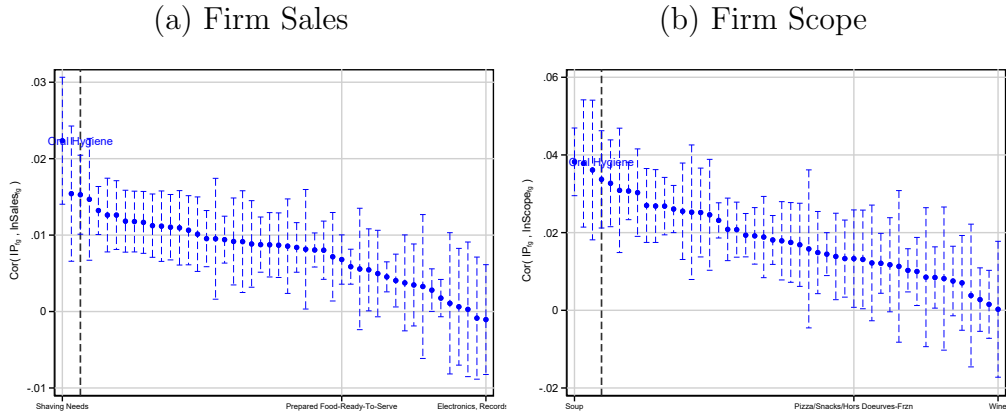


Figure A.17. : Extensiveness of Personalization and Firm Characteristics

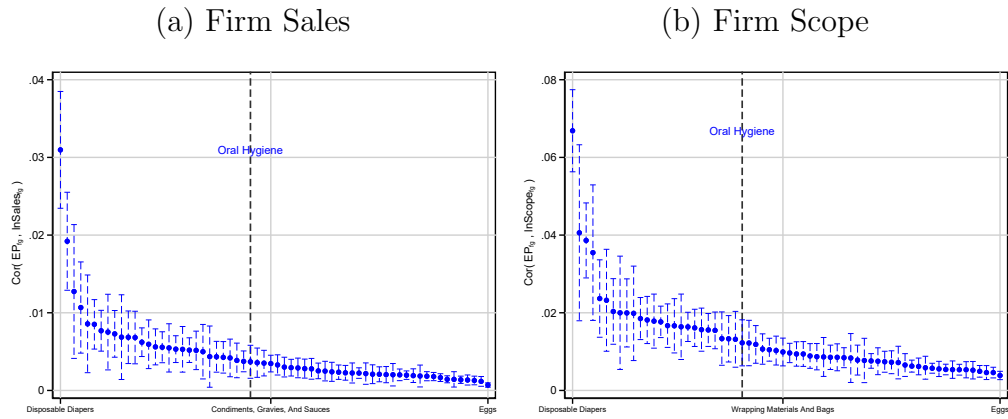
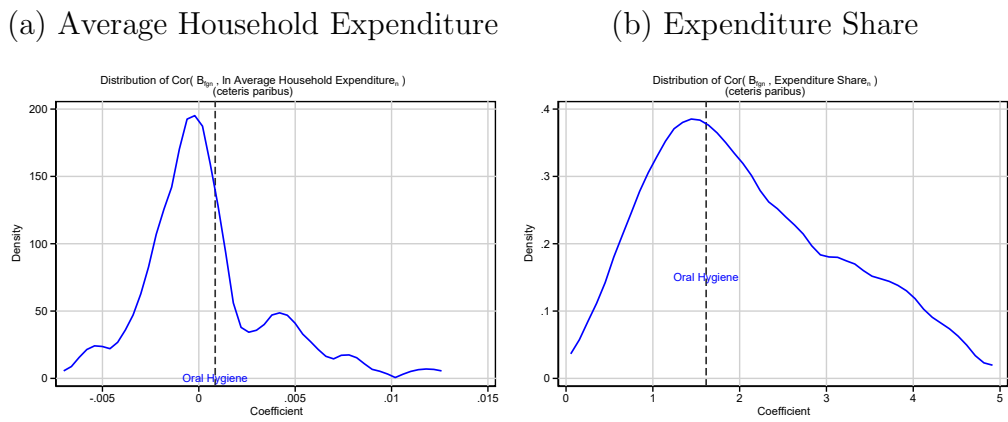


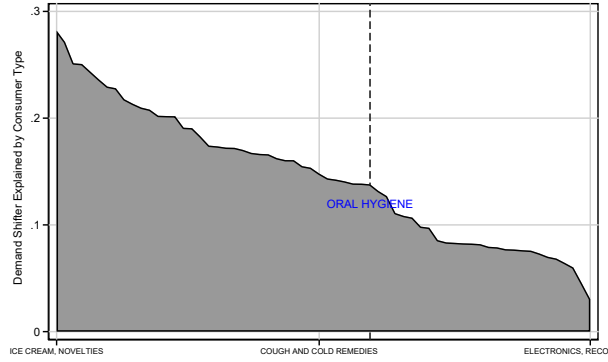
Figure A.18. : Consumer Characteristics and Product Personalization



segments. Panel (b) of Figure A.20 displays the slope of a regression of $\ln \bar{\phi}_{ifg}$ on the variance of $\ln \phi_{ifgn}$ across segments for all product groups. Both figures report the point estimate of the coefficient and the 95% confidence interval, where we control for firm fixed effects in each regression and cluster standard errors at the firm level. The results indicate that products that have larger common component of the demand shifters have larger sales and have lower variance of the segment-specific component.

Figure A.21 reports the coefficient of a regression of IP_{fg} on firm sales (panel (a)) and firm scope (panel (b)). The coefficients are generally close to zero and often statistically insignificant. Figure A.17 reports the coefficient of a regression of EP_{fg} on firm sales (panel (a)) and firm scope (panel (b)). Contrary to the results on the intensiveness of personalization, here we find a positive and statistically significant coefficient for all product groups. The robust pattern indicates that larger firms target more segments than smaller firms.

Figure A.19. : Contribution of Segments $\ln \phi_{ifgn}$ to Explain Product Appeal



FIRM PERSONALIZATION STRATEGIES

In this section, we determine the segment characteristics are mostly correlated with firm personalization strategies. Consider the share of best-ranked products of a firm f in segment n :

$$(A8) \quad B_{fgn} = \frac{\# \text{ best-ranked products of firm } f \text{ in segment } n}{\text{Total } \# \text{ of products of firm } f}$$

By definition, $B_{fgn} \in [0, 1]$. If a firm has no products targeting a given

Figure A.20. : Demand Shifters and Segments (All UPC) - Type (Consumer Panel)

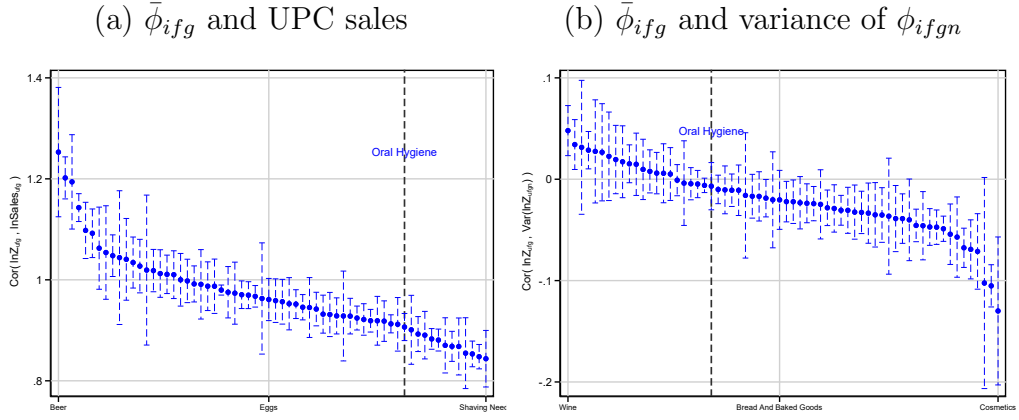


Figure A.21. : Intensiveness of Personalization and Firm Characteristics (All UPC) - Type (Consumer Panel Data)

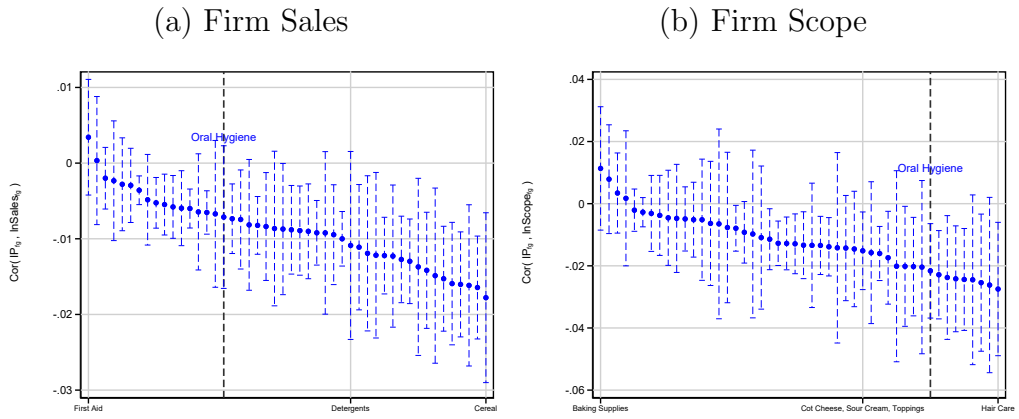
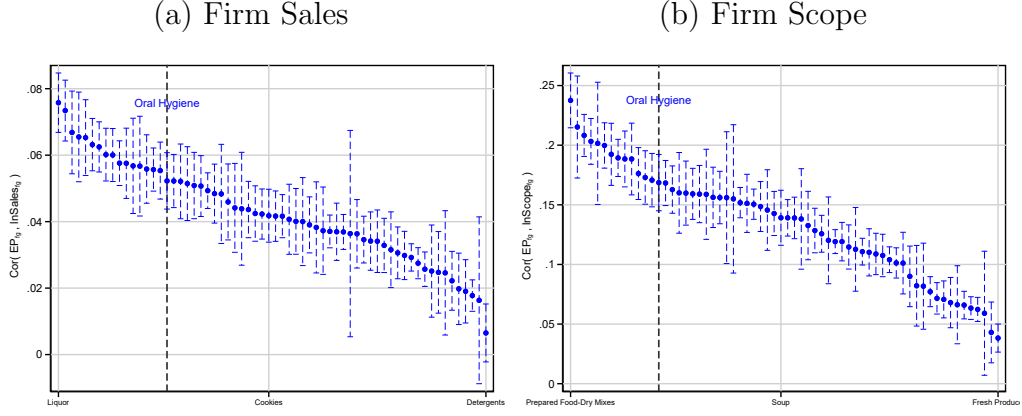


Figure A.22. : Extensiveness of Personalization and Firm Characteristics (All UPC) - Type (Consumer Panel Data)



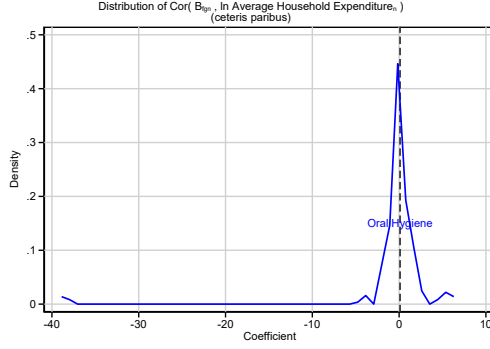
segment then $B_{fgn} = 0$. In contrast, if all products of a firm target a segment n then $B_{fgn} = 1$. To examine the main drivers of firms sorting into different segments, we run a univariate regression of B_{fgn} on segment size, defined as the share of total expenditures in the product group, and average expenditure per household.

Figure A.23 shows the distribution of the coefficients of univariate regression of B_{fgn} on the average household expenditures and expenditure share of each segment. On average, the effect of household expenditure is zero. In contrast, the size of a segment measured by its expenditure share tends to have a positive effect on B_{fgn} . This means that firms tend to mainly target the segment with the largest expenditure share.

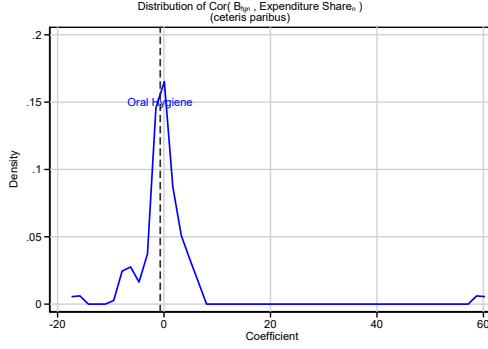
This fact, combined with the positive relationship between the extensiveness of personalization and firm size, suggests the presence of a segment ladder: the smaller firms tend to target a smaller number of segments, and these segments tend to be the larger ones. Larger firms are able to expand the number of segments they target, by further targeting the smaller segments. Although examining such a pattern for all product groups can be hard to illustrate, in the Appendix A.A9 on the oral hygiene product group, we confirm and show such a segment ladder.

Figure A.23. : Consumer Characteristics and Product Personalization (All UPC) - Type (Consumer Panel Data)

(a) Average Household Expenditure



(b) Expenditure Share



A9. The Oral Hygiene Product Case

THE ORAL HYGIENE PRODUCT CASE

The tables in this section show the differences in consumption patterns and demographic characteristics of the five segments described in Table 1 for the product group of oral hygiene products. Table A.8 shows the share of expenditures within segment on different firms. For instance, consumers of Segment 4 disproportionately purchase Procter & Gamble products, which account for 64% of their expenditure share on oral hygiene products. The second most purchased firm is Colgate-Palmolive, which accounts for 8% of expenditures. Table A.9 report the distribution across segments of different consumer demographic characteristics. The first two columns show the population shares of different race/ethnicity for each segment. The segmentation across segments does not follow these demographic variables, as the share of each race/ethnicity is very similar across segments. For example, the share of white households ranges between 0.88 and 0.92. The remaining columns show the share of the population by income, age, and education. We find that Segment 4 is overly represented by high-income households, since they account for 41% of the segment population, while in the other segments the share of high-income households is 30-37%.

Table A.8—: Segments Top Firms

Segment #	Top Brand		Second Top Brand	
	Name	Share	Name	Share
1	Procter & Gamble	0.09	Colgate-Palmolive	0.08
2	Warner-Lambert	0.38	Philips	0.15
3	Glaxosmithkline	0.40	Johnson & Johnson	0.10
4	Procter & Gamble	0.64	Colgate-Palmolive	0.08
5	Block Drug	0.52	Procter & Gamble	0.10
6	Colgate-Palmolive	0.64	Procter & Gamble	0.10
7	Church & Dwight	0.53	Colgate-Palmolive	0.09

Table A.9—: Segments Characteristics

Segment #	White	Black	Low-Income	High-Income	Young	Middle Age	High School	College
1	0.91	0.06	0.26	0.37	0.32	0.17	0.17	0.65
2	0.88	0.08	0.26	0.37	0.39	0.16	0.16	0.66
3	0.88	0.09	0.24	0.41	0.30	0.16	0.15	0.65
4	0.92	0.05	0.34	0.30	0.20	0.14	0.22	0.63
5	0.91	0.06	0.28	0.34	0.35	0.16	0.17	0.66
6	0.90	0.07	0.32	0.31	0.30	0.17	0.18	0.65
7	0.88	0.07	0.33	0.33	0.31	0.16	0.16	0.66

SEGMENT LADDER

Firms tend to mainly target the segments with the largest average expenditures. There is, in fact, a positive relationship between the average expenditure of a segment and the share of firm products targeting such segment. In addition, larger firms tend to target multiple segments, but they predominantly focus their products on catering to the tastes of the same segments targeted by the smaller firms.

We investigate a possible segment ladder for consumer type segments. We divide firms into three bins indexed by b according to their product scope. In particular, the first bin contains firms with a narrow scope (bottom 33 percentile with respect to the number of UPC products), the second firms with a middle scope (33 to 66 percentile), and the third firms with a wide scope (top 33 percentile). In each bin, there are F_b firms. For each bin and segment, we compute the average B_{fgn} previously defined in (A8). Table A.10 summarizes the average B_{fn} for firms with narrow, middle, and wide scope.²

Table A.10—: Segment Ladder and Firm Scope

Segment #	Narrow-scope	Middle-scope	Wide-scope
1	0.227	0.170	0.127
2	0.042	0.071	0.099
3	0.019	0.069	0.109
4	0.139	0.155	0.185
5	0.065	0.073	0.120
6	0.060	0.089	0.128
7	0.449	0.372	0.232

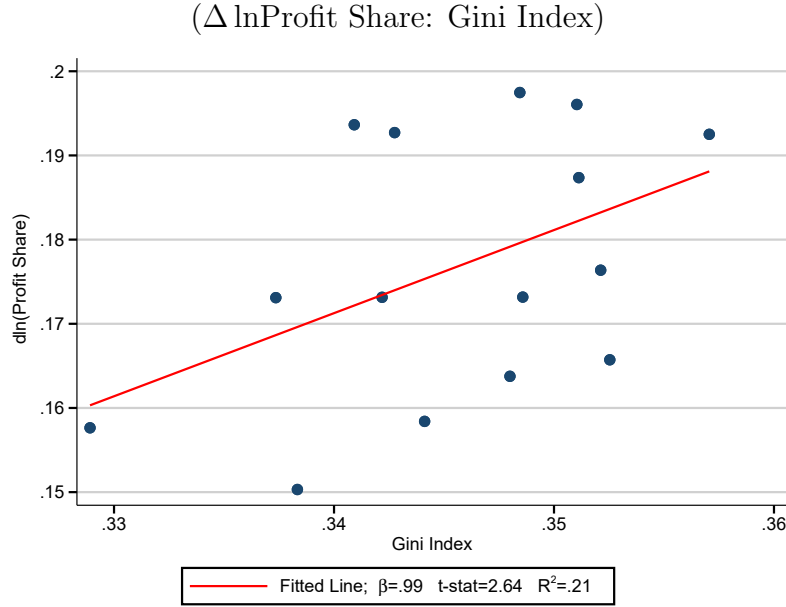
Narrow-scope firms tend to disproportionally offer large shares of their product varieties to segments 1 and 7. Segment 7 is also mainly targeted by middle- and wide-scope firms, and segment 1 by middle-scope firms. However, middle- and especially wide-scope firms tend to target other segments as well. The comparison of targeted segments across firms highlights a ladder in the scope expansion. Firms tend to first target segments 7 and 1. As firms add more products, these are targeted to the remaining segments.

²The average numbers of UPC products per firm are 2.6, 5.8, and 72 for the narrow-, middle-, and wide-scope firms.

A10. Inequality and Profit Share

Figure A.24 reports the positive correlation between the level of income inequality and the gap between the profit share of *HetC* and *RepC* models.

Figure A.24. : Difference between Profit Shares of *HetC* and *RepC* Models and Inequality (2004-2018)



A11. Fixed Costs of Targeting Consumers

In this section, we extend our earlier model to allow for fixed costs for each UPC item. We think of these fixed costs as reflecting marketing costs for targeting an item to a particular consumer segment. As in the previous section, we let $n(i)$ denote the consumer segment with the highest demand parameter for item i , meaning that $z_{ifn(i)} > z_{ifm}$ for all $m = 1, \dots, N$ with $m \neq n(i)$. Each consumer segment. We assume that targeting a particular segment n is associated with product design and marketing costs FC_n , which can differ across n because some segments might be easier to reach, or appeal to, than others. For each UPC i , we then denote the fixed cost of targeting that associated consumer segment by $FC_{n(i)}$. In addition, there can be any other fixed costs associated with firm f that we denote by FC_f .

Including the fixed marketing costs, the profits from UPC i are written as:

$$(A9) \quad \tilde{\pi}_{if} = \sum_{n=1}^N L_n y_n s_{fn} s_{ifn} \left(1 - \frac{1}{\mu_{if}}\right) - FC_{n(i)}.$$

Firm f 's total profits over all its UPCs are then:

$$(A10) \quad \tilde{\pi}_f(I_f) = \sum_{i \in I_f} \tilde{\pi}_{if}(I_f) - FC_f,$$

where FC_f are any additional fixed costs of the firm.

Note that the profits $\tilde{\pi}_{if}(I_f)$ appearing on the right of (A10) refer only to the profits earned on UPC item i , but they depend on the entire set of products I_f sold by firm f , as well as on the set of products sold by other firms. This dependence means that there are multiple equilibrium in the optimal set of products offered by each firm, i.e., what one firm chooses to offer depends on what other have already offered. Regardless of this multiplicity, the set of products sold by each firm in equilibrium must satisfy three conditions. First, profits must be non-negative, so $\tilde{\pi}_f(I_f) \geq 0$ in (A10). Second, profits cannot increase by dropping a product from the set being produced and sold (with no change in the products sold by other firms):

$$(A11) \quad \tilde{\pi}_f(I_f) \geq \tilde{\pi}_f(I_f / \{i\}) \quad \forall i \in I_f,$$

where $I_f / \{i\}$ denotes the set of products I_f but without item i . Third, profits cannot increase by adding a new product to the set being produced and sold (with no change in the products sold by other firms):

$$\tilde{\pi}_f(I_f) \geq \tilde{\pi}_f(I_f \cup \{j\}) \quad \forall j \notin I_f.$$

It is convenient to express the second of these conditions using variable profits π_{if} , so that $\tilde{\pi}_{if}(I_f) = \pi_{if}(I_f) - FC_{n(i)}$. Then it follows from (A10) that (A11) is rewritten as:

$$(A12) \quad \pi_{if}(I_f) - \sum_{j \in I_f / \{i\}} [\pi_{jf}(I_f / \{i\}) - \pi_{jf}(I_f)] \geq FC_{n(i)} \quad \forall i \in I_f.$$

To interpret this expression, $\pi_{if}(I_f)$ is the variable profits earned from item

i. The next term on the left reflects the *drop* in profits obtained on the other $I_f/\{i\}$ items already sold by the firm from adding *i* and cannibalizing their sales, so that $[\pi_{jf}(I_f/\{i\}) - \pi_{jf}(I_f)] \geq 0$. Using this inequality in (A12), we obtain:

$$(A13) \quad FC_{n(i)} \leq \pi_{if}(I_f).$$

Expression (A13) states that an upper bound on the marketing and design costs associated with segment *n* are the variable profits earned on each UPC item *i* targeting that segment. Let us denote the total set of UPCs that target segment *n* by I_n . We have allowed the costs of targeting consumer segment $n(i)$ to depend on the characteristics of that set of households, but not on the item *i* itself. It follows that we can tighten the inequality in (A13) as

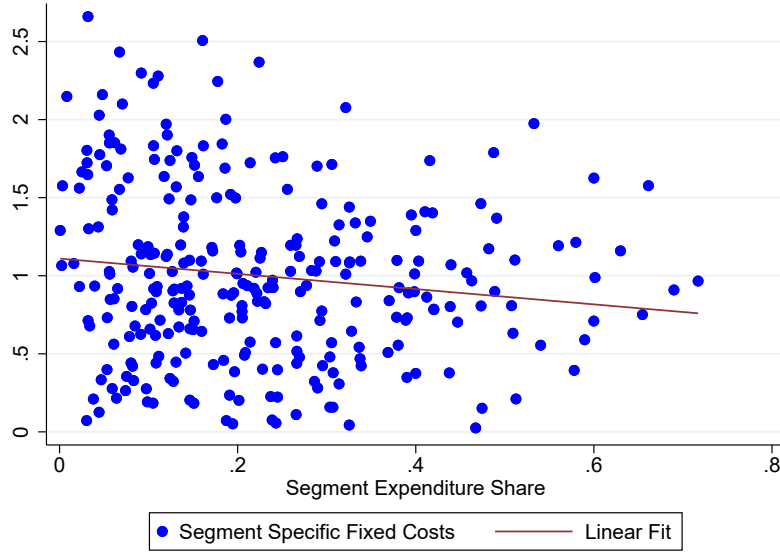
$$(A14) \quad FC_n \leq \min_{i \in I_n} \{\pi_{if}(I_f)\}.$$

In practice, we estimate these fixed marketing costs by treating the inequality above as equality. We stress that these marketing costs are only one component of the fixed costs of each firm, which also appear as FC_f on the right of (A10), and we do not attempt to estimate these broader firm-specific fixed costs.³ In Figure A.25, we plot the bounds for the fixed costs against the expenditure share of segments. We find a negative relationship: the marketing costs associated with targeting larger segments are lower than those for targeting niche segments. The result suggests that firms predominantly target those segments that have the lowest marketing costs. As a result, these segments are also the ones with the largest total revenues. Furthermore, the results rationalize the cross-sectional findings on the extensiveness of personalization. Smaller firms can only cover low marketing costs for the largest segments. Larger firms, in contrast, are able to afford the payment of larger marketing costs and thus can target smaller, niche segments, which tend to have larger marketing costs.

Using the estimated product-firm profits (see section IV), our procedure to estimate fixed marketing costs yields a vector of fixed costs (one per

³While the resulting estimate of $FC_{n(i)}$ from treating (A14) as equality constitutes an upper bound for the fixed marketing cost of targeting the segment, in practice we find that this upper bound is still quite small, simply because the minimum of the variable profits on the right of (A14) is small. If we deduct these fixed costs $FC_{n(i)}$ from the variable profits of the firm, we find that the profit shares computed as in section IV differ only in the third significant digit.

Figure A.25. : Fixed Marketing Costs and Segment Characteristics



segment) for each product group in each year. For each product group in each year, we compute the average fixed marketing cost and the minimum and maximum across segments within the product group. We normalize these fixed costs by dividing them by the average fixed cost in 2004 for a given product group. Then, we take the average of these three measures across all product groups for each year and plot the results in Figure A.26. In 2004, the minimum fixed cost is 50% of the average and the maximum fixed cost is 60% larger than the average.

With the exception of a spike in 2005, the estimated average fixed costs remain fairly constant until 2011. After 2011, the average fixed cost increases, attaining a 2018 value which is 54% larger than its value in 2004. This increase in the fixed cost corresponds to the decline in the profit share. This increase in the fixed cost can partially account for the decline in the role of consumer heterogeneity: as the fixed costs of marketing increase, it is more difficult for firms to place their products in a given segment. A similar pattern arises when we examine both the minimum and maximum fixed costs (averaged over product groups). We also consider the cross-section variation of fixed costs across segments for the year 2012.

Figure A.26. : Fixed Marketing Costs Over Time

