Uniform Pricing in US Retail Chains: Online Appendix

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Abstract

We show that most US food, drugstore, and mass merchandise chains charge nearly-uniform prices across stores, despite wide variation in consumer demographics and competition. Demand estimates reveal substantial within-chain variation in price elasticities and suggest that the median chain sacrifices $16m of annual profit relative to a benchmark of optimal prices. In contrast, differences in average prices between chains are broadly consistent with the optimal benchmark. We discuss a range of explanations for nearly-uniform pricing, highlighting managerial inertia and brand-image concerns as mechanisms frequently mentioned by industry participants. Relative to our optimal benchmark, uniform pricing may significantly increase the prices paid by poorer households relative to the rich, dampen the response of prices to local economic shocks, alter the analysis of mergers in antitrust, and shift the incidence of intra-national trade costs.

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A Online Appendix

A.1 Data

A.1.1 Data Source

The data in the Kilts Center are collected by Nielsen and made available through the Marketing Data Center at the University of Chicago Booth School of Business. Information on availability and access to the data can be found at https://research.chicagobooth.edu/kilts/marketing-databases/nielsen.

A.1.2 Store Selection

In the RMS data, Nielsen provides a basic categorization of stores into five "Channel Codes": Convenience, Food, Drug, Mass Merchandise, and Liquor. Of these, we select Food, Drug, and Mass Merchandise chains since the Convenience and Liquor stores are typically not covered in the Homescan data and thus would not be included in our final sample. In the Homescan data, there are more detailed "Retailer Channel Codes" and each store is assigned to one of 66 mutually exclusive categories such as Department Store, Grocery, Fruit Stand, Sporting Goods, and Warehouse Club. Our starting sample of food stores includes all stores that are categorized as "Food" stores in the RMS data. All food stores selected in the final sample fall into the "Grocery" category in the Homescan channel code categorization[41], all drugstores in the "Drug Store" category, and all Mass Merchandise stores in the "Discounters" category.

Some stores change DMA or FIPS code over the time that they are in the sample. Since Nielsen identifies store by the physical location of the store, this occurs because DMA regions or county lines are redefined over the nine years we observe. In other words, the stores themselves are not changing physical locations. For stores that switch, we use the modal DMA and FIPS code. This does not affect how we aggregate store-level demographics for our main analysis.

A.1.3 Demographics

All demographics are zipcode level data from the 2008-2012 5-year ACS. We aggregate this zipcode level demographics into store-level demographics as explained in Section 2. There are two special cases: (i) for one store with missing median home price data, we impute this value by regressing median home price on the other demographics (income, fraction with a bachelor's degree, race, and fraction of urban area); (ii) three drugstores are only visited by one household each, and these households provide a PO Box zipcode as its zipcode, making it impossible to use our usual procedure, so we use county-level demographics for these three stores.

A.1.4 Competition Measures

We use the Homescan panel data to help us construct a measure of competition based on geodesic distance for the food stores. To compute the location of each store, we use the more detailed location information in the Homescan data.[42] First, we assume that each Homescan household lives at the center of its zipcode. For each of the stores in the Homescan dataset, we use a trip-weighted average of the coordinates of each household in order to arrive at an imputed location

[41] The starting sample of 11,501 Food stores also contains some Discount Stores and Warehouse Clubs, as well as some (likely mislabeled) drugstores.

[42] Recall that the location of the store in the Nielsen publicly available data is only recorded up to the 3-digit zipcode or county.

for the store. For our measure of competition for store s, we then count the number of food stores within various distances (e.g., 5 or 10 km) of store s by geodesic distance, i.e., distance as the crow flies. For each store, we count separately the number of stores in the same chain and stores in different chains.

A.1.5 Product Selection

For our main sample, within a module, we keep all the products (UPCs) which satisfy an availability restriction: pooling across chains, a product must have positive revenue in at least 80% of store-weeks. For this calculation we include only store-weeks with at least $100 of sales across all products.

For the sample of food stores, we build three additional product samples for robustness. First, we select a set of chain-specific store-brand products. (These products are excluded from the main sample.) For each of the 40 modules, we take products with the Nielsen identifier "CTL BR", which identifies store-brand products; we also require that the products have at least 80% availability within their chain. This results in 12,423 generic products in 40 modules. All generic products are used to compute store-level generic product price levels, with an aggregation procedure parallel to the one for the main samples. In our product assortment analysis, the number of generic modules falls to 37 after applying the criteria outlined in A.1.9. These generic products are not comparable across chains.

Second, we identify products in the top decile or bottom decile by yearly revenue. For each product, we compute the annual revenue (taking into account the number of years in the sample) across all food stores. We then identify 135 products in the top 10% of this variable and 135 in the bottom 10%.

Third, we define the module-level baskets. For a given chain we include all products, including generic products, in a module such that the average share of weeks with non-zero sales for that product in that chain is at least 95 percent, where the average is taken across stores. We omit weeks from this calculation in which the store has zero recorded sales in all modules. Since the basket of products is defined by chain, the price indices are not comparable across chains.

A.1.6 Prices

As described in the text, we compute the weekly price P_{sjt} as the ratio of weekly revenue and weekly units sold for that store-product. We apply the following filters: (i) Following the Nielsen manual, we divide the weekly units sold by the variable 'prmult' (price multiplier); (ii) We drop all prices $\leq$ $0.10 since almost surely these represent cases of measurement error. This affects very few observations: 427,353 store-product-weeks (0.02% of observations) in food stores, 170,644 observations (0.07%) in drugstores, and 13,782 observations (0.008%) in mass merchandise stores.

A.1.7 Pairs Dataset for the Analysis of Store Pricing Similarity

For the measure of similarity in pricing across stores, we create a data set of pairs of stores as described in the text. We note the following special cases. For the between-chain pairs, for each chain r, we sample 200 store pairs where one store belongs to chain r and the other store belongs to a different chain r'; we then drop any store pairs where the stores belong to the same *parent_code*. We use the same set of pairs for each product j.

To compute the measure of within-chain similarity cases for the case where stores s and s' are in the same geographic market (DMA), for each chain r, we form 200 new pairs that satisfy the restriction of being in the same DMA, and then proceed as above; similarly for the between-chain similarity. We form new pairs also for the case where stores s and s' are in different geographic markets (DMA) and in different income thirds.

To compute the pricing similarity for pairs of stores within a state, or across state boundaries, we re-draw (up to) 200 pairs for each chain-product satisfying the within-state, and between-state, criteria.

A.1.8 Major Grocer's Data

As additional data, we use the scanner data for 250 stores from a major grocer as in Gopinath et al. (2011). The data-sharing agreement between this retailer and the research community is managed through the SIEPR-Giannini data center (http://are.berkeley.edu/SGDC). Since we want to compare the results using the Nielsen price measure versus the price measures in this major grocer's data, it is important to identify the stores in the Nielsen data which correspond to stores in this additional data set. Since the dataset in Gopinath et al. (2011) covers 2004 to mid-2007, while the RMS data set covers from 2006 on, we focus on the 52 weeks in year 2006. We match the two data sets using the 3-digit zipcode and (with a fuzzy match) using the sum of units sold in 2006 for 10 high-selling products. This results in 132 matches to stores in our main sample, all of which belong to a single Nielsen *retailer_code*. We validate the correctness of the matches using data on price and with an alternative matching algorithm.

For Figure V, we select products that are sold for at least 40 of 52 weeks in 131 of the 132 stores. For the Nielsen dataset, we demean log prices by the Nielsen average price prior to aggregating to the store-level. Since we have exactly one year of data, this process is identical to how we aggregate prices for our benchmark sample. For the major grocer dataset, we demean log prices by the major grocer price average.

A.1.9 Assortment

We construct a store-level assortment price index. We build an index with two characteristics in mind: (i) the index should identify availability of high-price versus low-price products, with the price of a product computed using all stores and chains, not just the store at hand; (ii) we should not conflate variation in price that is due to product size or quantity discounts with variation in product quality. With (ii) in mind, within each of the 40 modules we keep only products with the modal size unit (most commonly ounces) and we divide the products into up to five sub-modules based on product size. Within a sub-module, thus, we are comparing products that are not only the same category, but also of similar size. With (i) and (ii) in mind, we then define for each product j a per-unit constant price $\overline{u}_{jy}$ as the average log price charged for product j in year y across all stores s that carry it, divided by the unit size (e.g., 40 oz). The division by unit size aims to control for residual differences in size within a sub-module. Within a sub-module, we include products in the top 20% by units sold across all food stores (not just the stores in our main sample) to ensure comparability across stores and chains.[43] The assortment price index for a store s, sub-module b and year y is the average per-unit constant price for all the products j in sub-module b with positive sales in year y. To create the final assortment price index for store s, we demean the index by sub-module-year, take the simple average over the years, and then take the simple average over the sub-modules to the store-level.

As additional measures of assortment, within each sub-module, we compute the share of products that are organic, the share of generic products, and the share that is in the top 10% by unit

[43] While there is a possibility that each chain carries unique high and low quality items, we cannot control for chain-level pricing decisions for such products.

price (across all chains). The measures are not meaningful for some sub-modules, e.g., organic batteries. To exclude such cases, for each of these additional measures, we only include submodules where the average of the variable (e.g., share generics) across all stores of all chains is at least 0.01 and the standard deviation is at least 0.005.

A.1.10 Elasticity Computation

For the computation of elasticities, we instrument for log price $logP_{sjt}$ with the log price in the same week t, and the same product j, in other stores of that chain outside the DMA of store s. In cases where a chain operates only in a single DMA, of which there are 14 food chains and 0 in either drug or mass merchandise chains, we split the DMA into two sub-markets and define the instrument using other stores in s's chain located outside s's sub-market. The sub-markets composed of clusters of stores that are defined as follows:

1. If the DMA spans multiple states, define clusters as DMA-states as long as the smaller sub-market contains at least 4 stores.
2. If that fails, define clusters as DMA-counties, as long as the smaller sub-market contains at least 4 stores.
3. If that fails, define clusters as DMA-zip3 as long as the smaller sub-market contains at least 4 stores
4. If that fails, split stores randomly into two sub-markets.

In variations 1-3, store clusters are aggregated into sub-markets works as follows:

1. Assign the largest cluster to sub-market 1
2. Assign the second-largest cluster to sub-market 2
3. Work through the remaining clusters in descending size (third-largest cluster first) and assign each cluster to the sub-market that currently has fewer stores.

A.1.11 Empirical Bayes Procedure

To adjust for sampling error in our estimates $\hat{\eta}_{sj}$ of individual store-product level elasticities, we apply an Empirical Bayes (EB) correction following the approach that has become standard in the education literature (Kane and Staiger, 2008; Jacob and Lefgren, 2008; Angrist et al., 2017). We define EB-adjusted elasticities to be

$$\tilde{\eta}_{sj} = \left(\frac{\sigma_{rj}^2}{\sigma_{rj}^2 + Var\left(e_{sj}\right)} \right) \hat{\eta}_{sj} + \left(\frac{Var\left(e_{sj}\right)}{\sigma_{rj}^2 + Var\left(e_{sj}\right)} \right) \overline{\eta}_{rj},$$

where $\overline{\eta}_{rj}$ and σ_{rj}^2 are a prior mean and variance defined at the chain-product level and $e_{sj} = \hat{\eta}_{sj} - \eta_{sj}$ is the estimation error in $\hat{\eta}_{sj}$.

We define $Var\left(e_{sj}\right)$ to be the estimate of the asymptotic variance of $\hat{\eta}_{sj}$ from the regression in equation (3). Recall that these regressions are run at the store-product level and the asymptotic variance is clustered by two-month periods. We define the hyperparameter $\overline{\eta}_{rj}$ to be the simple average of $\hat{\eta}_{sj}$ within chain r and product j. We define the hyperparameter σ_{rj}^2 to be an estimate of the variance of η_{sj} across stores s within chain r and product j, which we form by computing the variance of $\hat{\eta}_{sj}$ across stores within chain r and product j and then subtracting the mean of $Var\left(e_{sj}\right)$ across stores within chain r and product j. In a small number of cases where this yields a negative estimate of σ^2_{rj} we set $\sigma^2_{rj} = 0$.

The adjusted elasticities are used for (i) plotting the distribution of elasticities in Figure VII Panel B; (ii) computing lost profits in Table IX; (iii) estimating average marginal cost for the analyses in figure XI and Table XI. All other analyses in the main paper use raw elasticities.

A.1.12 Event Study

In this Appendix, we provide the exact criteria by which we identify the sets of stores that switch owner, as well as how we identify the timing of the switch.

We identify switching stores as ones that switch once from one *parent_code* to another *parent_code* within the 2006-2014 sample. We consider as switchers only stores that change parent_code and not ones that change *retailer_codes* within a *parent_code*. Then, we identify switching cohorts or episodes as incidents where at least two stores switch from one *parent_code* to another *parent_code*.

To identify the timing of when a set of stores switches *parent_code*, we define a measure of assortment similarity between these switching stores and their respective old and new *parent_codes*. We compute this measure for two modules, the orange juice module and the cereal module. Specifically, for each quarter the measure of assortment similarity to the old (new) *parent_code* is the share of products sold for at least 5 weeks by the old (new) *parent_code* that are also sold by the switching stores for 5 weeks in that quarter. Then, we define switch t_0: if the switching stores close temporarily during the transition, then we take the midpoint of the quarters closed; if the switching stores do not close, then we take the first quarter when the assortment similarity to the new *parent_code* is greater the assortment similarity to the old *parent_code*; if the assortment similarity crosses more than once, then we drop these switchers. We compute the switch timing t_0 for the two modules, and we keep only the switchers such that the two modules identify the same t_0.

We define the pre-period as the quarters up to one quarter before t_0. The post-period starts the first quarter after t_0 where the assortment similarity to the new *parent_code* has closed 75% of the average gap between the assortment similarity to the old and new *parent_codes* during the pre-period. If this convergence takes longer than three quarters, we do not consider these switching stores to have a valid post-period. This definition of the post period does not depend on the assortment similarity to the old *parent_code* in the post-period. Mergers where the old chain closes all stores is still considered a valid merger as long as the assortment similarity to the new *parent_code* converges sufficiently quickly.

For the analysis of pricing similarity between stores, we define a measure similar to the measure of quarterly absolute price difference for store pairs, except that (i) it is computed using weekly, as opposed to quarterly, prices, (ii) we standardize the week t such that the week of the switch is week 0, and (iii) instead of comparing stores s and *s'* in a pair of stores, we instead compare each store-product-week *sjt* for the switching stores to the average log price for product j in week t in non-switching stores of the "old" (respectively, "new") chain. We aggregate to the weekly level taking the simple average of this measure across products j, and then the simple average across the switching stores s.

In order to compute longer-run elasticities, we keep up to 52 weeks of data from the start of the post-period and up to 52 weeks prior to the end of the pre-period. At minimum, there are three quarters of data available in the post-period for each episode. We sample up to 200 stores from the old and new *parent_code* as control stores. For the pre-specification and post-specification, we estimate equation (6) keeping only the old *parent_code* stores and new *parent_code* stores as controls, respectively.

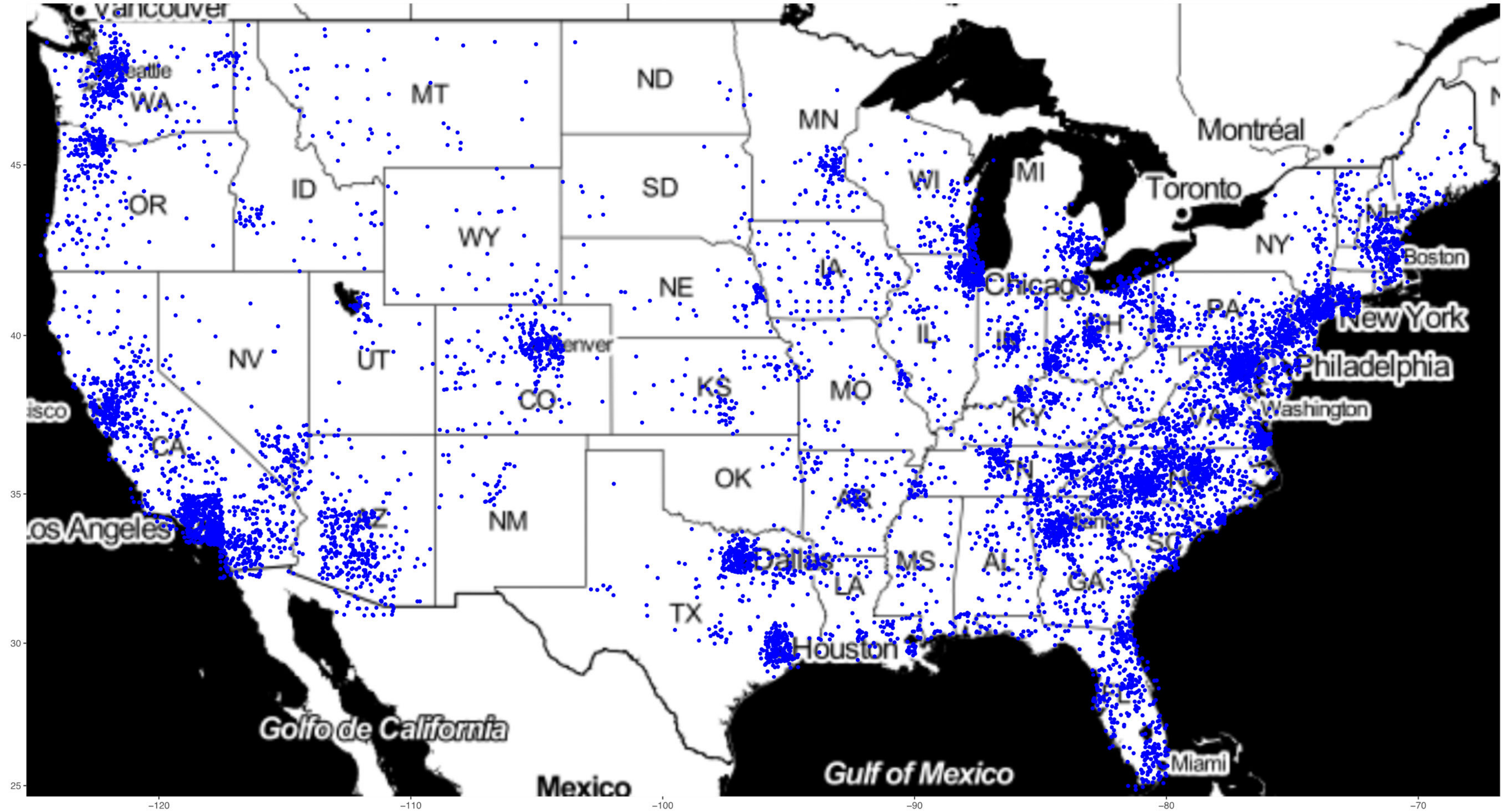
A.1.13 Inequality

In our income inequality exercise, we suppose that there is a representative product sold by every store with a marginal cost, c, constant across chains. Per our model, the optimal flexible pricing is $p_s^* = \lambda_s + log(c)$, where $\lambda_s = log(\frac{\eta_s}{1+\eta_s})$. We make two further assumptions: 1) the value of c is set equal to the median of the empirical estimates of marginal cost, $\hat{c}_{rj}$; 2) the value of λ_s is set according to the income first stage, exactly as in Table V, column 5. We add the overall mean of $\hat{\lambda}_{sj}$ for level.

Define the uniform log price $p_r^{Uniform}$ as the log of the chain-level uniform price that optimizes the profit equation $\sum_s k_s P_r^{\eta_s}(P_r - c)$. We assume that stores are all the same size with $k_s = 1$ for all s.

The yearly log price paid perturbs the uniform log price within each chain by the yearly IV coefficient, β^{Yearly}, of prices on elasticity (Table VIII, column 1) which is meant to include the "automatic stabilizer" effect of intertemporal substitution due to sales. Formally, the yearly log price paid is $p_s^{Yearly} = p_r^{Uniform} + \beta^{Yearly}(\lambda_s - \bar{\lambda}_r)$, where $\bar{\lambda}_r$ is the average of λ_s within chain r.

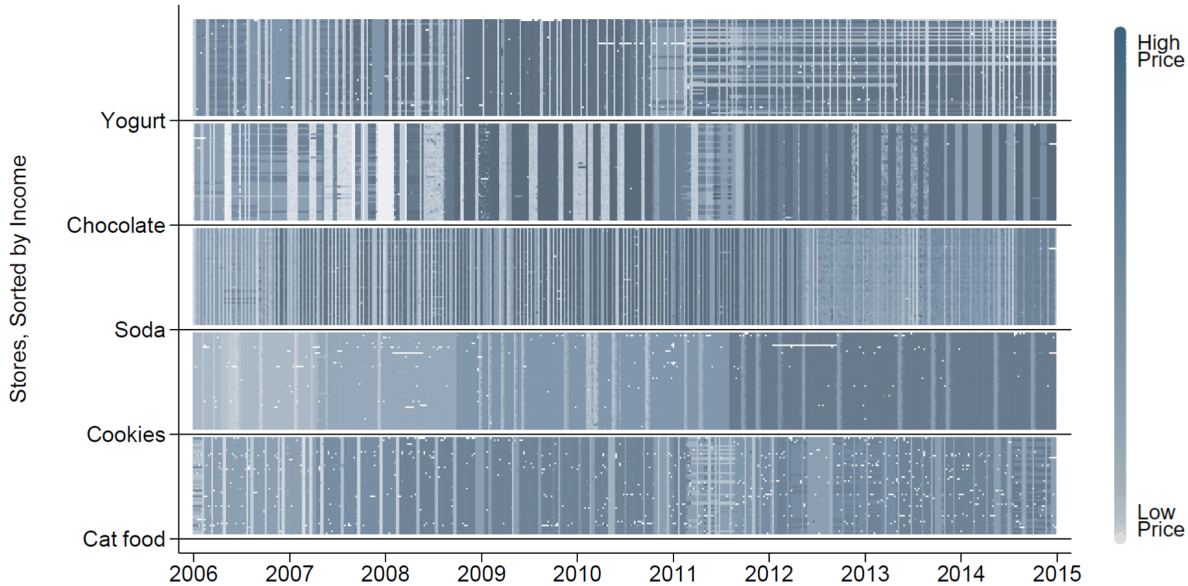
Online Appendix Figure 1
Store Locations



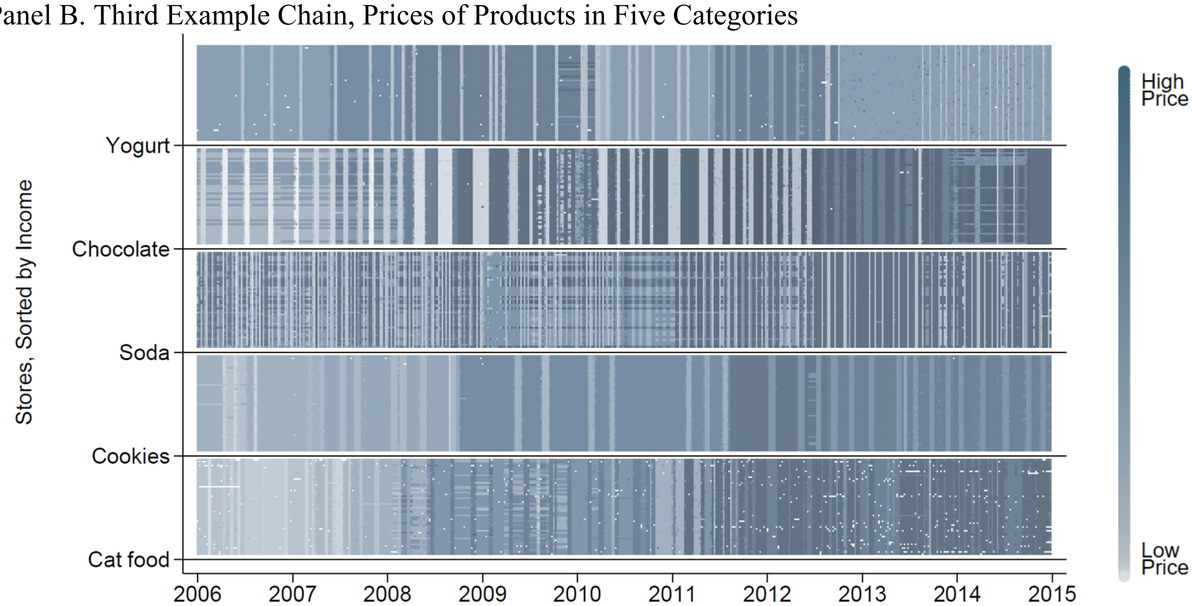
Notes: The figure plots the locations of the 22,680 stores (food, drug, and mass-merchandise) in our sample. The location is the midpoint of the county given in the RMS dataset and jittered so that stores do not overlap. In some cases, this may cause stores near state borders to be placed in the wrong state or in the ocean.

Online Appendix Figure 2
Additional Examples of Chains with *Uniform Pricing*

Panel A. Second Example Chain, Prices of Products in Five Categories



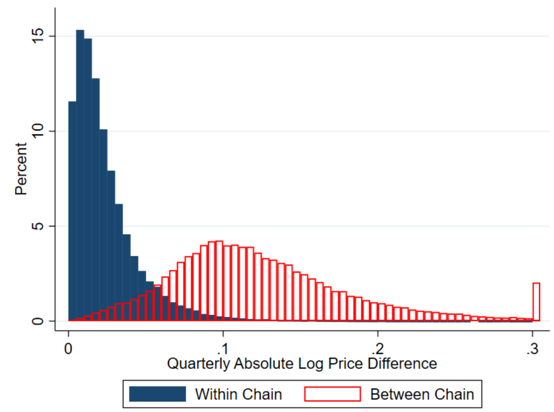
Panel B. Third Example Chain, Prices of Products in Five Categories



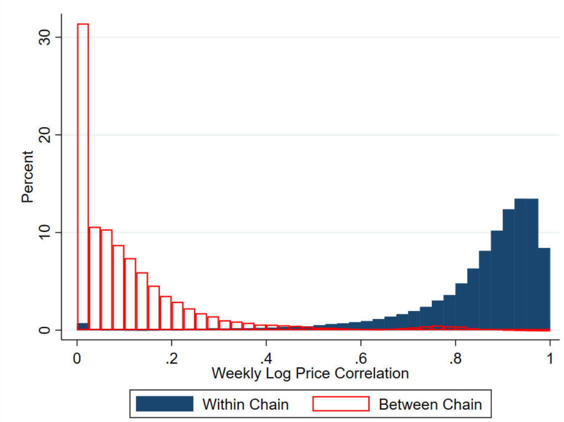
Notes. Figures depict log price in store s and week t for a particular product j. To facilitate comparison across products, we standardize prices by demeaning the log price by the average log price across all stores s in all chains. Darker colors indicate higher price and the figure is blank if price is missing. Each column is a week. Each row is a store, and stores are sorted by store-level income per capita. Within each figure, the same 50 stores appear for each product.

Online Appendix Figure 3
Similarity in Pricing Across Stores: Same-Chain Comparisons vs. Different-Chain Comparisons

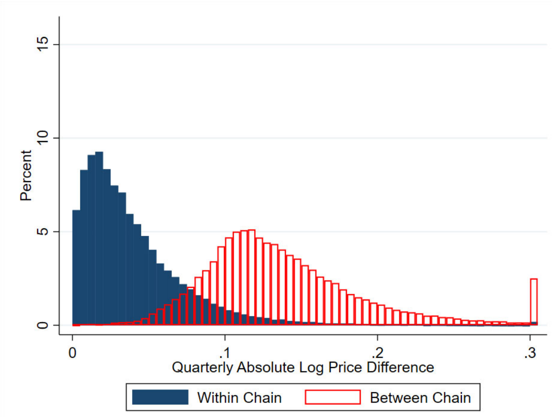
Panel A. Log Price Diff, Same DMA



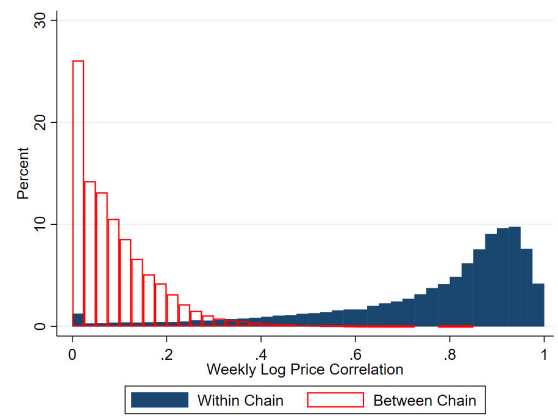
Panel B. Correlation, Same DMA



Panel C. Log Price Diff, Different DMA and Income



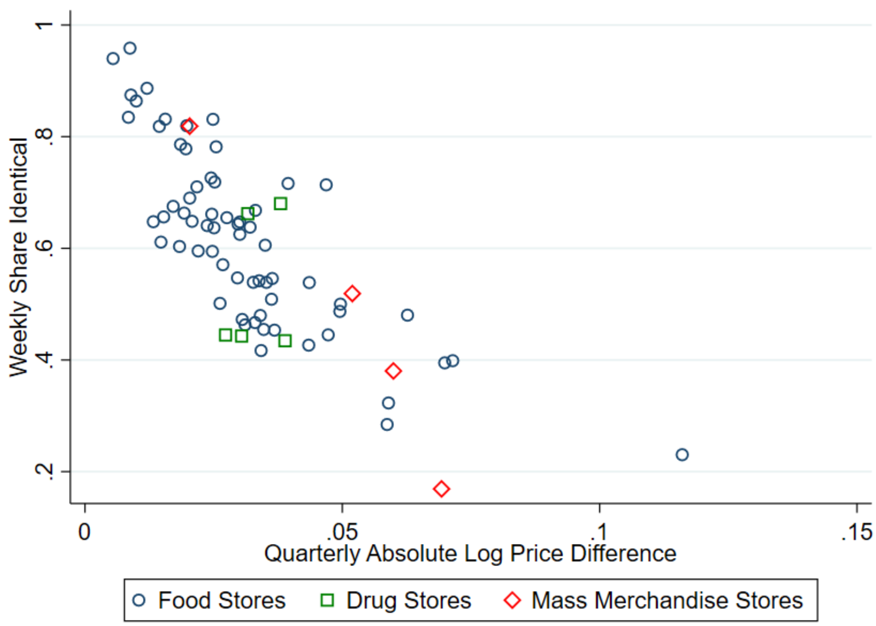
Panel D. Correlation, Different DMA and Income



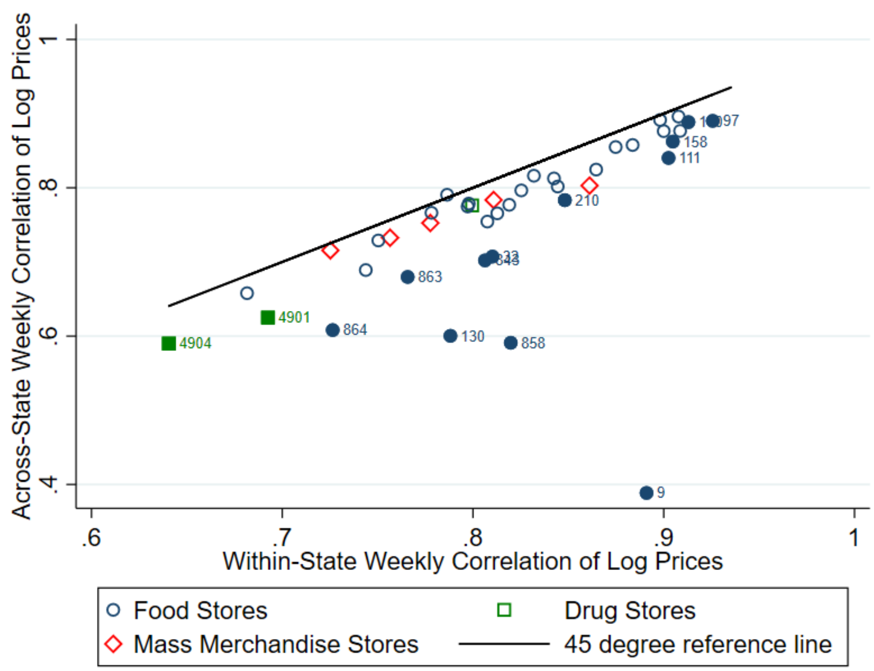
Notes. Each observation in the histograms is a chain-UPC representing the average relationship between up to 200 store-pairs belonging to each chain. The "same chain" pairs are formed from stores belonging to the same chain; the "different chain" pairs are formed from stores in different chains, requiring in addition that the two stores do not belong to the same *parent_code*. Panels A and B are restricted to pairs of stores located in the same DMA, while Panels C and D are restricted to pairs of stores located in different DMAs, with the additional restriction that one store in the pair has per-capita income in the bottom third among stores in our sample, and the other store in the pair has per-capita income in the top third among stores in our sample. Panels A and C display the distribution of the average absolute difference in log quarterly prices between two stores in a pair, winsorized at 0.3. Panels B and D display the distribution of the correlation in the weekly (demeaned) log prices between two stores, winsorized at 0.

Online Appendix Figure 4
Additional Evidence on Similarity in Pricing, Chain-Level Measures

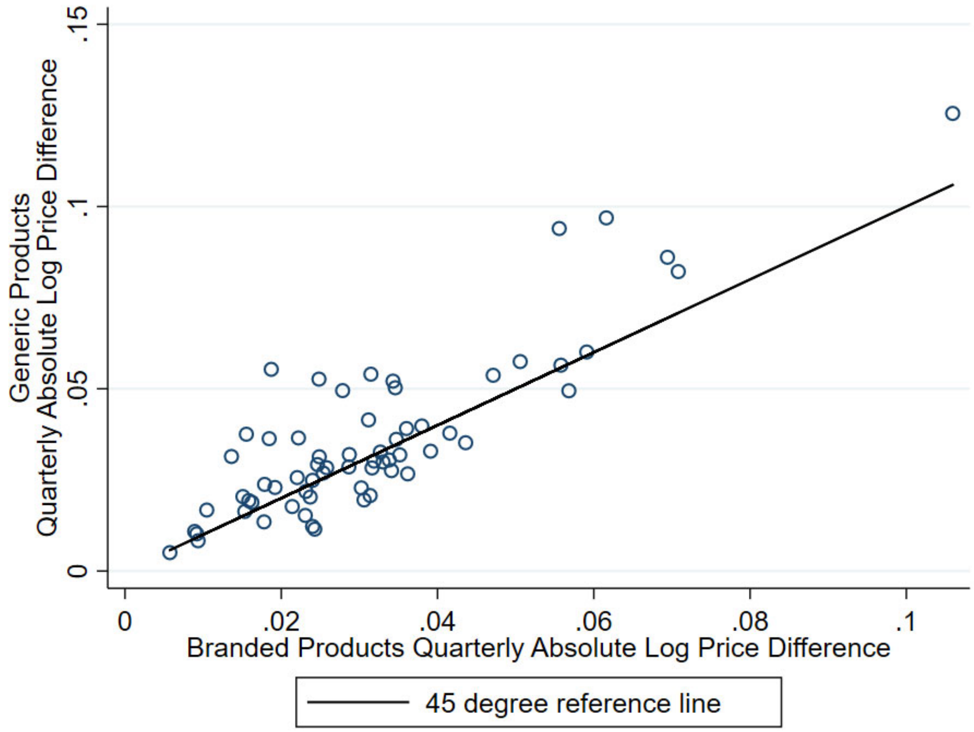
Panel A. Quarterly Similarity in Pricing vs. Share Identical Price, by Chain



Panel B. Between and Within-State Weekly Correlation of Log Prices

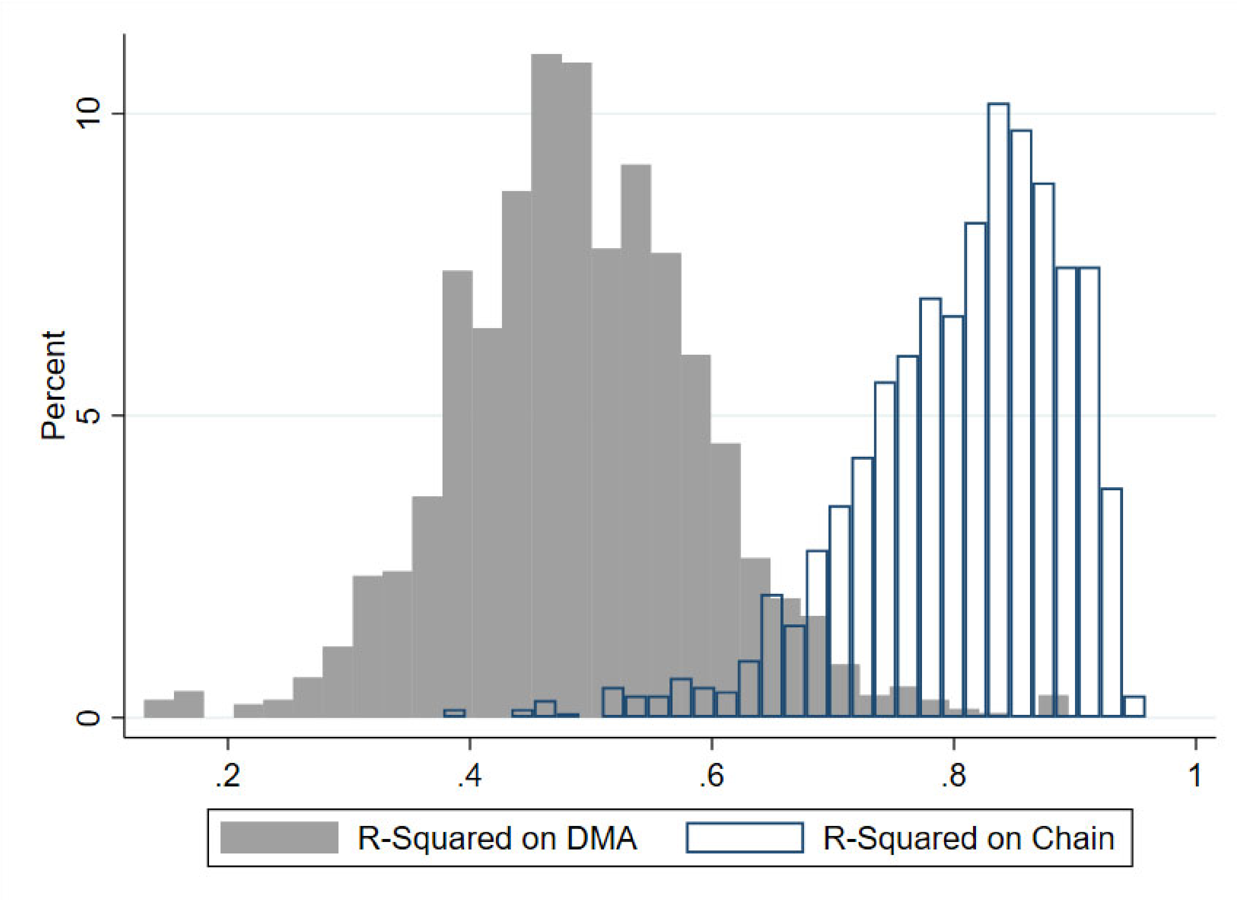


Panel C. Quarterly Absolute Log Price Difference, Generic vs. Benchmark Products (Food Stores)



Notes. Each observation is a chain that operates at least three stores in multiple states. In Panel B, chains that differentiate pricing geographically (identified based in Figure 3 Panel B) are denoted with solid markers. Each observation is a chain that operates at least three stores in each of at least two states. Circles represent food stores, diamonds represent mass merchandise stores, and squares represent drug stores. Panel C plots the chain-average quarterly absolute difference in log prices for generic products compared to the same measure computed for the benchmark products.

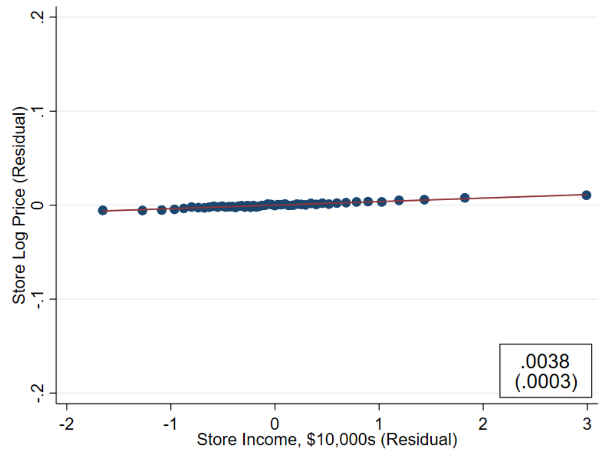
Online Appendix Figure 5
Share of Variance Explained by Chain and DMA



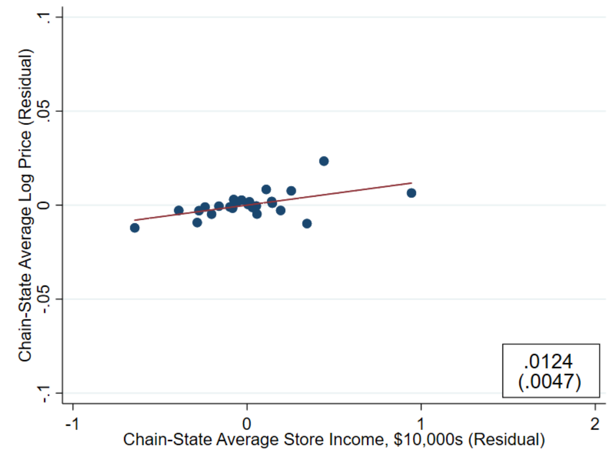
Notes. In this figure, we show the distribution of the R-Squared by regressing store-UPC price on fixed effects for either DMA or Chain, UPC-by-UPC. The median R-Squared on DMA is 0.486. The median R-Squared on chain is 0.824.

Online Appendix Figure 6
Zone Pricing: Price vs. Income (Food Stores)

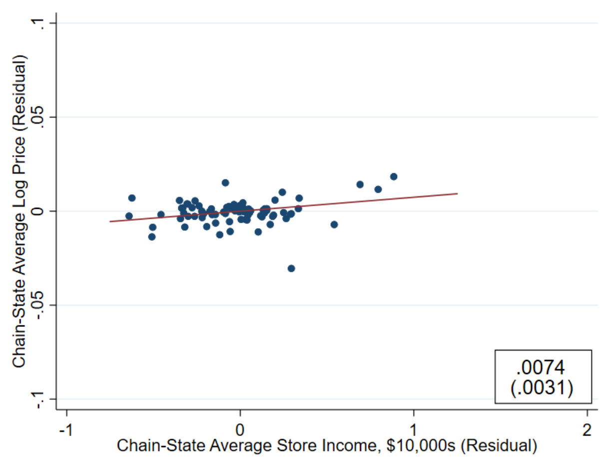
Panel A. Within Chain-State



Panel B. Between Chain-State



Panel C. Food Stores (Non-Zone-Pricing Chains Only), State Zones

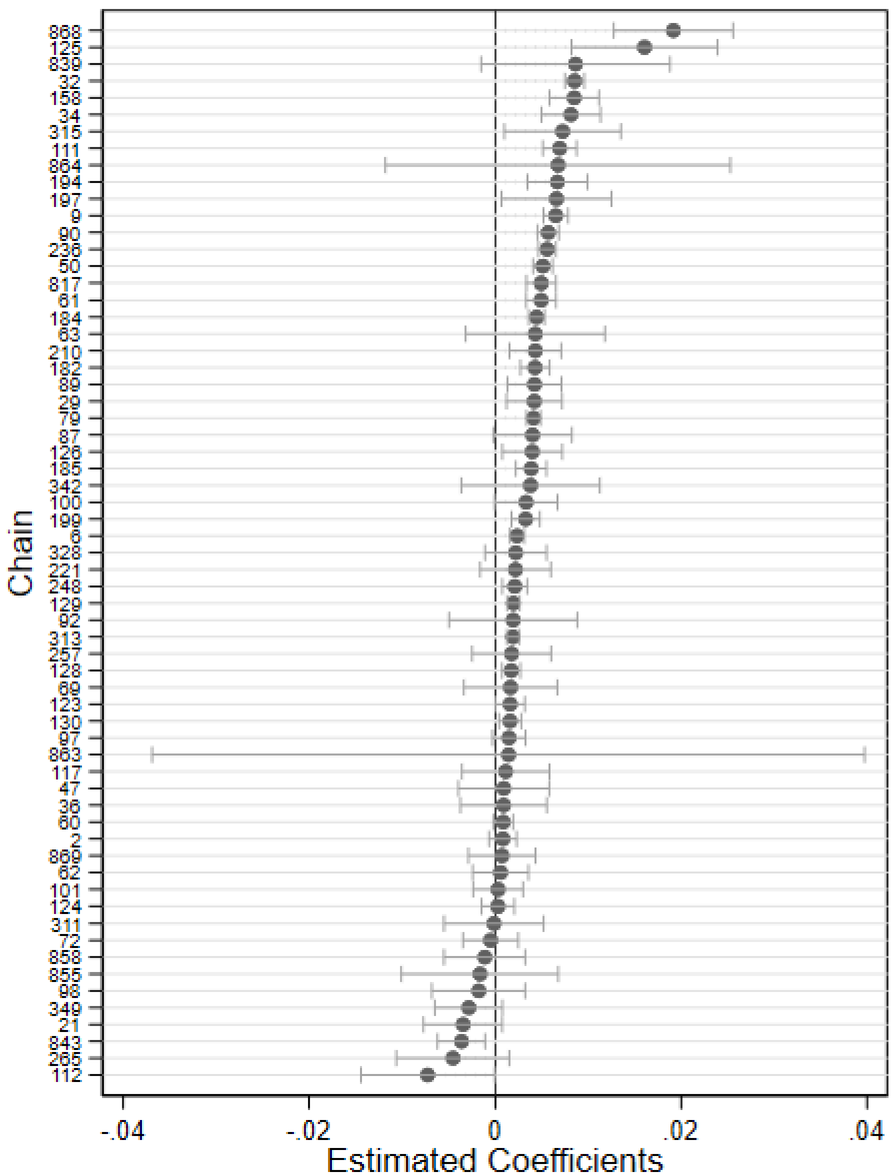


Panel D. Food Stores (Zone Pricing Chains), State Zones

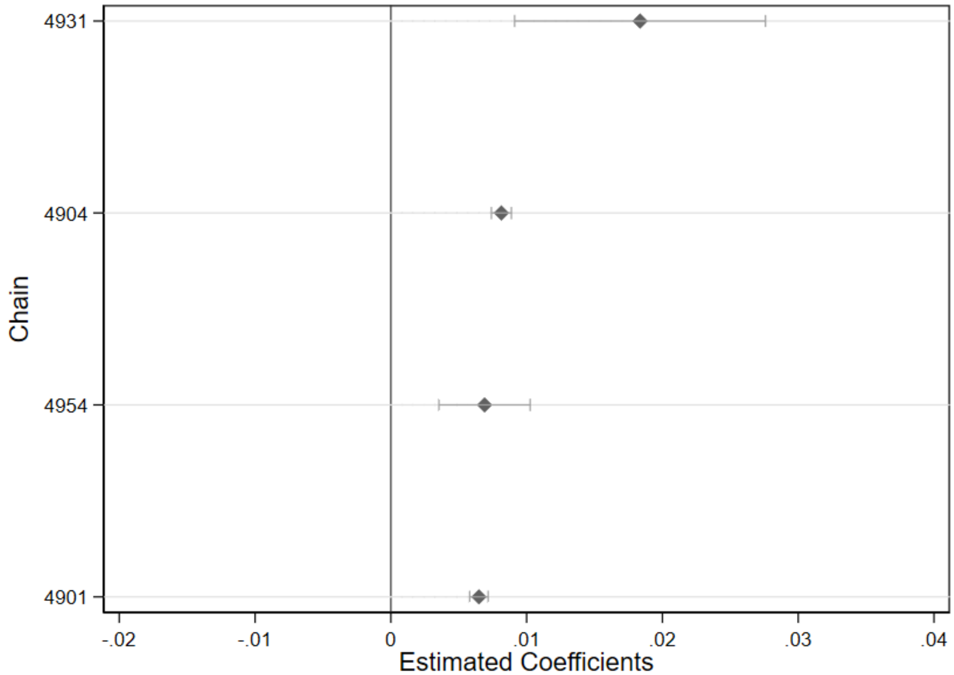
*Notes***.** Panels A and B show the usual within and between chain relationships except now demeaned (or aggregated) by chain-state to approximate pricing zones. Panel C is a scatter of the between-chain relationship for chains that are not zone pricers). Panel D is a scatterplot of this relationship for 12 zone-pricing chains. Chains in Panels C and D are identified in Figure 3 Panel B.

Online Appendix Figure 7
Within-Chain Response of Prices to Income, By Chain

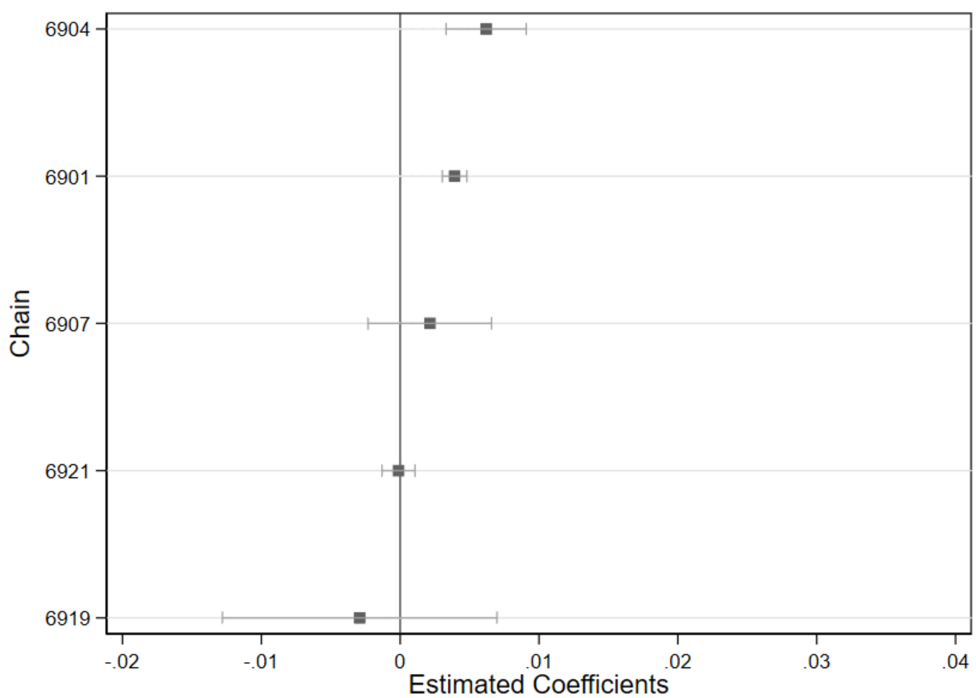
Panel A. Food Stores



Panel B. Drugstores



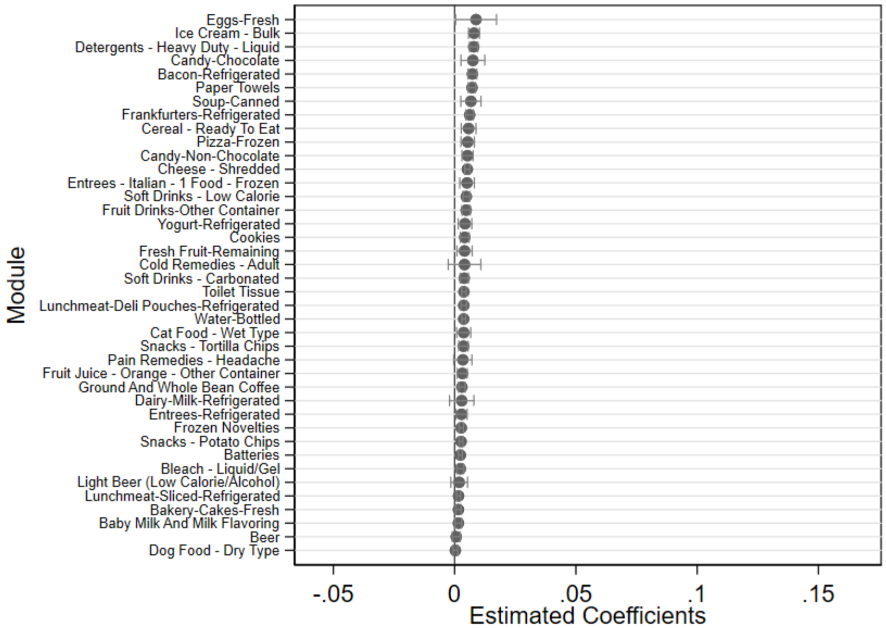
Panel C. Mass-Merchandise Stores



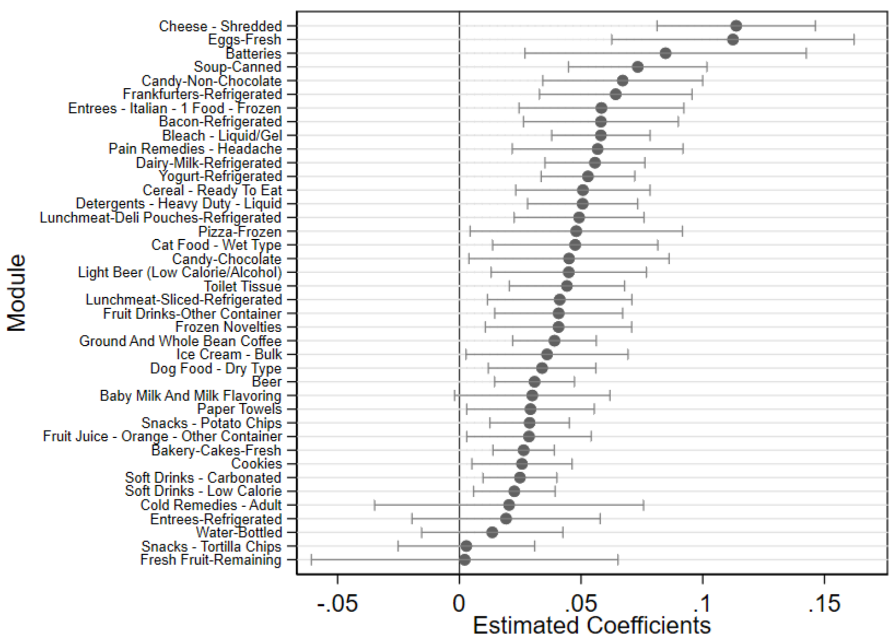
Notes. The figures plot the coefficients of regressions of log price in store-level income run chain-by-chain, with 95% confidence intervals based on robust standard errors. A coefficient of 0.01 means that within chain *c*, prices are set 1 log point (about 1%) higher for an increase in income of $10,000. In Panel A, two chains with standard errors > 0.02 are omitted.

Online Appendix Figure 8
Price vs. Income by Module/Product Group (Food Stores)

Panel A. Within-Chain Price vs. Income Regression



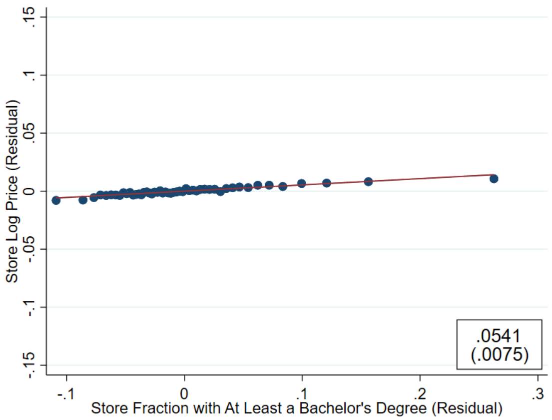
Panel B. Between-Chain Price vs. Income Regression



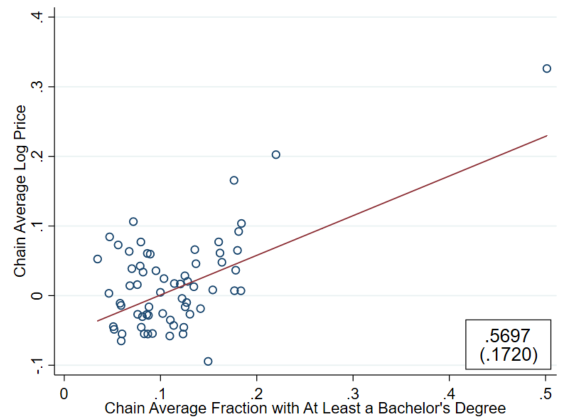
*Note***s.** Panel A plots the coefficients of regressions of log price on store-level income with chain fixed effects, where the regression is run separately for each module. 95% confidence intervals are based on standard errors clustered by *parent_code*. A coefficient of 0.01 means that within chain *c*, prices are set 1 log point (1%) higher for an increase in income of $10,000. Panel B plots the same relationship for the chain-level regression of average chain-level price on average chain-level income but for chain averages using analytic weights equal to number of stores and standard errors clustered by *parent_code*.

Online Appendix Figure 9
Price Response to Other Price Determinants (Food Stores)

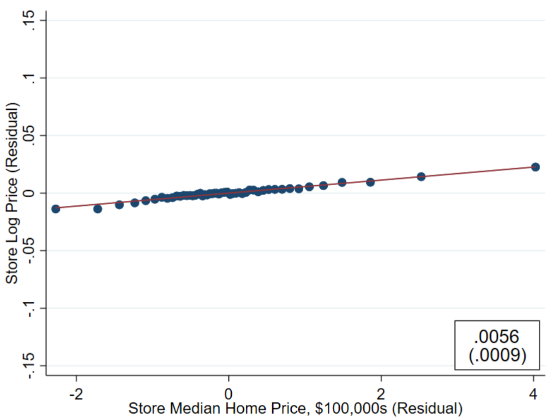
Panel A. Price vs. Education: Within-Chain



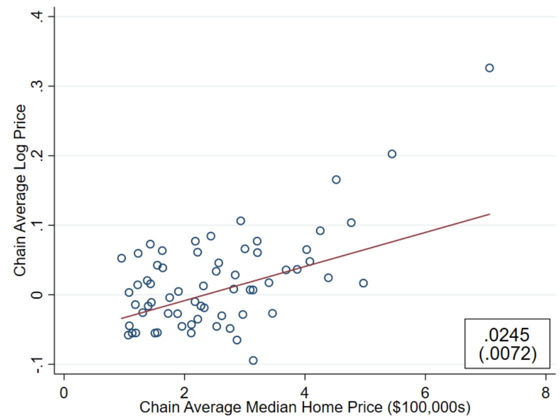
Panel B. Price vs. Education: Between Chain



Panel C. Price vs. Median Home Price: Within-Chain



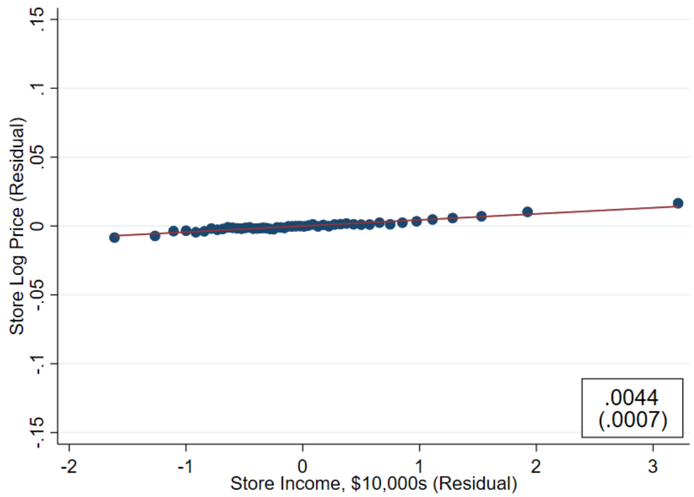
Panel D. Price vs. Median Home Price: Between Chain



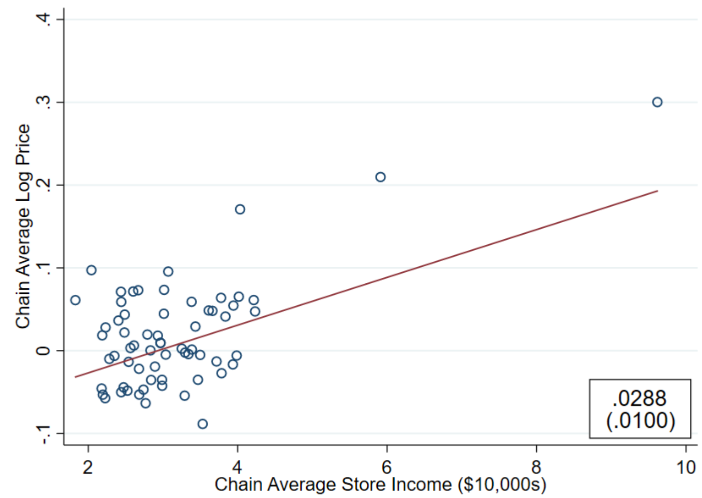
*Notes***.** Panel A is a binned scatterplot with 50 bins of the residual of log price on the residual of fraction of adults over the age of 25 with at least a bachelor's degree ("education") in store *s*. Residuals are after removing chain fixed effects. Panel B is a scatterplot of average price on average education at the chain level. Panels C and D are the same but using median home price as the independent variable. The figures report the coefficient of the relevant regressions, with standard errors clustered by *parent_code*. Axes ranges have been chosen to make the slopes visually comparable within each pair of figures. Analytic weights equal to the number of stores in each unit are used in the regressions in Panels B and D..

Online Appendix Figure 10
Robustness of Price vs. Income, Alternative Prices and Products (Food Stores)

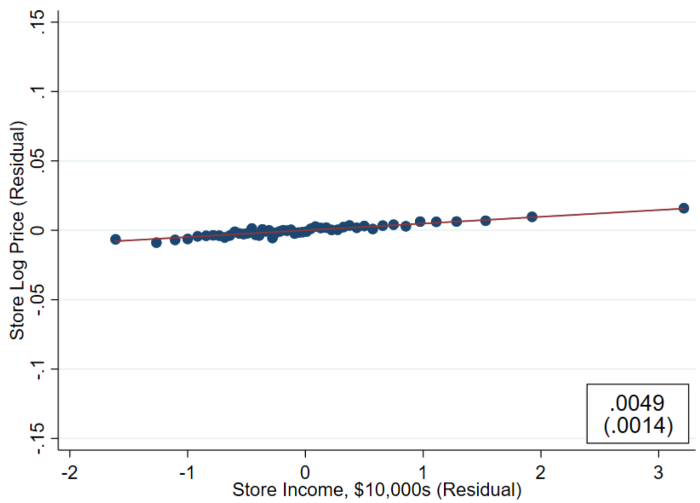
Panel A. Top Decile Products by Revenue: Within Chain



Panel B. Top Decile Products by Revenue: Between Chain

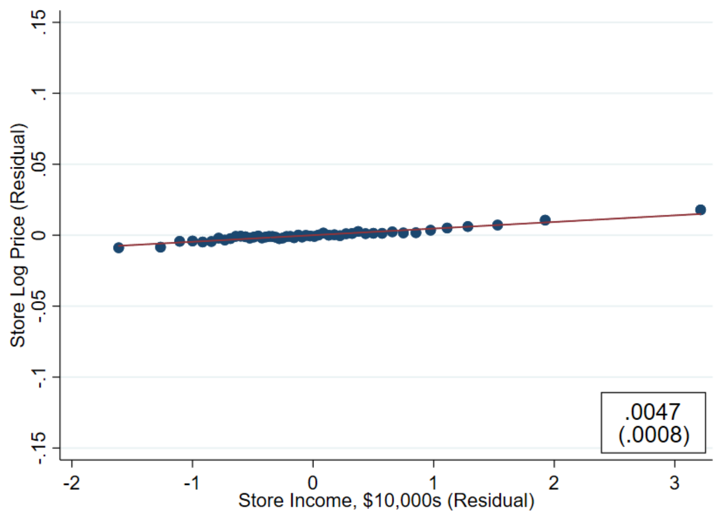


Panel C. Bottom Decile Products by Revenue: Within Chain



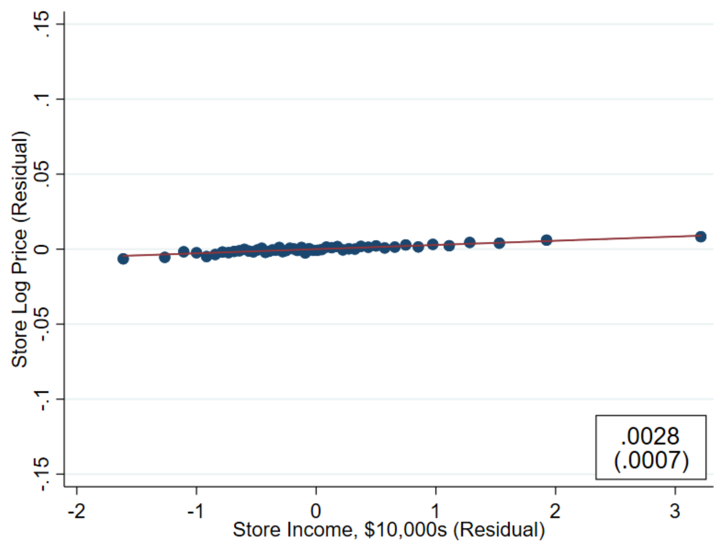
Panel D. Bottom Decile Products by Revenue: Between Chain

Panel E. All Products, Weighted by Revenue: Within Chain

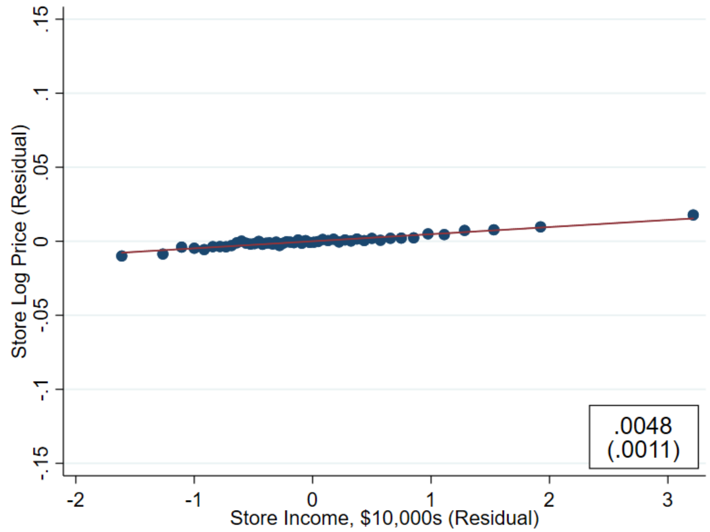


Panel F. All Products, Weighted by Revenue: Between Chain

Panel G. Generic Products: Within Chain



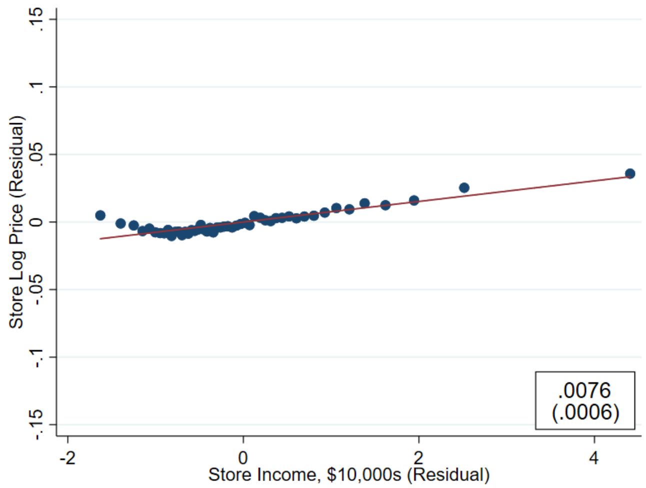
Panel H. Module-Level Price Index: Within Chain



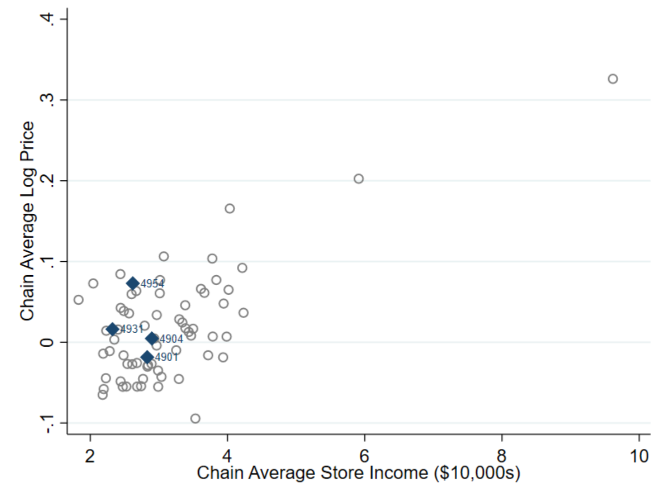
Notes. These figures plot key price-income results for a range of alternative products, for the food store chains. Panel A is a binscatter with 50 bins of store-level log price on store-level income keeping only the top decile of products by average yearly-revenue. We scale according to the number of years that a product appears in our sample. Panel B is a scatterplot of the average log price keeping the top decile of products (by average yearly revenue) on average income at the chain level. Similarly, Panels C and D are a binscatter and scatter using the bottom decile of products by average yearly revenue. Panels E and F show the within-chain and between-chain relationships using all products, weighting log prices by the overall store-UPC revenue. In Panel G, we select 80% available generic products within-chain for a total of 12,423 generic products. In Panel H, we show the within-chain relationship using our module-level price index. Panels A, C, E, G, and H residualize against chain-fixed effects. Axes ranges have been chosen to make the slopes visually comparable. Analytic weights equal to the number of stores in each aggregation unit is used for the regression in Panel B, D, and F.

Online Appendix Figure 11
Relationship of Price vs. Income (Drug and Mass Merchandise Stores)

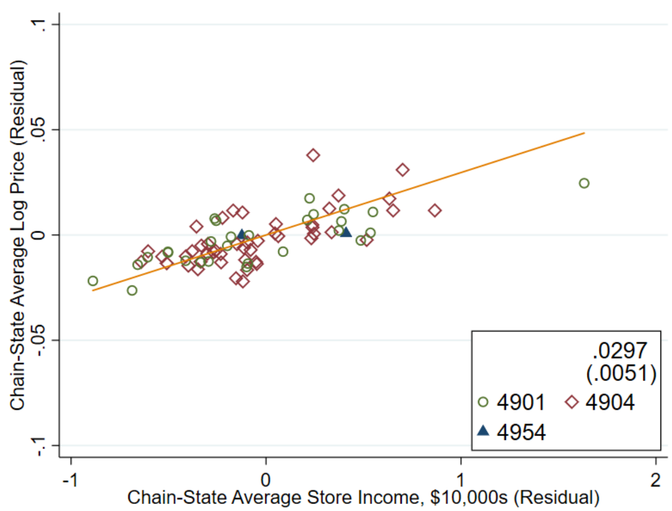
Panel A. Drug Stores: Within Chain



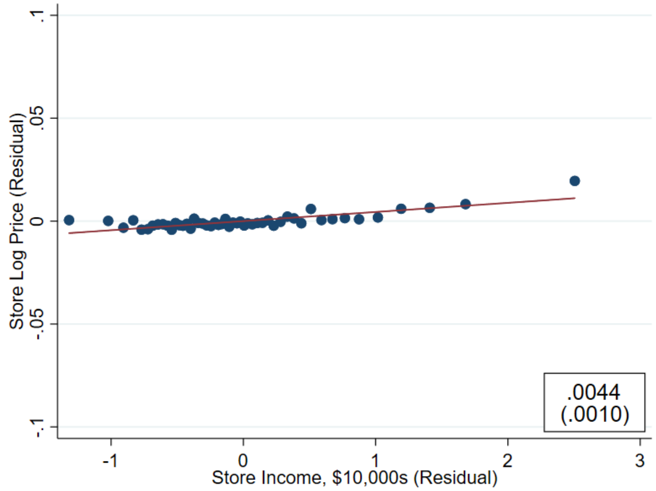
Panel B. Drug Stores: Between Chain



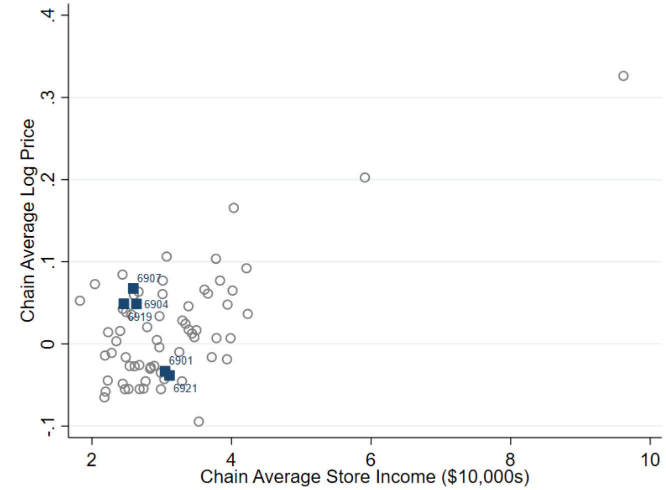
Panel C. Drug Stores: Between Chain-State Zones



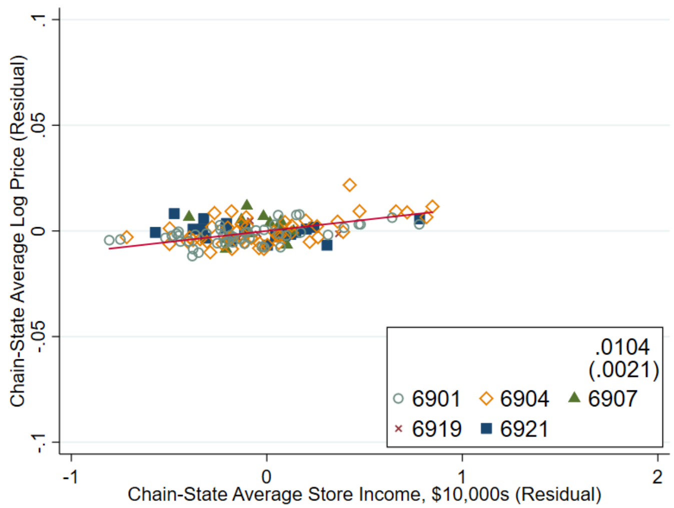
Panel D. Mass Merchandise Stores: Within Chain



Panel E. Mass Merchandise Stores: Between Chain



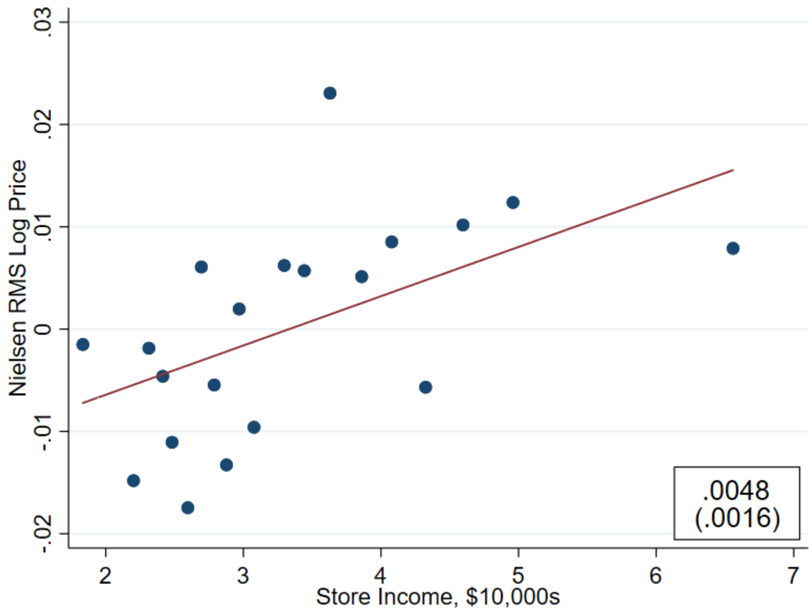
Panel F. Mass Merchandise Stores: Between Chain-State Zones



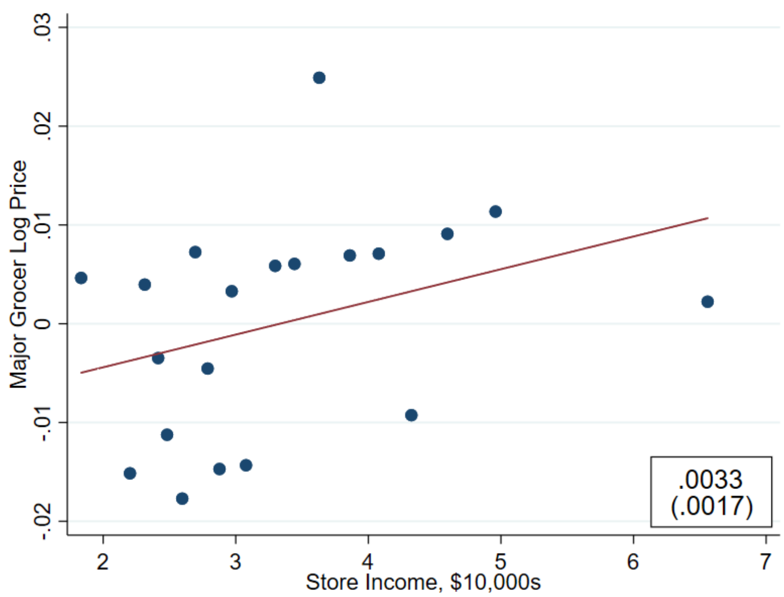
Notes. Panels A and D show the within-chain relationship between price and income for drug stores and for mass-merchandise stores, respectively. Panels B and E do the same for the between-chain relationship, while Panels C and F break down each chain into chain-states. Labels in Panels B and E are Nielsen's chain identifier and hollow circles representing food chains are shown for reference.

Online Appendix Figure 12
Major Grocer Data: Price vs. Income, No State Fixed Effects

Panel A. Nielsen Data: Average Weekly Log Price



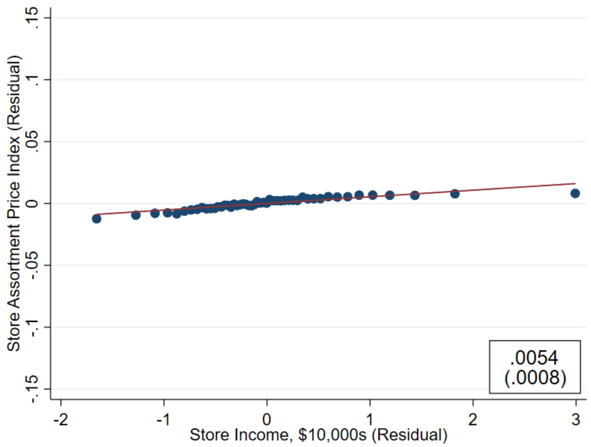
Panel B. Major Grocer Data: Average Weekly Price



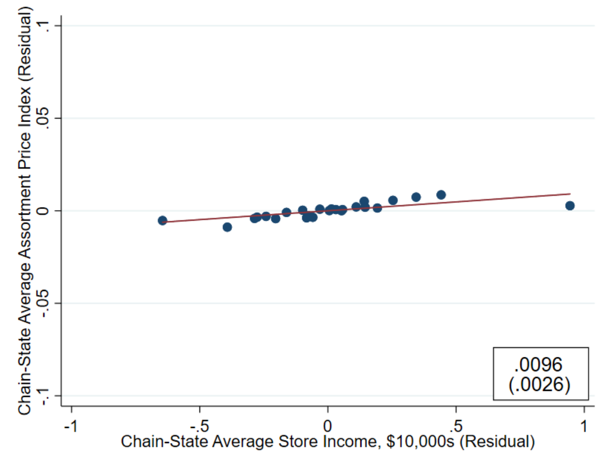
*Notes***.** Panel A shows the log price income relationship for identified Major Grocer stores within RMS. Panel B shows this relationship using the Major Grocer dataset for the same 132 stores. Unlike the panels in Figure 5, these figures do not demean the variables using state fixed effects.

Online Appendix Figure 13
Zone Pricing: Assortment Price Index (Food Stores)

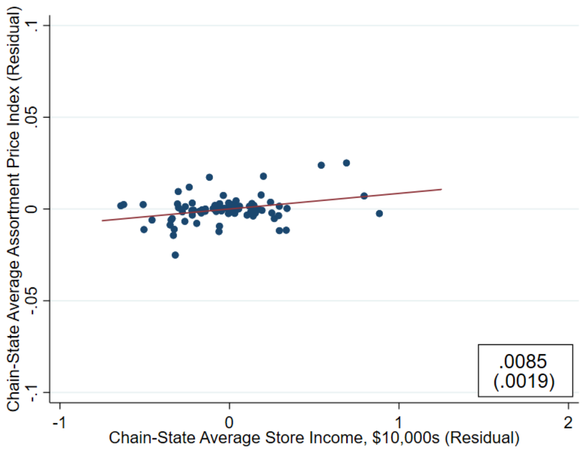
Panel A. Within-Chain-State



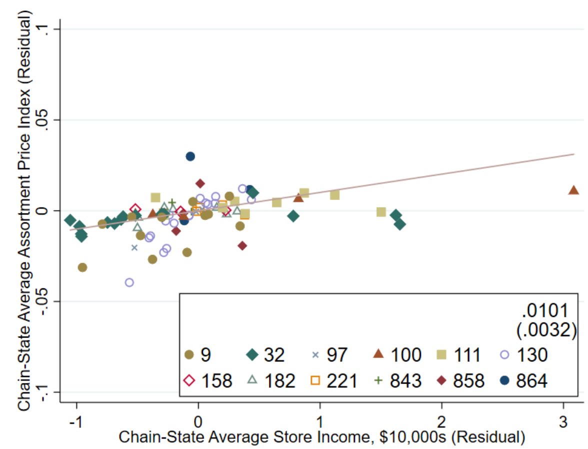
Panel B. Between Chain-State



Panel C. Non-Zone-Pricing Chains Only, State Zones

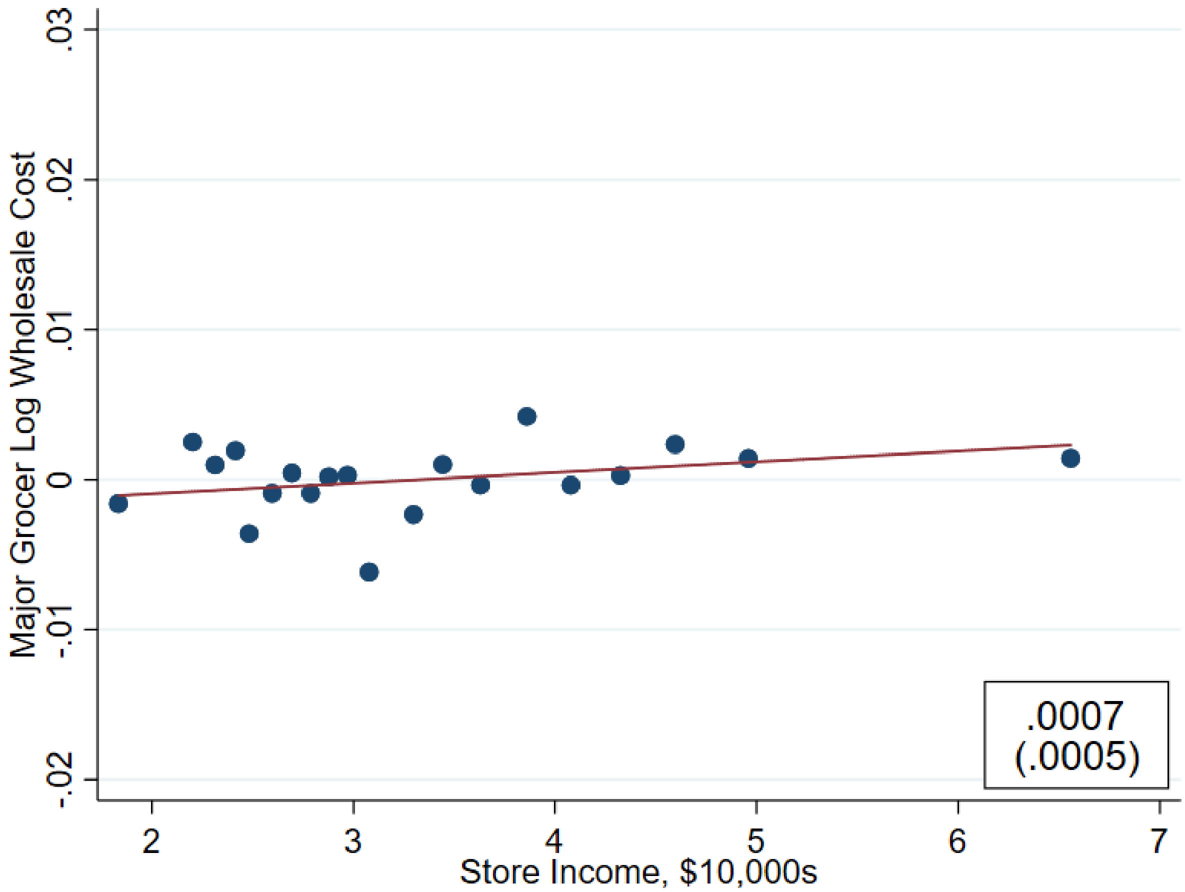


Panel D. Zone Pricing Chains, State Zones



*Notes***.** These figures are the product assortment analogue to Figure VI. They show the relationship of which products stores carry, a non-price measure of store-level decision making, vs. income. The assortment price index is constructed as follows: first, for each product that is in the top 20% of national units sold, we calculate the average national log unit price. Second, we divide each module into up to five sub-modules based on product package size. Third, we calculate the average log national unit price for each store-sub-module-year. We collapse this measure to a store level Assortment Price Index (API) by averaging over the sub-module-years for each store.

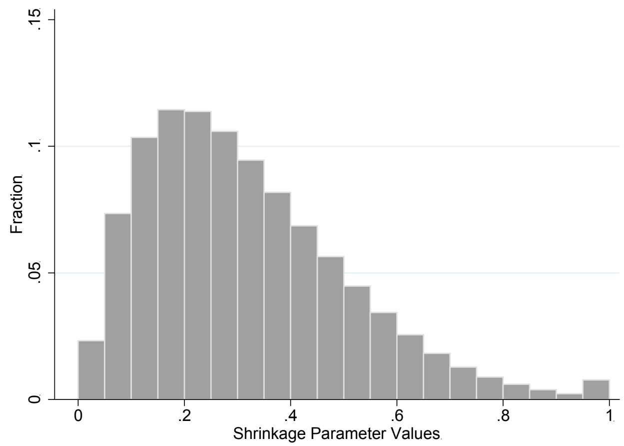
Online Appendix Figure 14
Marginal Costs and Income: Investigation Using Major Grocer's Data



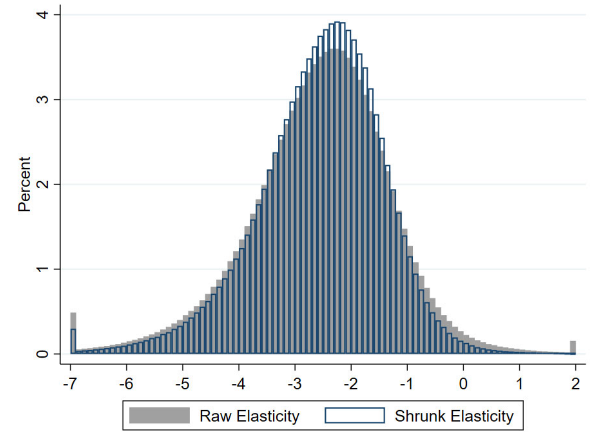
*Notes***.** The figure is a binned scatterplot of wholesale cost from the Major Grocer's data. The cost variable does not include transport or storage costs and is before supplier discounts. Robust standard errors are used.

Online Appendix Figure 15
Additional Evidence on Elasticity Specification (Food Stores)

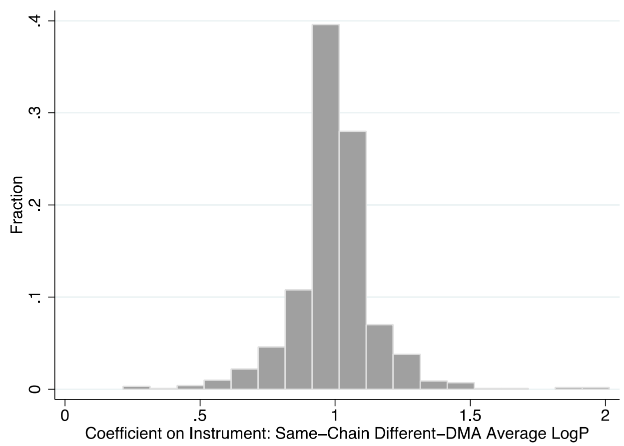
Panel A. Distribution of Shrinkage



Panel B. Distribution of Elasticity Estimates by Store-UPC



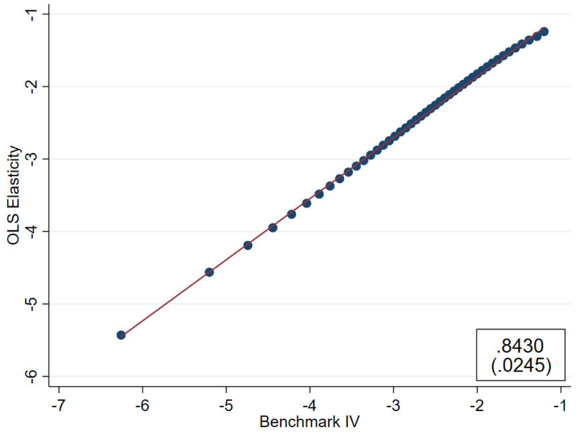
Panel C. First-Stage Coefficient Distribution



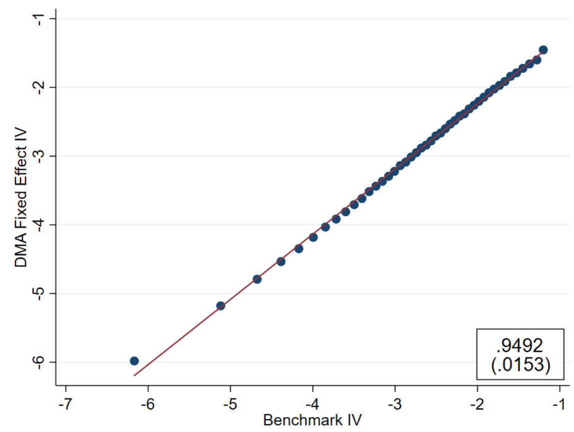
Notes. Panel A shows the distribution of our Empirical Bayesian Shrinkage Parameter for each store-UPC in food stores. Panel B shows the distribution of the store-UPC elasticity estimates, both before and after shrinkage. Elasticities are shrunk toward the chain-UPC average. Panel C shows the distribution of the coefficient on our instrument. We randomly sample 1000 store-UPCs and regress log price on the average log price of stores in the same-chain but different DMA along with our usual set of week-of-year and year fixed effects.

Online Appendix Figure 16
Correlation of Benchmark IV Elasticity Against Alternative Elasticity Specifications

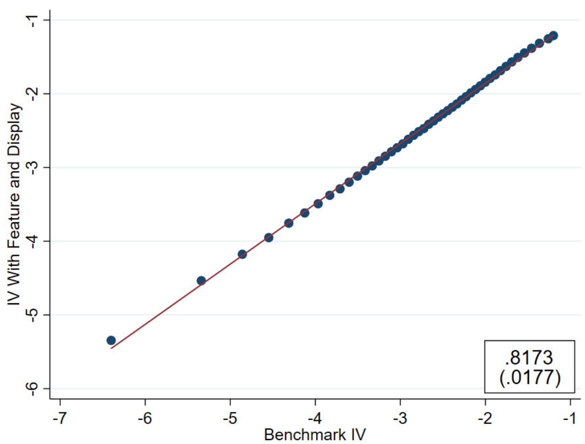
Panel A. Benchmark IV vs. OLS elasticities



Panel B. Benchmark IV vs. DMA-level IV Elasticities

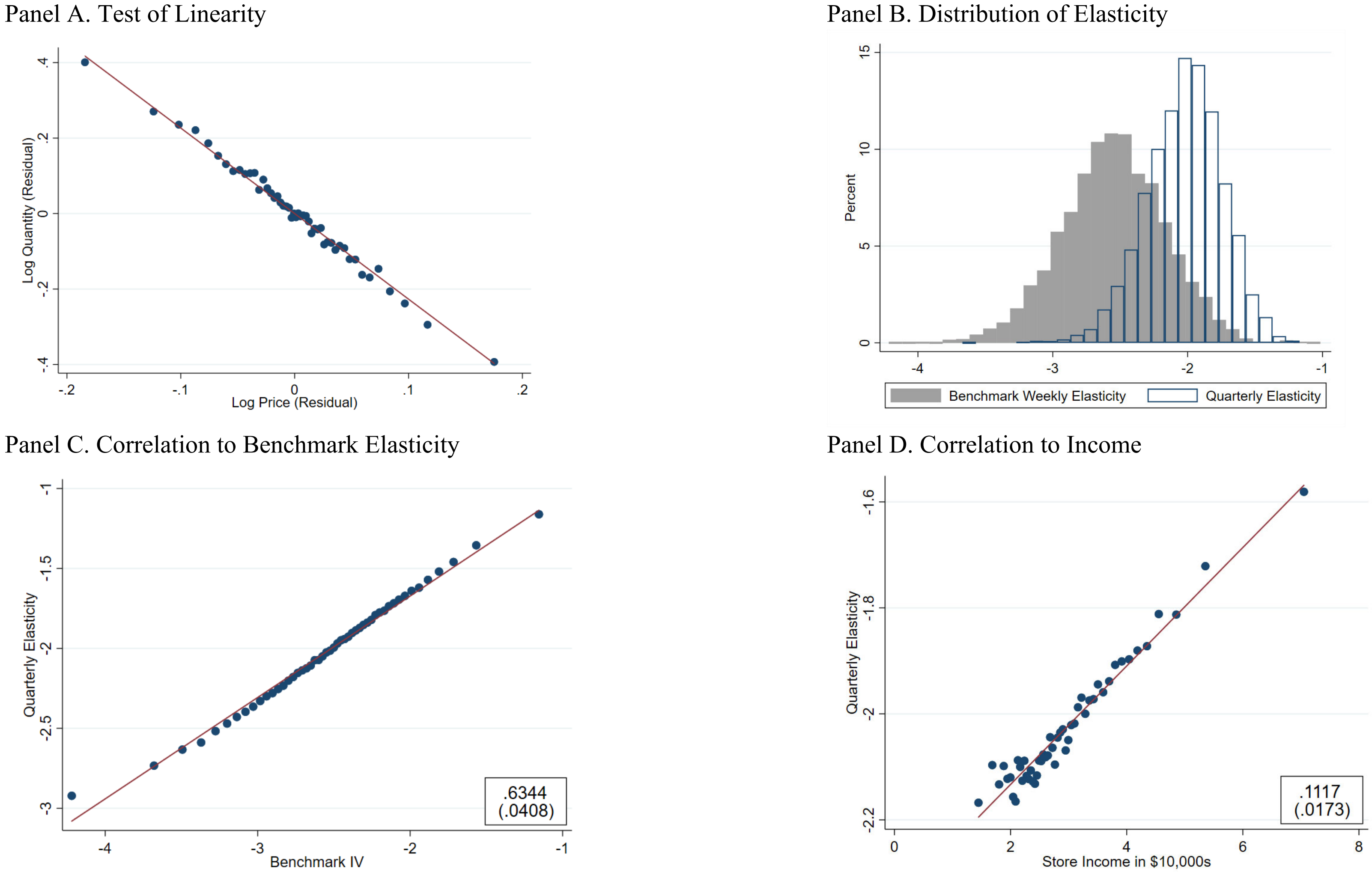


Panel C. Benchmark IV vs. IV with Advertising



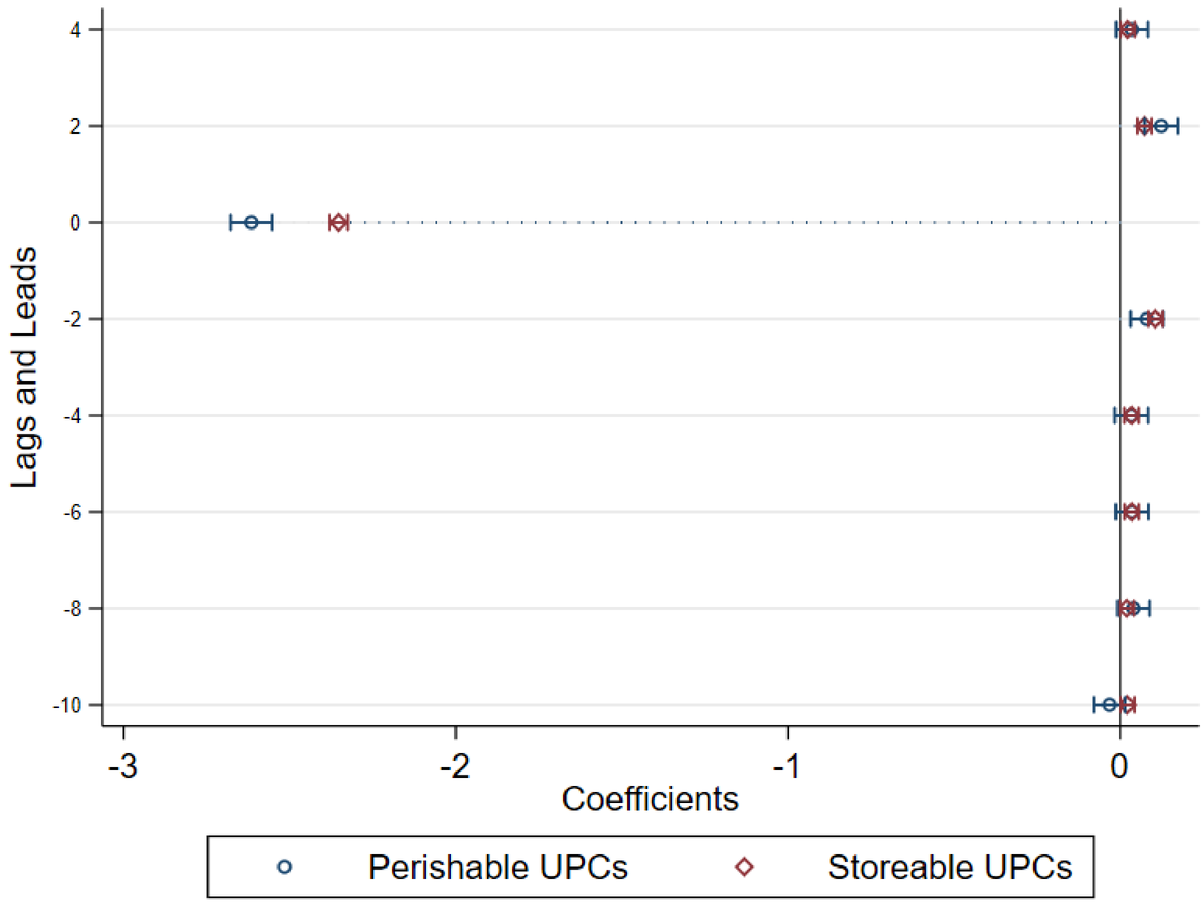
Notes. Panel A shows the correlation between the raw IV Elasticity Estimates and raw OLS Elasticity Estimates. Panel B shows the correlation between the raw IV Elasticity and raw IV estimates including a fixed effect for DMA in addition to the usual set of seasonality fixed effects. This is run at the DMA-level for DMAs with at least two chains and up to 50 stores, totaling 1537 stores. Panel C shows the correlation between the raw IV elasticity estimates and raw IV estimates including as controls advertising feature and display in addition to our usual seasonality fixed effects. Because Nielsen has many missing-values for feature and display, we have restricted this estimation to store-products with at least 104 consecutive non-missing weeks of feature and display, totaling 893,978 store-UPCs in 2,033 stores. All figures are binscatters at the store-UPC level with 50 bins.

Online Appendix Figure 17
Quarterly Elasticity Estimates and Validation (Food Store)



*Notes***.** Panel A is a binscatter of log P and log Q for 1,000 randomly sampled store-module-groups after residualizing for quarter-of-year and year fixed effects, ran product-by-product. Panel B shows the store-level distribution of our raw benchmark weekly IV elasticity against our raw grouped quarterly IV elasticity for 9,370 stores. Panel C is a binned scatterplot of our benchmark weekly store-module elasticity against the quarterly store-module elasticity, representing 400,256 store-module-groups. Panel D shows the correlation of the store-level quarterly elasticity against store-level income. Standard errors are clustered by *parent_code*.

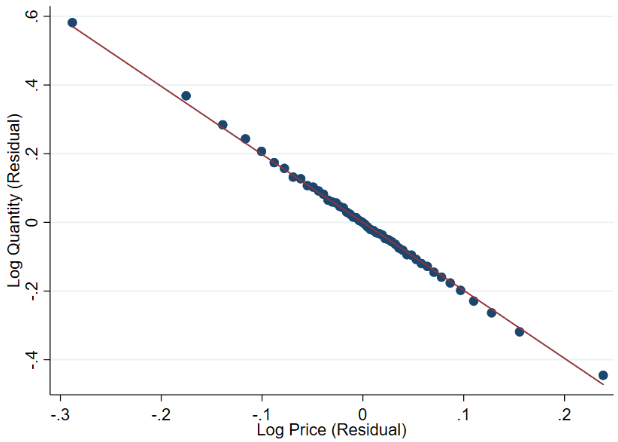
Online Appendix Figure 18
Elasticity Validation: Lags and Leads



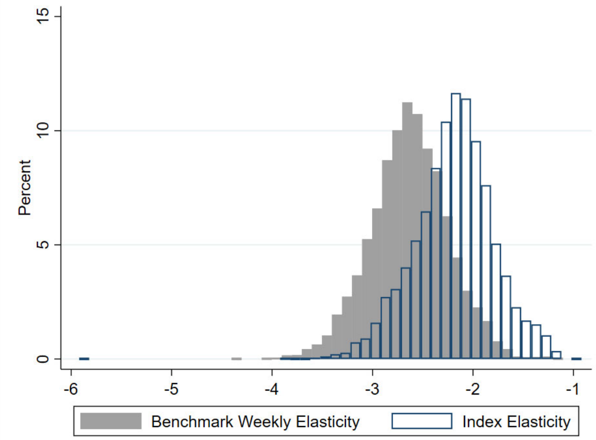
*Notes***.** The figure is a test of our specification: we classify the 40 modules we select as either Perishable or Storeable based on our judgement and run two pooled elasticity regressions including the contemporaneous price as well as 2, 4, 6, 8, and 10 week lags, 2 and 4 week leads. The regressions constrain elasticity to be the same in all stores and products but interact our usual set of seasonality controls with store-product fixed effects. The sample is not the full benchmark sample but instead the same subset of products that were used in our linearity robustness check (Figure VII Panel A).

Online Appendix Figure 19
Weekly Price Index Elasticity Estimates and Validation (Food Stores)

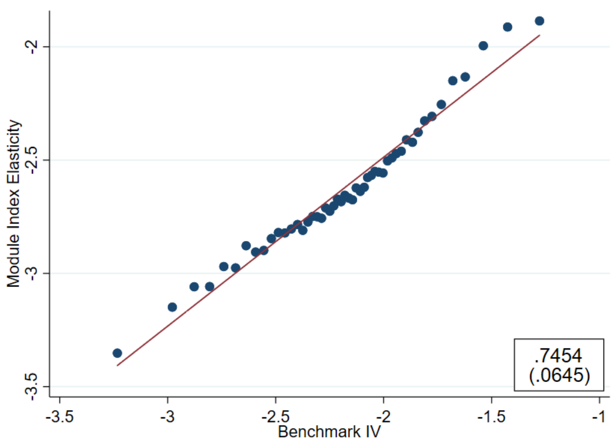
Panel A. Test of Linearity



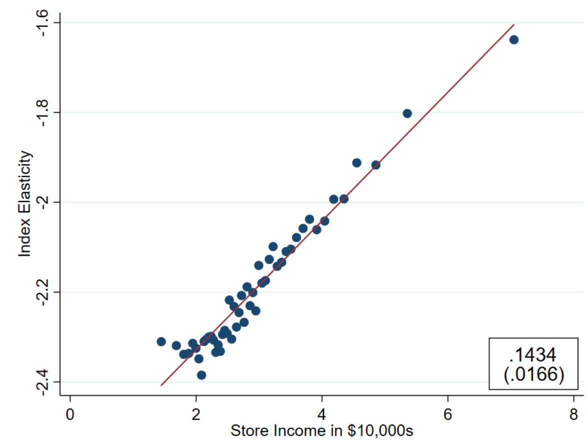
Panel B. Distribution of Elasticity



Panel C. Correlation to Benchmark Elasticity



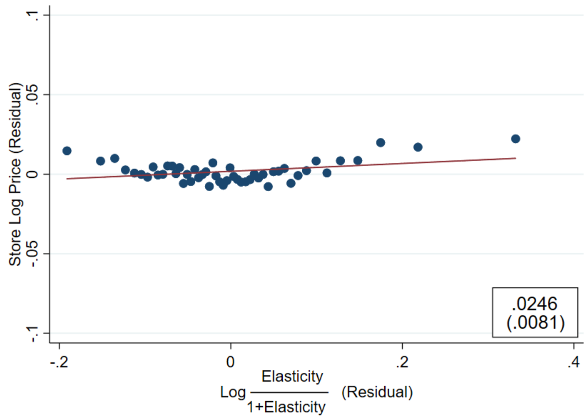
Panel D. Correlation with Income



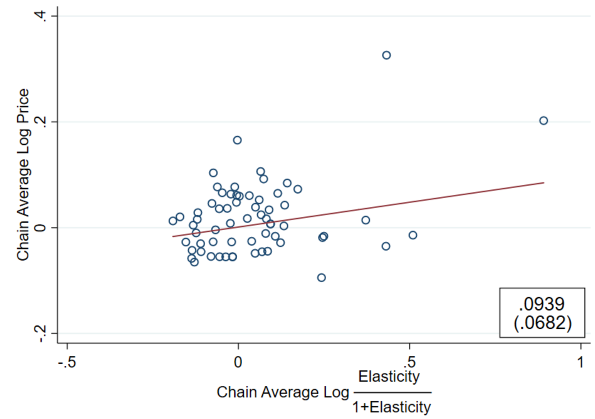
*Notes***.** Panel A is a binscatter of log P and log Q for 1,000 randomly sampled store-modules after residualizing for week-of-year and year fixed effects. Panel B shows the store-level distribution of our raw benchmark weekly IV elasticity against our raw index elasticity for 9,415 stores. Panel C is a binned scatterplot of our benchmark weekly store elasticity against the index elasticity using 50 bins, representing 9,415 stores. Panel D shows the correlation of the store-level index elasticity against store-level income. Standard errors are clustered by *parent_code.*

Online Appendix Figure 20
Price vs. Log Elasticity: Not Instrumented with Income (Food Stores)

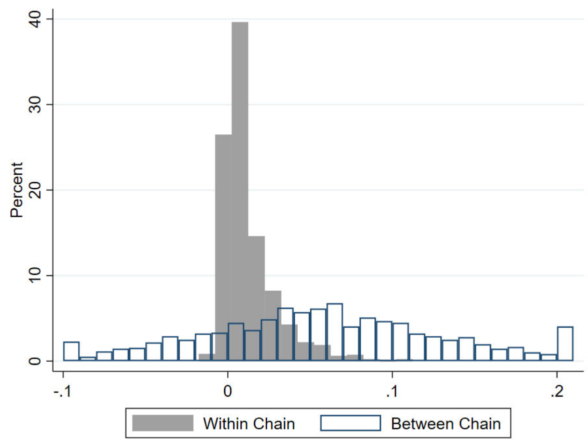
Panel A. Within Chain



Panel B. Between Chain

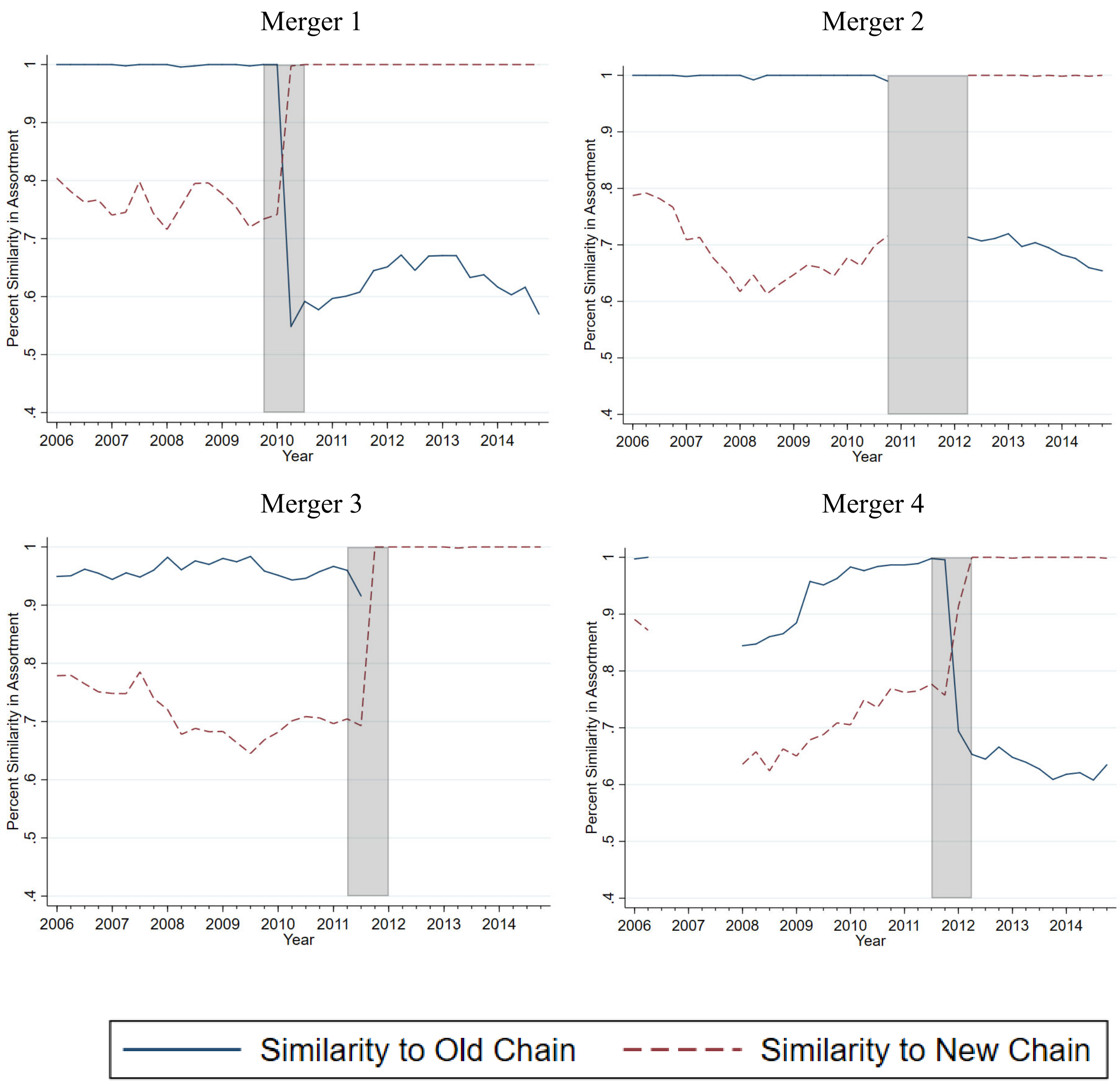


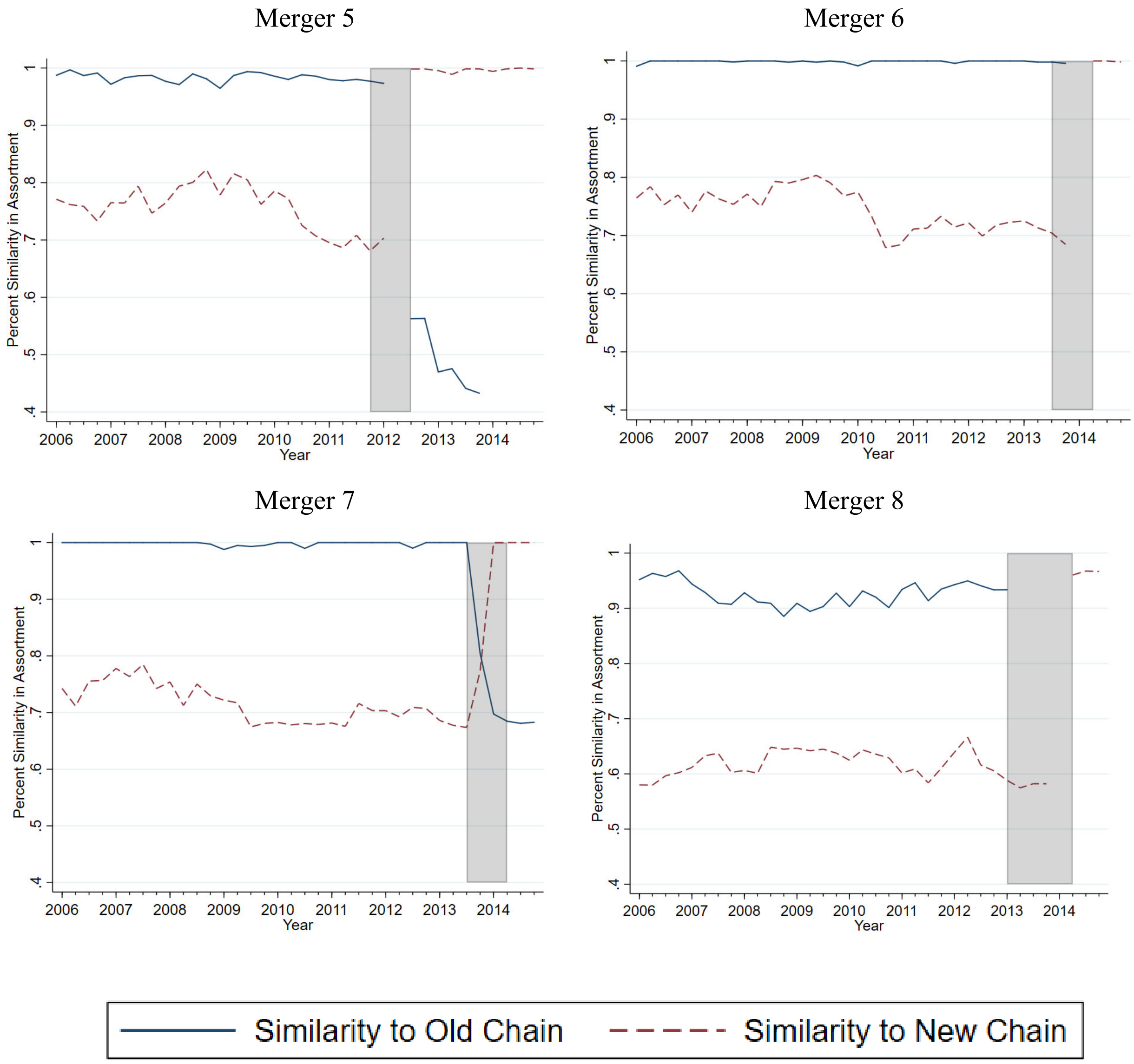
Panel C. Histogram of Coefficients, UPC-by-UPC



*Notes***.** Panel A is a binned scatterplot with 50 bins of the residual of log price on the residual of $\log\left(\frac{\eta}{1+\eta}\right)$ in store s. Residuals are after removing chain fixed effects. Panel B is a scatterplot of average price on the average log elasticity term at the chain level for the food stores, with the labels indicating a chain identifier. Axes ranges have been chosen to make the slopes visually comparable. Analytic weights equal to the number of stores in each unit are used for the regression in Panel B. Panel C shows the coefficients UPC-by-UPC. The figures report the coefficients of the relevant regressions, with standard errors clustered by *parent_code*.

Online Appendix Figure 21
Changes in Assortment by Merger

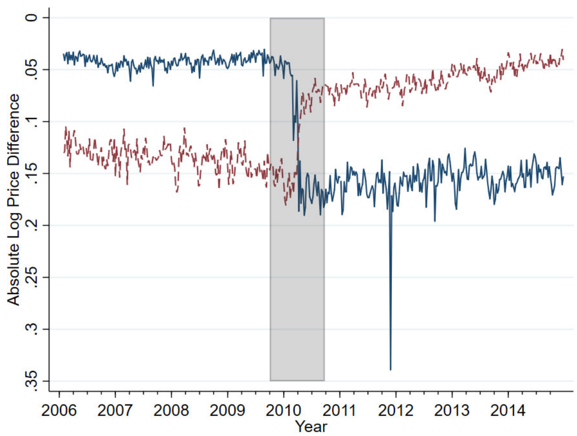




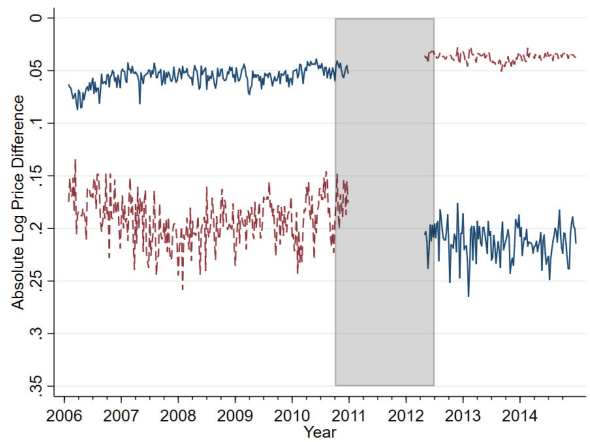
Notes. Each panel plots the quarterly similarity in assortment of products of switching stores compared to their old and new chains. Each panel represents an individual merger. The Panel Similarity variable is calculated by first counting the number of products sold by the switching stores and then counting which of these products are sold by the old and new chain. We do this for both Orange Juice and Cereal modules and average. The grey box shows the approximate window in which the stores switch *parent_code* based on changes in assortment similarity.

Online Appendix Figure 22
Changes in Prices by Merger

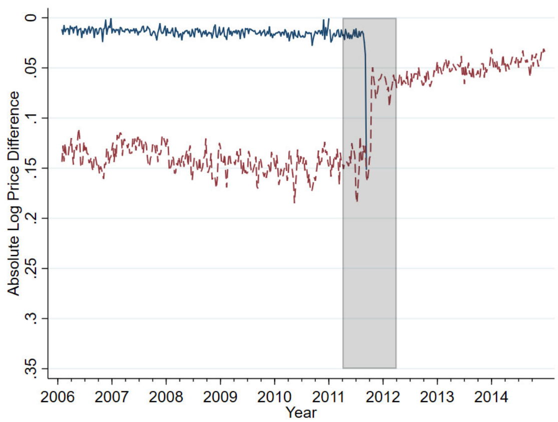
Merger 1



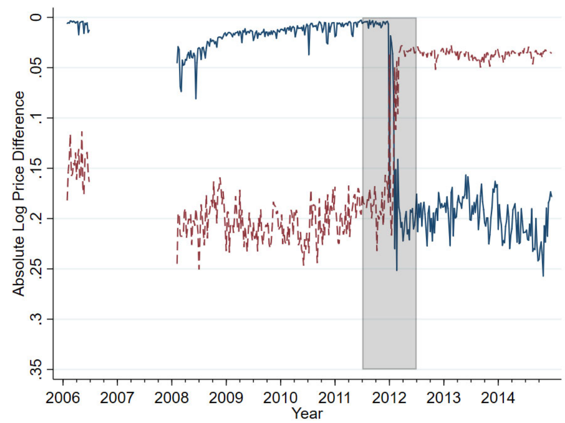
Merger 2

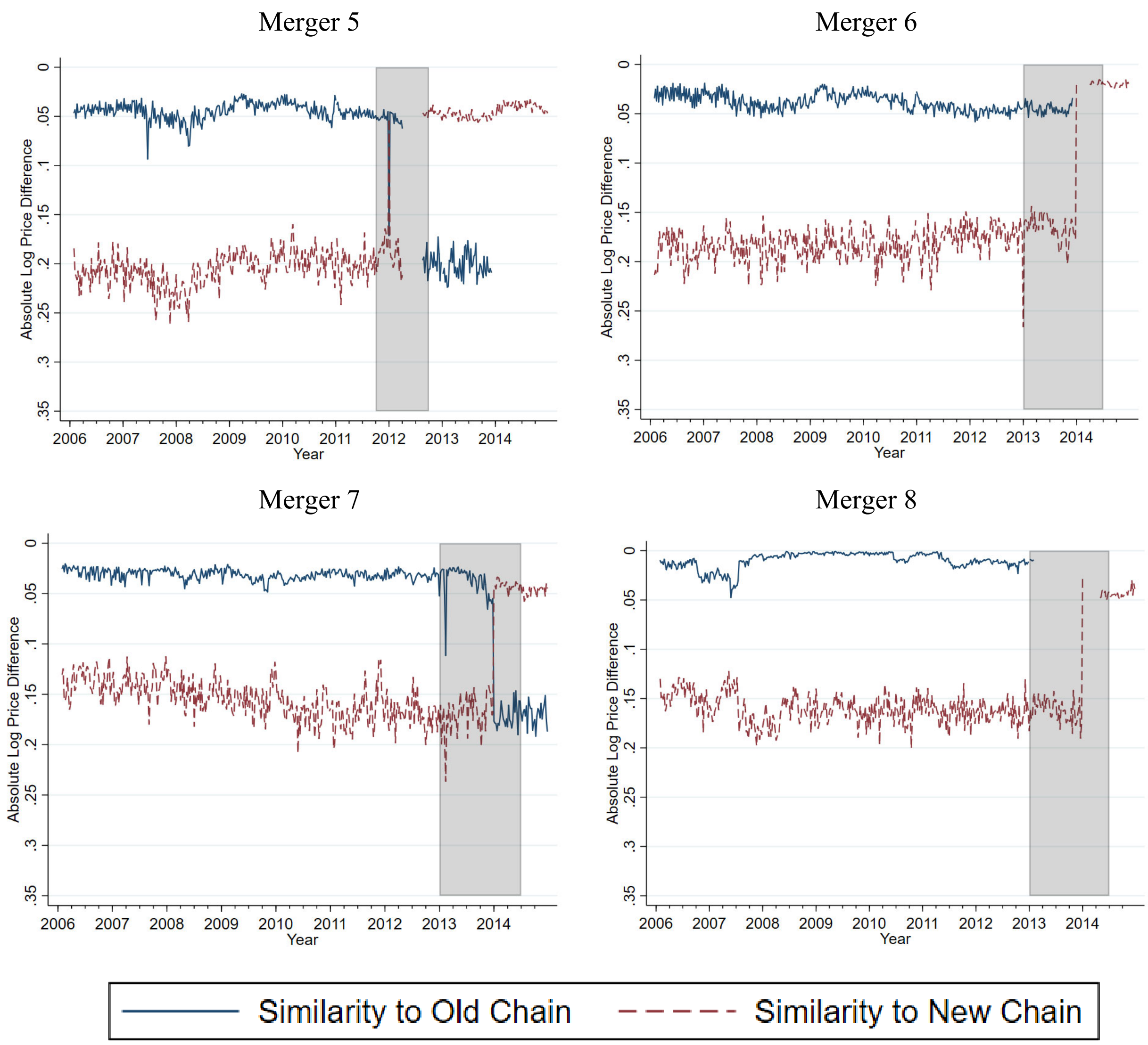


Merger 3



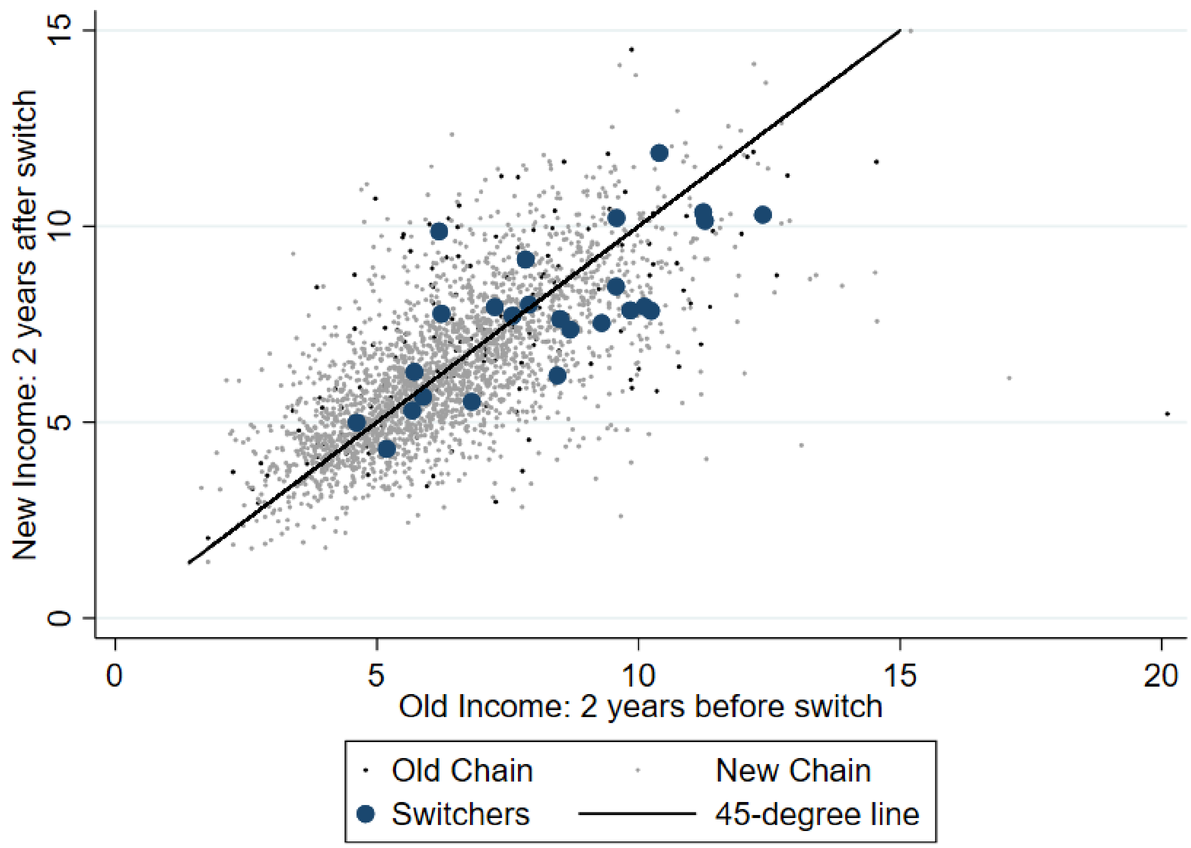
Merger 4





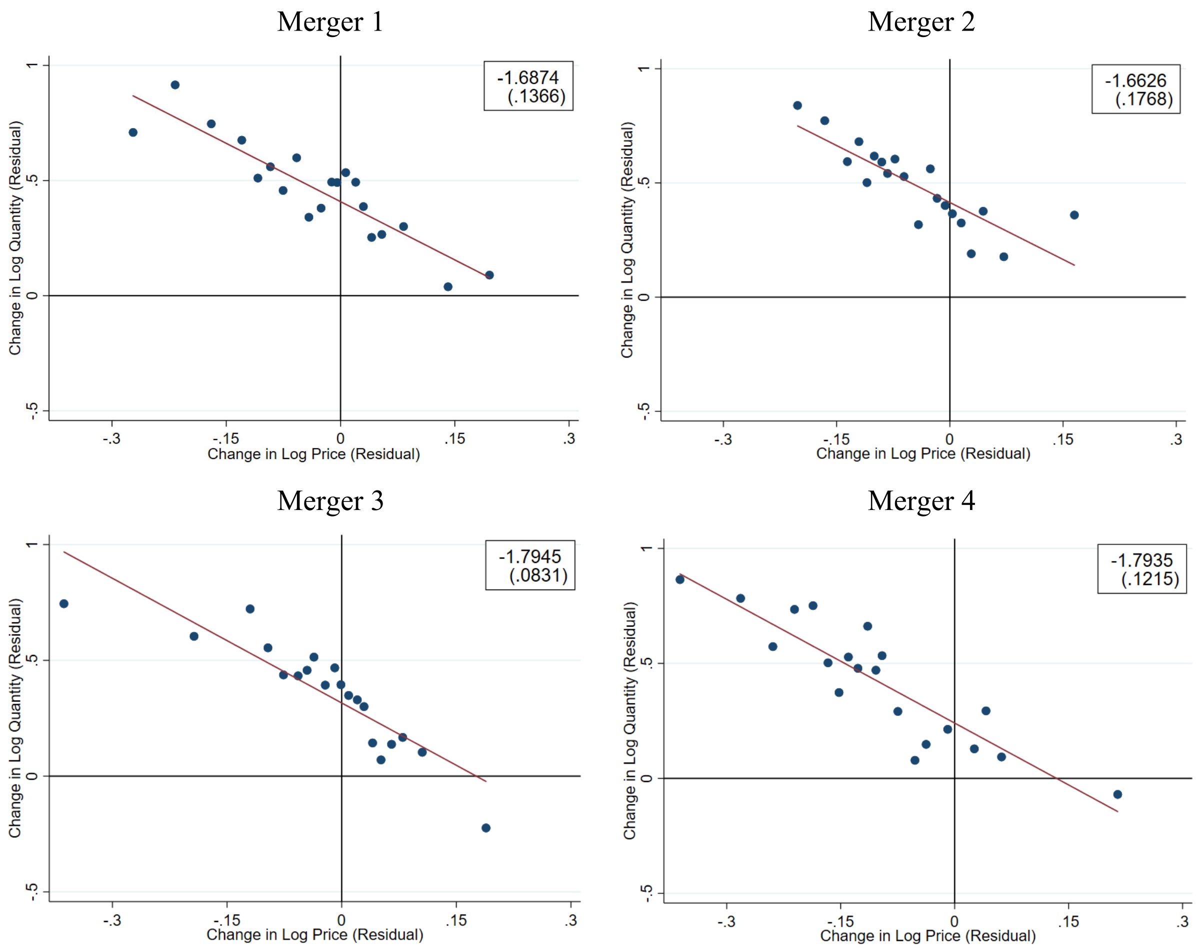
Notes. Each panel plots the average weekly absolute log price difference of switching stores compared to the average weekly log price in their old and new chains. Each panel represents an individual merger. This measure is the average of highly available products across 40 modules. The absolute log price difference is first averaged from the store-UPC-week level to the store-week level, and then finally to the week level. The grey box shows the approximate window in which the stores switched *parent_code* based on assortment similarity (Online Appendix Figure 19).

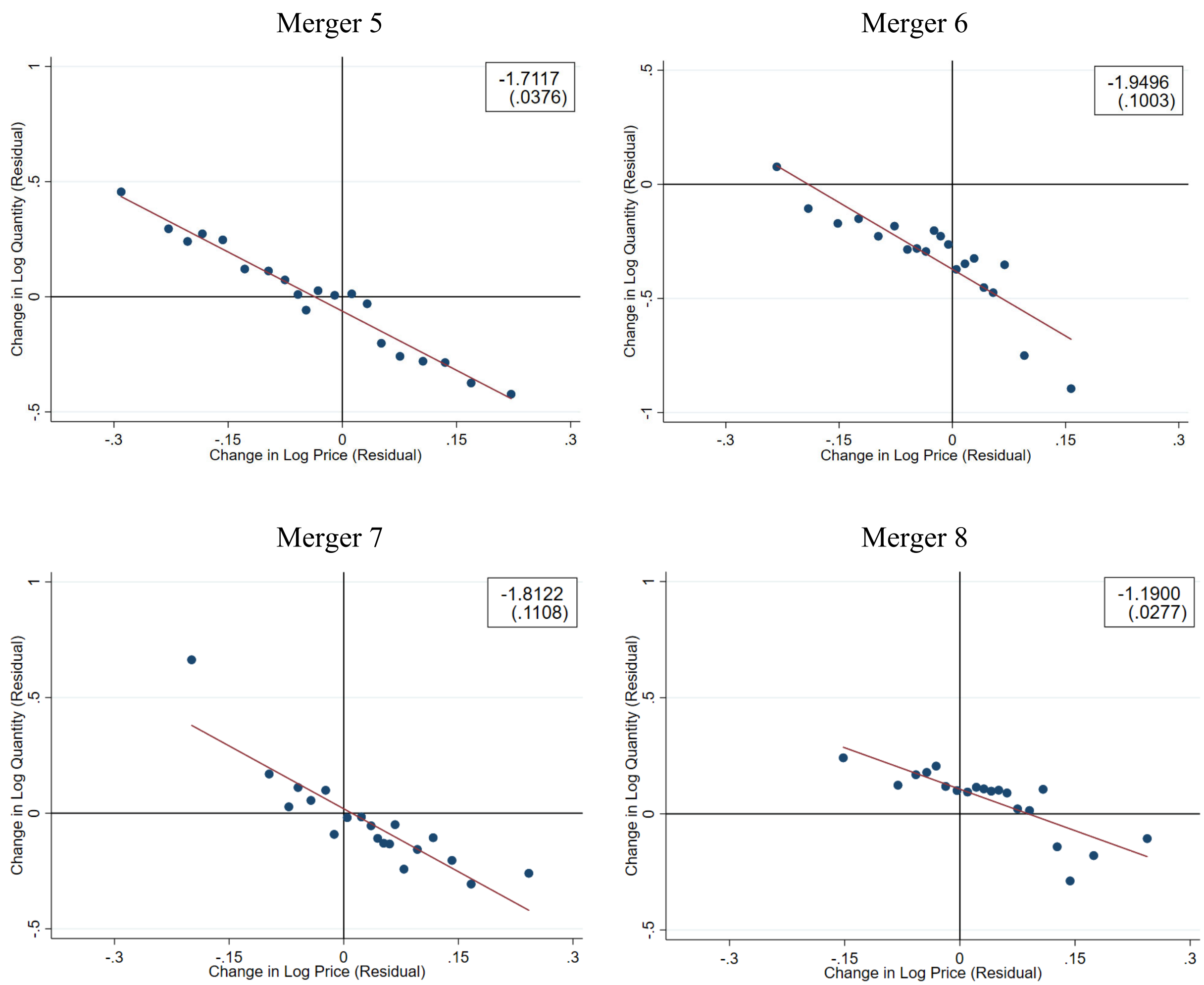
Online Appendix Figure 23
Consumer Demographics, Pre- and Post- Acquisition



Notes. This figure shows the average Homescan income for each store constructed using consumers who report trips to each store in the pre-merger and post-merger period. Each observation is either a store that changes ownership or a store that belongs to the old chain or new chain that does not switch ownership. In each store, Old Income is based on trips that occur in the two full years before the year of switch and New Income is similarly based on trips that occur in the two full years after the year of the switch. The years of the switch (shaded area in Online Appendix Figures 21 and 22) are excluded throughout. We do not allow income to vary over time: each household's income is the average income reported by the households for all years within 2006-2014 that they report at least one trip in the Homescan sample. The store average income is the trip-weighted average income of all households that visit the store. Stores that are visited by fewer than 5 households are excluded.

Online Appendix Figure 24
Long-Run Price Elasticities, By Merger

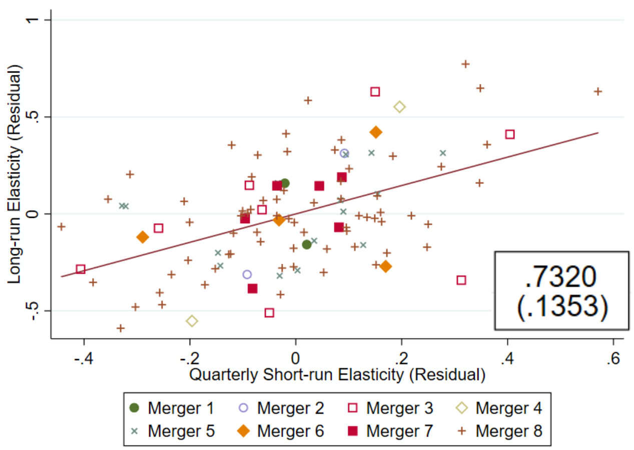




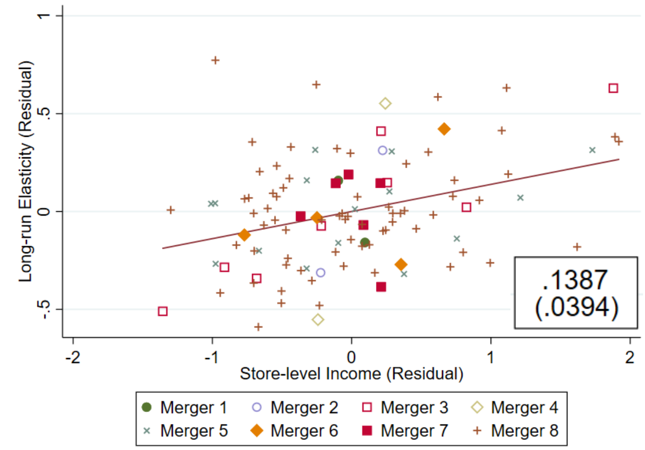
*Notes***.** The figure shows by-merger binscatter plots of changes in log quantity versus changes in log price after a store has been acquired by a different chain for the universe of products. For each merger, the long-run elasticity is computed as in Figure 10a, restricting the observations to the particular merger.

Online Appendix Figure 25
Long-Run Price Elasticities Estimated from Store Acquisitions, Robustness

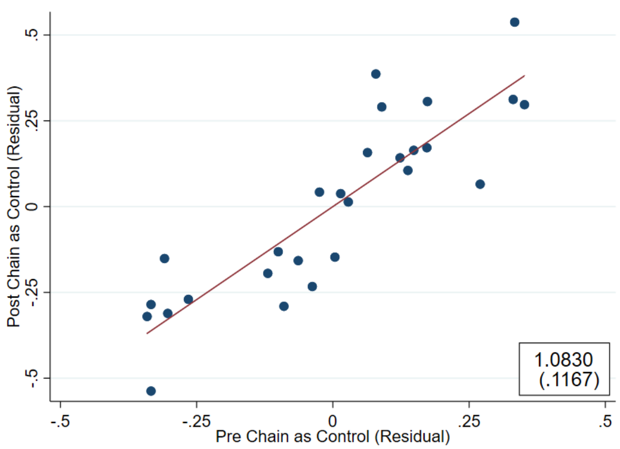
Panel A. Long-run vs. Quarterly Elasticity



Panel B. Long-run Elasticity vs. Income



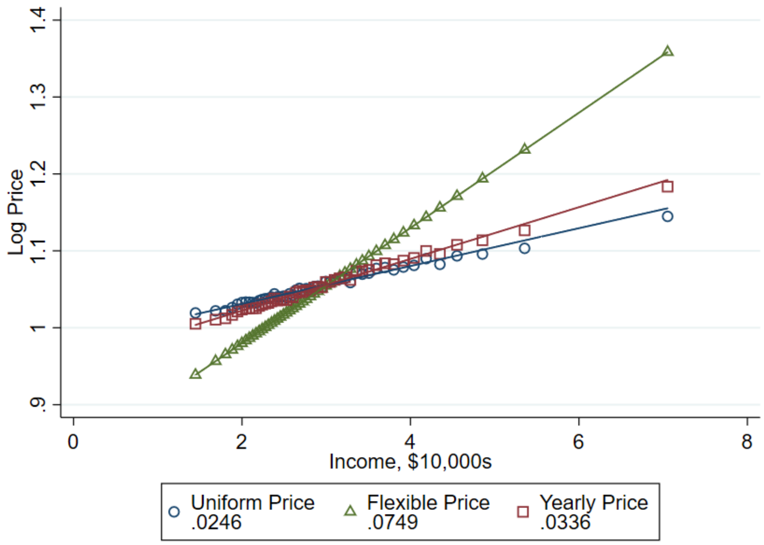
Panel C. Pre-Switch vs. Post-Switch Control Elasticity Estimates



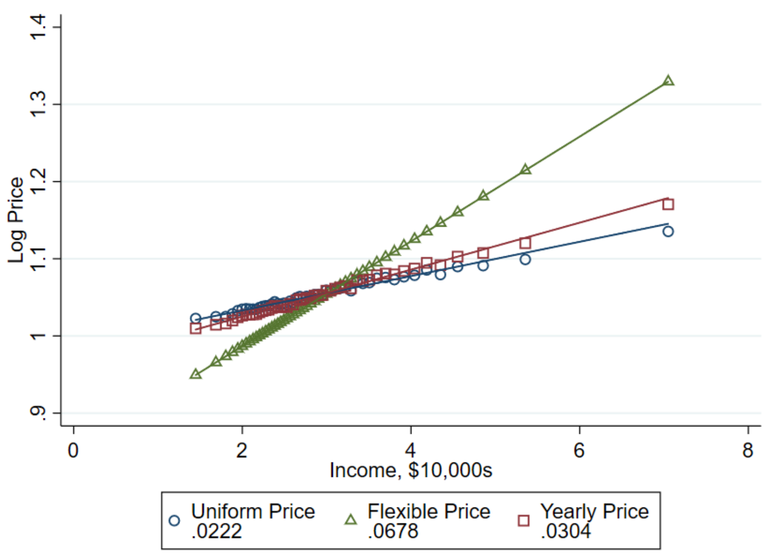
*Notes***.** This figure shows robustness on the evidence on the long-run elasticity obtained from the before-after merger comparison. Panel A shows store-level long-run elasticities versus (quarterly) short-run elasticities after demeaning both variables on the merger-level. Short run elasticities are computed using only pre-period data. Panel B shows store-level long-run elasticities versus store-level income after demeaning both variables on the merger-level. Panel C shows store-level long-run elasticities using either stores from the acquiring or original chain as control stores after demeaning both variables on the merger-level.

Online Appendix Figure 26
Price Rigidity with Representative Product: Alternative Elasticities

Panel A. Quarterly Elasticity



Panel B. Module Index Elasticity



*Notes***.** This figure is the analogue to Figure XI but instead using store-level quarterly elasticity (Panel A) and store-level module index elasticity (Panel B). The elasticity of each store is according to the predicted elasticity, replacing our benchmark elasticity with the corresponding quarterly and module index elasticity.

ONLINE APPENDIX TABLE 1

LITERATURE REVIEW, PAPERS ON *UNIFORM PRICING*

Setting:	Data Set	Years	No. of Products	No. of Chains	No. of Stores	Results on Uniformity	Elasticity Estimates	Comparison to Optimal Benchmark
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DellaVigna and Gentzkow (2019)	Nielsen	2006-14	1,930	73 US food chains, drug & merch. chains	23,715	Measures of price differences; Response to consumer store income; Uniformity for switching stores; Uniformity of assortment	Yes	Yes
Panel A. Published Papers								
Hoch et al. (1995)	Dominick's; IRI	160 weeks	4,636	1 US food chain	83	Chain uses three price zones	Yes	No
Nakamura (2008)	Nielsen	2004	100	33 US food chains	7,000	Variance decomposition of prices: chain fixed effects account for 65%	No	No
Hwang, Bronnenberg,and Thomadsen (2010)	Nielsen	2006	1,987	US food chains	2,017	No analysis on pricing; Assortment is better predicted by chain f.e. than by other predictors	No	No
Cavallo, Nieman, and Rigobon (2014)	Retailer websites	2008-13	117,046	4 chains worldwide	NR	Online prices typically identical across countries in currency union (eg, Euro)	No	No
Kaplan and Menzio (2015)	Nielsen	2007:Q1	36,104	Retail chains in Nielsen	NR	Variance decomposition of prices: chain-product part accounts for modest share	No	No
Cavallo (2017)	Retailer websites	2014-16	24,000	56 chains in 10 countries	NR	For US chains, in 77% of observations, offline prices identical across locations.	No	No
Adams and Williams (2019)	Retailer websites	2013	10	3 US retail chains	4,426	Uniform pricing for some products; zone pricing for others	Yes	Yes
Gagnon and Lopez-Salido (2019)	IRI	2001-11	29	Several retail chains	1,500	Temporary, localized negative demand shocks (e.g., Katrina) have small or no impact on prices	No	No
Panel B. Working Papers								
Dobson and Waterson (2008)	UK Competition Commission	NA	NA	UK food chains	NA	Refers to UK Competition report that documents prevalence of uniform pricing among UK food chains	No	No
Hitsch, Hortacsu and Lin (2017)	Nielsen	2008-10	47,355	81 US retail chains	17,184	Documents similarity of pricing, higher within chain than between-chain; Decomposes regular price and discount	Yes	No
Cavallo (2018)	Retailer websites	NR	10,292	3 US retail chains, Amazon	NR	78% of prices are identical across different locations of a retailer	No	No

Notes. Summary of selected papers related to the uniform pricing findings. "NA" indicates not applicable. "NR" indicates value not reported.

ONLINE APPENDIX TABLE 2a

ADDITIONAL SUMMARY STATISTICS

	(1)	(2)	(3)	(4)	(5)
Panel A. Stores by Year	No. of Stores	No. of Chains	No. of Food Stores	No. of Food Chains	
2006	19,252	64	8,487	55	
2007	20,311	73	8,943	64	
2008	21,164	73	9,082	64	
2009	21,564	73	9,133	64	
2010	21,663	73	9,126	64	
2011	21,666	73	9,031	64	
2012	21,669	73	8,929	64	
2013	21,331	73	8,717	64	
2014	20,666	70	8,221	61	
Panel B. Store Characteristics, Drugstores	Mean	25th	Median	75th	
Average per-capita Income	$29,350	$21,900	$26,690	$33,780	
Percent with at least Bachelor Degree	29.4%	17.8%	26.0%	38.0%	
Number of Homescan Households	14	6	12	19	
Number of Trips of Homescan Households	310	89	215	419	
Number of Competitors within 10 km	2.4	0	0	2	
Panel C. Chain Characteristics, Drugstores	Chain 4901	Chain 4904	Chain 4931	Chain 4954	
Number of Stores	3000	6853	55	69	
Number of DMAs	118	201	9	6	
Number of States	32	48+DC	1	2	
Panel D. Store Char., Mass-Merchandise Stores	Mean	25th	Median	75th	
Average per-capita Income	$28,070	$23,200	$26,460	$31,360	
Percent with at least Bachelor Degree	27.6%	19.0%	25.3%	33.9%	
Number of Homescan Households	57	27	47	73	
Number of Trips of Homescan Households	932	318	669	1262	
Number of Competitors within 10 km	1.0	0	1	1	
Panel E. Chain Char., Mass-Merchandise Stores	Chain 6901	Chain 6904	Chain 6907	Chain 6919	Chain 6921
Number of Stores	1565	1311	138	30	244
Number of DMAs	190	189	36	13	48
Number of States	47+DC	48	13	11	22

Notes. Panel A reports the number of stores and chains in our main sample for each year. In Panels B and D, we report store-level Homescan characteristics for drugstores and mass-merchandise stores, respectively. Similarly, Panels C and E report Chain-level characteristics for the number of stores, DMAs and states for drugstores and mass-merchandise stores, respectively.

ONLINE APPENDIX TABLE 2b

FOOD STORE MODULES

Module	Type of Product	Total Yearly Revenue in Module	Yearly Sample Revenue	Unique Number of Products
1040	FRUIT JUICE - ORANGE - OTHER CONTAINER	$1,083.58M	$494.29M	41
1042	FRUIT DRINKS- OTHER CONTAINER	$1,668.36M	$617.51M	105
1272	BABY MILK AND MILK FLAVORING	$932.80M	$36.85M	1
1290	SOUP - CANNED	$1,393.92M	$499.49M	86
1303	CAT FOOD - WET TYPE	$419.56M	$105.65M	54
1311	DOG FOOD - DRY TYPE	$805.35M	$38.37M	6
1323	SNACKS - POTATO CHIPS	$1,333.21M	$385.94M	82
1326	SNACKS - TORTILLA CHIPS	$928.98M	$353.62M	53
1344	CEREAL - READY TO EAT	$2,481.79M	$1,221.73M	195
1362	COOKIES	$1,621.66M	$424.59M	90
1463	GROUND AND WHOLE BEAN COFFEE	$1,455.17M	$177.63M	18
1484	SOFT DRINKS - CARBONATED	$3,496.68M	$1,813.82M	85
1487	WATER-BOTTLED	$1,797.55M	$313.21M	30
1493	CANDY - CHOCOLATE	$938.73M	$297.71M	67
1498	CANDY - NON-CHOCOLATE	$477.08M	$51.60M	22
1553	SOFT DRINKS - LOW CALORIE	$2,131.38M	$1,115.68M	73
2623	ENTREES - ITALIAN - 1 FOOD - FROZEN	$787.90M	$175.19M	33
2631	PIZZA - FROZEN	$1,321.20M	$204.74M	25
2672	ICE CREAM - BULK	$1,561.60M	$121.40M	17
2675	FROZEN NOVELTIES	$1,049.81M	$125.75M	22
3574	LUNCHMEAT - SLICED - REFRIGERATED	$884.41M	$77.07M	13
3576	FRANKFURTERS - REFRIGERATED	$680.23M	$233.07M	18
3577	BACON - REFRIGERATED	$988.51M	$188.09M	8
3580	ENTREES - REFRIGERATED	$1,151.77M	$3.71M	3
3590	CHEESE - SHREDDED	$1,179.67M	$57.22M	7
3603	YOGURT - REFRIGERATED	$1,724.72M	$397.64M	90
3618	LUNCHMEAT - DELI POUCHES - REFRIGERATED	$771.37M	$195.09M	21
3625	DAIRY - MILK - REFRIGERATED	$3,284.94M	$47.79M	4
4004	BAKERY - CAKES - FRESH	$841.59M	$69.80M	10
4100	EGGS - FRESH	$1,282.31M	$71.19M	2
4225	FRESH FRUIT - REMAINING	$1,100.98M	$79.32M	1
5000	BEER	$1,587.66M	$186.58M	6
5010	LIGHT BEER (LOW CALORIE/ALCOHOL)	$1,817.71M	$204.06M	10
7012	DETERGENTS - HEAVY DUTY - LIQUID	$945.96M	$49.92M	15
7080	BLEACH - LIQUID/GEL	$111.23M	$43.52M	12
7260	TOILET TISSUE	$1,368.29M	$266.18M	25
7734	PAPER TOWELS	$845.03M	$36.81M	7
7870	BATTERIES	$265.36M	$21.68M	3
8420	PAIN REMEDIES - HEADACHE	$360.56M	$4.19M	4
8423	COLD REMEDIES - ADULT	$381.57M	$0.62M	1

Notes. Yearly Sample Expenditure is taken by dividing the revenue of the products covered by the sample and dividing by the total number of years (9).

ONLINE APPENDIX TABLE 2c

DRUG AND MASS MERCHANDISE STORE MODULES

Module	Type of Product	Total Yearly Revenue in Module	Yearly Sample Revenue	Unique Number of Products
Panel A. Drug Store Modules				
1042	FRUIT DRINKS - OTHER CONTAINER	$108.83M	$16.66M	6
1290	SOUP - CANNED	$38.35M	$0.38M	1
1323	SNACKS - POTATO CHIPS	$85.83M	$10.64M	10
1326	SNACKS - TORTILLA CHIPS	$38.02M	$5.02M	7
1484	SOFT DRINKS - CARBONATED	$385.49M	$193.80M	25
1487	WATER - BOTTLED	$226.96M	$26.73M	8
1493	CANDY - CHOCOLATE	$487.08M	$95.00M	47
1498	CANDY - NON - CHOCOLATE	$332.21M	$21.96M	16
1553	SOFT DRINKS - LOW CALORIE	$183.81M	$68.66M	11
7260	TOILET TISSUE	$195.99M	$3.00M	4
7870	BATTERIES	$288.34M	$12.04M	2
8412	ANTACIDS	$266.74M	$1.60M	1
8420	PAIN REMEDIES - HEADACHE	$408.06M	$5.58M	2
8423	COLD REMEDIES - ADULT	$671.40M	$5.20M	2
Panel B. Mass Merchandise Modules				
1040	FRUIT JUICE - ORANGE - OTHER CONTAINER	$63.81M	$5.15M	4
1042	FRUIT DRINKS - OTHER CONTAINER	$178.48M	$6.56M	11
1272	BABY MILK AND MILK FLAVORING	$303.98M	$7.27M	1
1290	SOUP - CANNED	$104.35M	$1.90M	3
1303	CAT FOOD - WET TYPE	$102.10M	$6.11M	16
1311	DOG FOOD - DRY TYPE	$304.64M	$17.33M	6
1323	SNACKS - POTATO CHIPS	$131.93M	$18.98M	24
1326	SNACKS - TORTILLA CHIPS	$95.79M	$17.42M	14
1344	CEREAL - READY TO EAT	$323.92M	$31.98M	27
1362	COOKIES	$224.11M	$30.06M	24
1463	GROUND AND WHOLE BEAN COFFEE	$322.31M	$22.21M	6
1484	SOFT DRINKS - CARBONATED	$401.50M	$201.88M	26
1487	WATER - BOTTLED	$325.88M	$96.15M	17
1493	CANDY - CHOCOLATE	$390.24M	$70.33M	74
1498	CANDY - NON - CHOCOLATE	$287.02M	$20.52M	33
1553	SOFT DRINKS - LOW CALORIE	$315.26M	$136.55M	19
4004	BAKERY - CAKES - FRESH	$43.69M	$3.96M	3
7012	DETERGENTS - HEAVY DUTY - LIQUID	$605.10M	$21.91M	16
7080	BLEACH - LIQUID/GEL	$46.01M	$21.44M	9
7260	TOILET TISSUE	$647.46M	$112.28M	38
7734	PAPER TOWELS	$387.49M	$37.74M	21
7870	BATTERIES	$324.01M	$25.99M	9
8412	ANTACIDS	$115.18M	$8.56M	2
8420	PAIN REMEDIES - HEADACHE	$187.11M	$8.51M	10
8423	COLD REMEDIES - ADULT	$202.48M	$0.40M	1
8444	DISPOSABLE DIAPERS	$851.64M	$18.98M	9

Notes. Yearly Sample Expenditure is taken by dividing the revenue of the products covered by the sample and dividing by the total number of years (9).

ONLINE APPENDIX TABLE 3

SIMILARITY IN PRICING, ROBUSTNESS

Measure of Similarity:	Absolute Difference in Quarterly Log Prices		Correlation in (Demeaned) Weekly Log Prices		Share of Weekly Log Prices within One Log Point	
Wtihin vs. Between:	Same Chain	Different Chain	Same Chain	Different Chain	Same Chain	Different Chain
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Food Stores, Generic Product UPCs, All Store Pairs						
Mean	0.038		0.702		0.661	
Standard Deviation	(0.055)		(0.251)		(0.225)	
Number of Chain-UPCs	80,631		72,821		73,389	
Panel B. Food Stores, Top-Decile Products by Revenue						
Mean	0.029	0.124	0.828	0.085	0.571	0.085
Standard Deviation	(0.026)	(0.054)	(0.181)	(0.091)	(0.229)	(0.068)
Number of Chain-UPCs	8,130	8,219	8,102	8,166	8,130	8,171
Panel C. Food Stores, Bottom-Decile Products by Revenue						
Mean	0.035	0.154	0.785	0.083	0.660	0.099
Standard Deviation	(0.038)	(0.065)	(0.203)	(0.092)	(0.216)	(0.063)
Number of Chain-UPCs	8,318	8,470	8,132	7,714	8,318	8,314

Notes. This table presents measures of similarity of pricing for pairs of stores both within a chain, and across chains. To form the pairs we select a maximum of 200 pairs per chain (within the appropriate channel only) that correspond to the comparison criteria we impose (see text for additional details). Panel A is for Generic products in Food Stores only; between chain comparisons of Generic products are not possible because we cannot ensure that unobservable attributes of generic products are comparable across chains. In Panel B, we keep the top decile of products by average yearly revenue. In Panel C, we keep the bottom decile of products by average yearly revenue. We scale revenue according to the number of years a product appears in our sample.

ONLINE APPENDIX TABLE 4

PRICE VS. INCOME, WITHIN CHAIN AND BETWEEN CHAIN

Specification:	Within-Chain Specification					Zone Pricing Sp.	Between-Chain Specification			
Dependent Variable:	Log Price					Average Log Price	Average Log Price			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A. Food Stores										
Income Per Capita	0.0048***	0.0047***	0.0047***	0.0047***	0.0038***	0.0124**	0.0431***	0.0419***	0.0442***	0.0376***
(in $10,000s)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0003)	(0.0050)	(0.0055)	(0.0094)	(0.0056)	(0.0115)
Fixed Effects	Chain x UPC	Chain, UPC	Chain, UPC	Chain	Chain x State	Chain	UPC			
Weighted by number of stores						X	X	X		X
Includes Only Store-UPCs with Elasticities			X							
Drop Two Outlier Chains										X
Observation Level	Store-UPC	Store-UPC	Store-UPC	Store	Store	Chain-State	Chain-UPC	Chain	Chain	Chain
Observations	12,027,499	12,027,499	6,593,513	9,415	9,415	171	84,480	64	64	62
R-squared	0.823	0.256	0.315	0.931	0.960	0.962	0.208	0.280	0.481	0.190
Panel B. Drugstores										
Income Per Capita	0.0076***	0.0076***	0.0074***	0.0076***	0.0054***	0.0297***				
(in $10,000s)	(0.0008)	(0.0008)	(0.0007)	(0.0008)	(0.0006)	(0.0050)				
Fixed Effects	Chain x UPC	Chain, UPC	Chain, UPC	Chain	Chain x State	Chain				
Weighted by number of stores						X				
Includes Only Store-UPCs with Elasticities			X							
Observation Level	Store-UPC	Store-UPC	Store-UPC	Store	Store	Chain-State				
Observations	1,333,933	1,333,933	703,201	9,976	9,976	83				
R-squared	0.423	0.061	0.098	0.314	0.555	0.682				
Panel C. Mass-Merchandise Stores										
Income Per Capita	0.0044***	0.0044***	0.0036***	0.0044***	0.0033***	0.0104***				
(in $10,000s)	(0.0011)	(0.0011)	(0.0002)	(0.0010)	(0.0010)	(0.0021)				
Fixed Effects	Chain x UPC	Chain, UPC	Chain, UPC	Chain	Chain x State	Chain				
Weighted by number of stores						X				
Includes Only Store-UPCs with Elasticities			X							
Observation Level	Store-UPC	Store-UPC	Store-UPC	Store	Store	Chain-State				
Observations	1,283,150	1,283,150	426,677	3,288	3,288	142				
R-squared	0.811	0.368	0.524	0.931	0.946	0.986				

Notes. Standard errors are clustered by *parent_code* in Panel A and are clustered by *parent_code* *state in Panels B and C. In columns 1-3, we show the specifications disaggregated at the store-UPC level. In column 8 we omit chains 98 and 124 which are outliers for the average store income (see Figure VIII Panel B). In Panels B and C we do not report between-chain regressions given that there are only 4 drug chains and only 5 mass merchandise chains. Panels B and C are clustered by *parent_code* *state.

*** p<0.01, ** p<0.05, * p<0.1

ONLINE APPENDIX TABLE 5

DETERMINANTS OF PRICING, ROBUSTNESS II

Dependent Variable:	*Log* Price		
	(1)	(2)	(3)
Demographic Controls			
Income Per Capita	0.0168***	0.0047***	-0.0021**
(in $10,000s)	(0.0041)	(0.0009)	(0.0009)
Fraction with College			0.0117
Degree (or higher)			(0.0083)
Median Home Price			0.0065***
(in $100,000s)			(0.0013)
Controls for Urban Share			X
Controls for Number of Competitors w/in 10km			
1 Other Store			-0.0020
			(0.0012)
2 Other Stores			-0.0035**
			(0.0014)
3+ Other Stores			-0.0049**
			(0.0020)
Fixed Effect for Chain		X	X
Observation Level	Store	Store	Store
Observations	9,415	9,415	9,415
R-squared	0.128	0.931	0.962

Notes. Standard errors are clustered by *parent_code* . All independent variables are our estimate of store-level demographics at the zip-code level based on Nielsen Homescan (HMS) panelists' residences. Demographics are from 2012 ACS 5-year estimates. Fraction with College Degree (or higher) is the fraction of adults 25 and older with at least a bachelor's degree. Controls for Urban Share are a set of dummy variables for Percent Urban for values in [.8, .9), [.9, .95), [.95, .975), [.975, .99), [.99, .999), and [.999, 1].

*** p<0.01, ** p<0.05, * p<0.1

ONLINE APPENDIX TABLE 6

DETERMINANTS OF PRICING, ROBUSTNESS (FOOD STORES)

Dependent Variable:	Log Price				
	(1)	(2)	(3)	(4)	(5)
Panel A. Generic Products					
Own Store Income	0.0102***			0.0020***	0.0020***
(in $10,000s)	(0.0026)			(0.0003)	(0.0003)
Chain-State Average Income				0.0206***	0.0075
(in $10,000s)				(0.0055)	(0.0046)
Fixed Effect for Chain					X
Observation Level	Store			Store	Store
Observations	9,415			9,415	9,415
R-squared	0.079			0.156	0.879
Panel B. Top-Decile Products by Revenue					
Own Store Income	0.0123***	0.0044***	0.0039***	0.0040***	0.0040***
(in $10,000s)	(0.0040)	(0.0007)	(0.0009)	(0.0004)	(0.0004)
Chain Average Income		0.0244**	0.0187*	0.0211*	
(in $10,000s)		(0.0101)	(0.0104)	(0.0112)	
Chain-State Average Income				0.0037	0.0037
(in $10,000s)				(0.0026)	(0.0026)
Fixed Effect for County			X		
Fixed Effect for Chain					X
Observation Level	Store	Store	Store	Store	Store
Observations	9,415	9,415	9,415	9,415	9,415
R-squared	0.083	0.154	0.652	0.155	0.928
Panel C. Bottom-Decile Products by Revenue					
Own Store Income	0.0210***	0.0049***	0.0041***	0.0031***	0.0031***
(in $10,000s)	(0.0036)	(0.0014)	(0.0011)	(0.0004)	(0.0004)
Chain Average Income		0.0498***	0.0496***	0.0359***	
(in $10,000s)		(0.0101)	(0.0134)	(0.0104)	
Chain-State Average Income				0.0157***	0.0157***
(in $10,000s)				(0.0052)	(0.0052)
Fixed Effect for County			X		
Fixed Effect for Chain					X
Observation Level	Store	Store	Store	Store	Store
Observations	9,415	9,415	9,415	9,415	9,415
R-squared	0.136	0.303	0.715	0.308	0.914
Panel D. All Products, Weighted by Revenue					
Own Store Income	0.0150***	0.0047***	0.0050***	0.0041***	0.0041***
(in $10,000s)	(0.0040)	(0.0008)	(0.0008)	(0.0004)	(0.0004)
Chain Average Income		0.0317***	0.0316***	0.0274**	
(in $10,000s)		(0.0093)	(0.0095)	(0.0107)	
Chain-State Average Income				0.0049	0.0049
(in $10,000s)				(0.0036)	(0.0036)
Fixed Effect for County			X		
Fixed Effect for Chain					X
Observation Level	Store	Store	Store	Store	Store
Observations	9,415	9,415	9,415	9,415	9,415
R-squared	0.114	0.226	0.711	0.227	0.922

Notes. In Panel A, we select generic products within each chain with at least 80% availability for a total of 12,423 chain-UPCs. In Panel B we keep the top decile of our 1,365 products by yearly average revenue, scaled by the number of years a product appears in the sample. In Panel C we keep the bottom decile of our 1,365 products bt yearly average revenue, scaled by the number of years a product appears in the sample. In Panel D, we weight the store-level log price by store-UPC revenue.

*** p<0.01, ** p<0.05, * p<0.1

ONLINE APPENDIX TABLE 7

SIMILARITY IN PRICING, MAJOR GROCER

Measure of Similarity:	Absolute Difference in Quarterly Log Prices	Correlation in (Demeaned) Weekly Log Prices	Share of Weekly Log Prices within One Log Point
	(1)	(2)	(3)
Store Pairs Within a DMA			
Panel A. Major Grocer, RMS Data			
Mean	0.026	0.874	0.475
Standard Deviation	(0.012)	(0.102)	(0.155)
Number of Chain-UPCs	567	567	567
Panel B. Major Grocer, Grocer Data			
Mean	0.018	0.944	0.652
Standard Deviation	(0.010)	(0.092)	(0.126)
Number of Chain-UPCs	567	567	567
Panel C. Major Grocer, Nonfractional Cents			
Mean	0.013	0.949	0.814
Standard Deviation	(0.009)	(0.104)	(0.126)
Number of Chain-UPCs	567	567	567
Panel D. Major Grocer, Nonsale Price, Nonfractional Cents			
Mean	0.015	0.685	0.777
Standard Deviation	(0.011)	(0.298)	(0.152)
Number of Chain-UPCs	567	567	567

Notes. In this table, we present pairs results as in Table 2, computed using Major Grocer's data. In Panel A, we compute the three measures for the 132 identified stores in Nielsen. In Panel B, we compute the three measures now using the Major Grocer's data. In Panel C, we filter prices by keeping only prices with nonfractional cents. In particular, we keep all observations like $1.43 but drop observations like $1.434. This drops 1,229,899 of 6,669,780 observations. In Panel D, we compute the measures for nonsale prices, also keeping prices with nonfractional cents. This drops 88,267 of 6,669,780 observations. The measures are computed keeping only weeks where prices are nonmissing for both stores in a pair.

ONLINE APPENDIX TABLE 8

DETERMINANTS OF ELASTICITY, OWN- VS. CHAIN-LEVEL INCOME

Dependent Variable:	Elasticity				
	(1)	(2)	(3)	(4)	(5)
Panel A. Food Stores					
Own Store Income	0.1395***	0.1329***	0.1439***	0.1363***	0.1363***
(in $10,000s)	(0.0226)	(0.0146)	(0.0114)	(0.0146)	(0.0146)
Chain Average Income		0.0203	0.1211	0.0478	
(in $10,000s)		(0.0590)	(0.0975)	(0.0645)	
Chain-State Average Income				-0.0309	-0.0309
(in $10,000s)				(0.0255)	(0.0256)
Fixed Effect for County			X		
Fixed Effect for Chain					X
Observation Level	Store	Store	Store	Store	Store
Observations	9,415	9,415	9,415	9,415	9,415
R-squared	0.138	0.138	0.629	0.139	0.667
Panel B. Drug Stores					
Own Store Income	0.0612***			0.0624***	0.0624***
(in $10,000s)	(0.0080)			(0.0079)	(0.0079)
Chain-State Average Income				-0.0129	0.0209
(in $10,000s)				(0.0582)	(0.0464)
Fixed Effect for Chain					X
Observation Level	Store			Store	Store
Observations	9,954			9,954	9,954
R-squared	0.057			0.057	0.154
Panel C. Mass Merchandise Stores					
Own Store Income	0.0277			0.1146***	0.1145***
(in $10,000s)	(0.0236)			(0.0097)	(0.0097)
Chain-State Average Income				-0.3912***	-0.0400
(in $10,000s)				(0.0705)	(0.0551)
Fixed Effect for Chain					X
Observation Level	Store			Store	Store
Observations	3,288			3,288	3,288
R-squared	0.003			0.118	0.395

Notes. Elasticities are winsorized at -1.2 and -7. In Panel A, standard errors are clustered by *parent_code* . In Panels B and C, standard errors are clustered by *parent_code* *state. In Panels B and C we do not report the specifications with chain-average income given that there are only 4 drug chains and only 5 mass merchandise chains.

*** p<0.01, ** p<0.05, * p<0.1

ONLINE APPENDIX TABLE 9

DETERMINANTS OF ELASTICITY USING ALTERNATIVE INCOMES

Dependent Variable:	Elasticity				$\text{Log}\ \frac{\text{Elasticity}}{1 + \text{Elasticity}}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Demographic Controls								
Benchmark Income	0.1329***			0.1300***	0.0503***			0.0537***
(in $10,000s)	(0.0146)			(0.0117)	(0.0051)			(0.0050)
County Income		0.1124***		-0.0026		0.0357***		-0.0100*
(in $10,000s)		(0.0194)		(0.0146)		(0.0071)		(0.0056)
Homescan Range Midpoints			0.0309***	0.0037			0.0104***	0.0001
(in $10,000s)			(0.0055)	(0.0028)			(0.0020)	(0.0009)
Fixed Effect for Chain	X	X	X	X	X	X	X	X
Observation Level	Store	Store	Store	Store	Store	Store	Store	Store
Observations	9,415	9,415	9,415	9,415	9,415	9,415	9,415	9,415
R-squared	0.666	0.607	0.604	0.666	0.688	0.628	0.627	0.688

Notes. Standard errors are clustered by *parent_code* . Elasticities are winsorized at -1.2 and -7. All independent variables are our estimate of store-level demographics at the zip-code level based on Nielsen Homescan (HMS) panelists' residences. Demographics are from 2012 ACS 5-year estimates. Fraction with College Degree (or higher) is the fraction of adults 25 and older with at least a bachelor's degree. Controls for Urban Share are a set of dummy variables for Percent Urban for values in [.8, .9), [.9, .95), [.95, .975), [.975, .99), [.99, .999), and [.999, 1].

*** p<0.01, ** p<0.05, * p<0.1

ONLINE APPENDIX TABLE 10

LOG PRICE AND LOG ELASTICITY, OLS

Dependent Variable:	Log Price		Average Log Price	
Specification:	Within-Chain		Between Chain-State	Between Chain
	(1)	(2)	(3)	(4)
Panel A. Food Stores				
$\text{Log}\,\dfrac{\text{Elasticity}}{1+\text{Elasticity}}$	0.0246***	0.0288***		
	(0.0081)	(0.0063)		
$\text{Average Log}\,\dfrac{\text{Elasticity}}{1+\text{Elasticity}}$			0.0084	0.0939
			(0.0299)	(0.0682)
Fixed Effect for Chain	X		X	
Fixed Effect for Chain*State		X		
Observation Level	Store	Store	Chain-State	Chain
Observations	9,415	9,415	171	64
Panel B. Drug Stores				
$\text{Log}\,\dfrac{\text{Elasticity}}{1+\text{Elasticity}}$	0.0438***	0.0505***		
	(0.0102)	(0.0109)		
$\text{Average Log}\,\dfrac{\text{Elasticity}}{1+\text{Elasticity}}$			0.0303	
			(0.0238)	
Fixed Effect for Chain	X		X	
Fixed Effect for Chain-State		X		
Observation Level	Store	Store	Chain-State	
Observations	9,975	9,975	83	
Panel C. Mass Merchandise Stores				
$\text{Log}\,\dfrac{\text{Elasticity}}{1+\text{Elasticity}}$	0.0204***	0.0213**		
	(0.0069)	(0.0082)		
$\text{Average Log}\,\dfrac{\text{Elasticity}}{1+\text{Elasticity}}$			0.0188*	
			(0.0111)	
Fixed Effect for Chain	X		X	
Fixed Effect for Chain-State		X		
Observation Level	Store	Store	Chain-State	
Observations	3,288	3,288	142	

Notes. This table presents the results of regressions of prices on the log elasticity term. Unlike the benchmark results in Table VI, we do not instrument for the log elasticity term with income. For Panel A, standard errors are clustered by *parent_code*. For Panels B and C, they are clustered by *parent_code* *state. Elasticities are winsorized at -1.2 and -7. Retailer means for the Between-Chain specification are average log elasticity term. Analytic weights equal to the number of stores in each group are used in columns 3 and 4. In Panels B and C we do not report the specifications with chain-average income given that there are only 4 drug chains and only 5 mass merchandise chains.

*** p<0.01, ** p<0.05, * p<0.1

ONLINE APPENDIX TABLE 11

ESTIMATED CHAIN-LEVEL LOSS OF PROFITS

Panel A. Food Stores, Benchmark Elasticity	10th	25th	Median	75th	90th
Loss of Profits: Flexible Pricing vs. Uniform Pricing	1.18%	1.43%	1.93%	2.26%	2.82%
Loss of Profits: Flexible Pricing vs. Actual Price-Elasticity Slope	0.97%	1.17%	1.59%	1.84%	2.33%
Loss of Profits: Flexible Pricing vs. State-Zone Flexible Pricing	0.89%	1.35%	1.61%	1.95%	2.66%
Loss of Profits: Flexible Pricing vs. Actual Pricing (Raw Prices)	1.19%	1.45%	1.95%	2.26%	3.01%
Panel B. Food Stores, Quarterly Elasticity	10th	25th	Median	75th	90th
Loss of Profits: Flexible Pricing vs. Uniform Pricing	0.53%	0.82%	1.33%	1.82%	2.40%
Loss of Profits: Flexible Pricing vs. Actual Price-Elasticity Slope	0.44%	0.67%	1.09%	1.49%	1.97%
Loss of Profits: Flexible Pricing vs. State-Zone Flexible Pricing	0.48%	0.77%	1.26%	1.69%	2.03%
Loss of Profits: Flexible Pricing vs. Actual Pricing (Raw Prices)	0.58%	0.86%	1.36%	1.79%	2.54%
Panel C. Food Stores, Module Index Elasticity	10th	25th	Median	75th	90th
Loss of Profits: Flexible Pricing vs. Uniform Pricing	0.18%	0.42%	0.75%	1.40%	2.01%
Loss of Profits: Flexible Pricing vs. Actual Price-Elasticity Slope	0.15%	0.35%	0.61%	1.15%	1.61%
Loss of Profits: Flexible Pricing vs. State-Zone Flexible Pricing	0.18%	0.41%	0.69%	1.15%	1.80%
Loss of Profits: Flexible Pricing vs. Actual Pricing (Raw Prices)	0.25%	0.48%	0.84%	1.44%	2.38%
Panel D. Drugstores, Benchmark Elasticity	Chain 4901	Chain 4904	Chain 4931	Chain 4954	
Loss of Profits: Flexible Pricing vs. Uniform Pricing	4.83%	4.18%	3.84%	1.80%	
Loss of Profits: Flexible Pricing vs. Actual Price-Elasticity Slope	1.86%	2.00%	1.53%	0.82%	
Loss of Profits: Flexible Pricing vs. State-Zone Flexible Pricing	3.78%	2.87%	3.82%	1.69%	
Loss of Profits: Flexible Pricing vs. Actual Pricing (Raw Prices)	4.72%	4.06%	3.79%	1.80%	
Panel E. Mass Merchandise Stores, Benchmark Elasticity	Chain 6901	Chain 6904	Chain 6907	Chain 6919	Chain 6921
Loss of Profits: Flexible Pricing vs. Uniform Pricing	4.01%	3.97%	3.04%	1.52%	3.00%
Loss of Profits: Flexible Pricing vs. Actual Price-Elasticity Slope	2.69%	2.66%	2.06%	1.01%	2.02%
Loss of Profits: Flexible Pricing vs. State-Zone Flexible Pricing	3.18%	3.05%	2.42%	0.87%	2.01%
Loss of Profits: Flexible Pricing vs. Actual Pricing (Raw Prices)	4.06%	4.01%	3.12%	1.63%	3.09%

Notes. This table presents profit losses as a percent of revenue for a variety of different elasticity measures. Flexible pricing assumes the monopolistic competition model and thus deriving optimal prices using $\log(P) = \lambda + \log(c)$, where λ is log elasticity, with the estimated store-level elasticities (Winsorised at -1.2 and -7). Uniform pricing assumes that each chain sets the optimal uniform price across its stores. Pricing according to the actual price-elasticity slope assumes that chains set prices according to β, the IV estimate in Table VI column 3 for Panel A, Table VII row 3 for Panel B, Table VII row 4 for Panel C, Table VII row 10 for Panel D, and Table VII row 11 for Panel E. State-Zone Optimal Pricing assumes that the chain charges a uniform price within each state, with the price set optimally in the chain-state. Actual Pricing (Raw Prices) are unadjusted observed prices. All panels use average weekly prices and quantities to estimate marginal cost and the demand constant. Panels A, D, and E use benchmark weekly elasticity, while Panel B uses elasticity computed using quarterly average log prices and quantities and Panel C uses weekly index price and quantity.

ONLINE APPENDIX TABLE 12

DETERMINANTS OF FLEXIBLE PRICING II

Dependent Variable:	Average Absolute Log Price Difference			
	(1)	(2)	(3)	(4)
Log (No. of Stores)	-0.0014	-0.0027		
	(0.0028)	(0.0029)		
Log (No. of States)	0.0127***	0.0138***		
	(0.0038)	(0.0037)		
Log (Average Yearly Store Sales)	0.0122**	0.0096*		
	(0.0057)	(0.0055)		
Standard Deviation of Store-level Per-capita Income, $10,000s		0.0131*		
		(0.0067)		
Log Dollar Profit Loss from Uniform Pricing			0.0071***	
			(0.0015)	
Percent Profit Loss from Uniform Pricing			-0.0029	
			(0.0023)	
Share of Stores with Competitor Stores within 10 km				-0.0099
				(0.0140)
Share of Store with Same-Chain Stores within 10 km				-0.0044
				(0.0190)
Analytic Weights	X	X	X	X
Observation Level	Chain	Chain	Chain	Chain
Number of observations	64	64	64	64
R-squared	0.473	0.511	0.301	0.033

Notes. The dependent variable is the chain-by-chain average within-chain absolute log price difference, as in Table II column 1. Standard errors are clustered by *parent_code* . Analytic weights equal to the number of stores in each chain are used. The chain-level percent profit loss from uniform pricing is as in Table IX, Panel B, row 1. The log dollar profit loss from uniform pricing is computed taking the store-level loss from uniform pricing in dollar terms, and scaling it up by the share of revenue in that store due to the selected UPCs; we then sum the dollar losses across stores in a chain, and take the log.

*** p<0.01, ** p<0.05, * p<0.1

ONLINE APPENDIX TABLE 13

EVIDENCE FOR EXPLANATIONS

Dependent Variable:	Log Price		
	(1)	(2)	(3)
$\text{Log} \frac{\text{Elasticity}}{1 + \text{Elasticity}}$	0.1129***	0.0901***	0.0813***
	(0.0276)	(0.0217)	(0.0106)
$\text{Log} \frac{\text{Elasticity}}{1 + \text{Elasticity}}$ * (Zero Competitors Within 10 km)			0.0352
			(0.0238)
$\text{Log} \frac{\text{Elasticity}}{1 + \text{Elasticity}}$ * (Zero Same-Chain Stores Within 10 km)			0.0047
			(0.0114)
Sample Years	2006-2008	2012-2014	2006-2014
Chain Fixed Effects	X	X	X
Observation Level	Store	Store	Store
Observations	8,642	8,642	9,415

Notes. Throughout, the first stage uses within-chain variation in income and λ, log elasticity, as in Table V column 5 using all stores. In columns 1 and 2, each observation is a store-level log price in 2006-2008 or 2012-2014, respectively. Only stores present in both periods are included. In column 3, we interact λ with having 0 competitors and 0 same-chain stores within 10 kilometers. Standard errors are block bootstrapped by *parent_code* .

*** p<0.01, ** p<0.05, * p<0.1

ONLINE APPENDIX TABLE 14

RESPONSE TO LOCAL SHOCKS, ROBUSTNESS (FOOD STORES)

Outcome:	Estimated Log Point Change in Prices: $2,000 Decrease in Income		
Assumed Price Setting:	Flexible Pricing	Uniform Pricing	Yearly Pricing
	(1)	(2)	(3)
Panel A. Impact on Prices from a $2,000 Negative Income Shock, Benchmark Elasticity:			
National Shock, Impact on All Stores	-1.01	-1.00	-1.00
State-Level Shock, Impact on Same-State Stores	-1.01	-0.32	-0.45
County-Level Shock, Impact on Same-County Stores	-1.01	-0.04	-0.21
Panel B. Impact on Prices from a $2,000 Negative Income Shock, Quarterly Elasticity:			
National Shock, Impact on All Stores	-1.50	-1.49	-1.49
State-Level Shock, Impact on Same-State Stores	-1.50	-0.48	-0.67
County-Level Shock, Impact on Same-County Stores	-1.50	-0.06	-0.32
Panel C. Impact on Prices from a $2,000 Negative Income Shock, Module Index Elasticity:			
National Shock, Impact on All Stores	-1.36	-1.35	-1.35
State-Level Shock, Impact on Same-State Stores	-1.36	-0.44	-0.60
County-Level Shock, Impact on Same-County Stores	-1.36	-0.06	-0.29

Notes. Displayed are the estimated log point price responses to a permanent $2,000 decrease in income, assuming that the income shock translates into a change of the log elasticity term as estimated in Table V column 5 (Panel A), as in Table VII row 3 (Panel B) and Table VII row 4 (Panel C). The averages are the mean response for stores in each locality, weighting each locality equally. Uniform Pricing assumes that chains set one uniform price across all stores. Yearly pricing takes into account consumer substitution by adjusting using the coefficient in Table VIII column 1. For more detail, see section 7.1 Inequality.