Uniform Pricing in US Retail Chains

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September 23, 2017

Abstract

We show that most US grocery, drug, and mass-merchandise chains charge nearly-uniform prices across stores, despite wide variation in consumer demographics and the level of competition. Estimating a model of consumer demand reveals substantial within-chain variation in price elasticities and suggests that the average chain sacrifices seven percent of profits relative to a benchmark of flexible prices. In contrast, differences in average prices between chains broadly conform to the predictions of the model. We show that the uniform pricing we document dampens the overall response of prices to local economic shocks, may shift the incidence of intranational trade costs, and significantly increases the prices paid by poorer households relative to the rich. We discuss tacit collusion, fairness concerns, and fixed costs of managerial decision as concerns as possible explanations for near-uniform pricing.

∗ E-mail: sdellavi@econ.berkeley.edu, gentzkow@stanford.edu. We thank Nicholas Bloom, Liran Einav, Benjamin Handel, Ali Hortacsu, Kei Kawai, Peter Rossi, Stephen Seiler, Steven Tadelis, Sofia Villas-Boas and seminar participants at Stanford GSB, UC Berkeley, UCLA, the University of Bonn, and the University of Chicago Booth, and at the 2017 Berkeley-Paris conference in Organizational Economics for helpful comments. We thank Angie Acquatella, Sahil Chinoy, Bryan Chu, Johannes Hermle, Ammar Mahran, Akshay Rao, Sebastian Schabe, Avner Shlain, Patricia Sun, and Brian Wheaton for outstanding research assistance. Gentzkow acknowledges funding from the Stanford Institute for Economic Policy Research (SIEPR).
1 Introduction

Recent research across several domains highlights the importance of retail price adjustment to local shocks. Beraja, Hurst, and Ospina (2016) and Stroebel and Vavra (2014) find that local retail prices increase in response to positive shocks to consumer demand, and argue that such price responses have important implications for understanding business cycles. Atkin and Donaldson (2015) show that retail prices are higher in more remote areas due to intra-national trade costs, and that consumers in these areas benefit less from globalization as a result. Jaravel (2016) shows that local prices have fallen more in high-income areas, possibly due to higher rates of product innovation, and that this has significantly exacerbated rising inequality. In interpreting the data, authors in these areas typically start from models in which local prices are set optimally in response to local costs and demand.

In this paper, we show that most large US grocery, drugstore, and mass-merchandise chains in fact set uniform or nearly-uniform prices across their stores. This fact echoes uniform pricing “puzzles” in other domains, such as movie tickets (Orbach and Einav, 2007), sports tickets (Zhu, 2014), rental cars (Cho and Rust, 2010), and online music (Shiller and Waldfogel, 2011), but is distinct in that prices are held fixed across separate markets, rather than across multiple goods sold in a single market. We show that limiting price discrimination in this way costs firms significant short-term profits. We then show that the result of nearly-uniform pricing is a significant dampening of price adjustment, and that this has important implications for the pass-through of local shocks, the incidence of trade costs, and the extent of inequality.

Our analysis is based on store-level scanner data for 9,415 grocery stores, 9,977 drugstores, and 3,288 mass-merchandise stores from the Nielsen-Kilts retail panel. In our baseline results, we focus on prices of ten widely available items, and we use the standard price measure in these data, which is defined to be the ratio of weekly revenue to weekly units sold.

Our first set of results documents the extent of uniform pricing. While we observe no cases in which the measured price is the same for all products across stores, we find that the variation in prices within chains is very small in absolute terms and far smaller than variation between stores in different chains. This is true despite the fact that consumer demographics and levels of competition vary significantly within chain. For example, consumer income per capita ranges from $22,450 at the 25th-percentile store to $33,450 at the 75th-percentile store. Prices are highly similar within chain even if we focus on store pairs that face very different income levels, or that are in geographically separated markets. We can also look directly at the relationship of price to consumer income. Within chain, prices increase by 0.72 percent (s.e. 0.12) for each $10,000 increase in the income of local customers. Between chains—that is, comparing chain average prices to chain average income—they increase by 4.48 percent (s.e. 1.01). Another way of looking at the same fact is to regress a store’s log price on (i) the income of consumers in its own market and (ii) the average income of consumers
in its chain; we find that the coefficient on the former is an order of magnitude smaller than the coefficient on the latter (0.004 vs. 0.040). All of these results remain similar for various alternative sets of products, including store brands, lower-selling items, and high priced items.

Next, we show that the way prices are measured in the Nielsen data means that the degree of uniform pricing is likely even greater than these results would suggest. If not all consumers pay the same price within a given week, the weekly ratio of revenue to units sold will yield the quantity-weighted average price. This ratio can vary across stores not only because of variation in the prices but also because of variation in the quantity weights. In particular, we would expect stores facing more elastic demand (e.g., lower income) to sell a larger share of units at relatively low prices, leading the weekly price measure to be lower in such stores even if posted prices do not vary at all. Thus, the aggregation to weekly average prices can lead not only to excess variance in measured prices, but also to strong apparent correlation between measured prices and income.

To assess the importance of this compositional bias, we turn to more detailed data from a large retailer studied in Gopinath, Gourinchas, Hsieh, and Li (2011) that allows us to see posted non-sale prices directly. These data suggest two reasons that consumers within a given week pay different prices. First, Nielsen’s weeks run from Sunday to Saturday while this retailer typically changes prices mid-week. Second, consumers with loyalty cards pay lower prices than those without loyalty cards.\(^1\) We show that when we use the standard price measure, this chain looks similar to other grocery chains in having a small but clearly non-zero price-income gradient. When we adjust for the compositional biases and look directly at the posted prices, however, this relationship completely disappears and we see prices are essentially identical.

For the large majority of chains in our data—56 grocery chains out of 64 total—measured prices vary very little across stores, and we suspect based on our analysis of the large retailer that their posted prices are in fact essentially uniform. For 6 of the remaining grocery chains as well as the major drug and mass merchandise chains, prices vary at the level of large geographic zones, but are uniform within them. Finally, we observe 2 grocery chains that appear to vary prices more substantially at the store level.

Our second set of results uses a simple constant-elasticity model of demand to assess the extent to which uniform pricing represents a deviation from (short-run) optimal prices. The model fits the data well, with an observed relationship between weekly log quantity and weekly log price very close to linear. The store-level estimate of elasticity is both statistically quite precise and closely predicted by store-level measures of demographics and competition. Estimated elasticities vary widely within chains, ranging from -2.28 at the 10th percentile to -2.98 at the 90th percentile in food stores, -1.94 to -2.65 in drugstores, and -2.92 to -3.67 in mass-merchandise stores. Our model implies that the ratio of the optimal price to marginal cost for a store with elasticity \(\eta_s\) is \(\eta_s / (1 + \eta_s)\). Assuming

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\(^1\)See Einav, Leibtag, and Nevo (2010) for further discussion of measurement error due to loyalty cards in Nielsen data.
no variation in marginal costs across stores, this implies that prices at stores with elasticities in
the 90th percentile should be 18 percent higher than stores with elasticities in the 10th percentile
in food stores, 29 percent higher in drugstores, and 11 percent higher in mass-merchandise stores,
whereas observed prices are on average only 0.4 percent higher in food stores, 0.8 percent higher in
drugstores, and 0.4 percent higher in mass-merchandise stores. Regressing log prices on the term
$log \left[ \frac{\eta_s}{1 + \eta_s} \right]$, instrument for elasticity with store-level per-capita income, yields a between-chain
coefficient for grocery chains of 0.94 (s.e. 0.22), very close to the value of 1 that the model would
predict. The within-chain coefficient is an order of magnitude smaller, at 0.09 (s.e. 0.03), and the
compositional issues discussed above suggest this is likely an over-estimate.

The model allows us to quantify the lost profits from uniform pricing. We estimate that the chain
could increase profits by 7 percent were they to adopt flexible pricing. The increase is 8 percent for
the average food chain and drug change, and about half as large for mass merchandise chains.

We consider a number of potential threats to the validity of our model predictions. First, our
baseline model abstracts from variation in marginal costs across stores. stroebel and Vavra (2014)
present a range of evidence suggesting that such variation is likely to be small, and this is supported
by our analysis of the large retailer data. To the extent that marginal costs do vary, we would expect
them to be positively correlated with income, meaning that our model if anything understates the gap
between observed and optimal prices. Second, our baseline estimates assume that short-run week-
to-week elasticities are equal to long-run elasticities. The long-run elasticities relevant to the store’s
problem could in fact be smaller (due to consumer stockpiling) or larger (due to search). We repeat
our analysis using prices and quantities aggregated to the quarterly level and find that the broad
patterns are unchanged, and also show that the results are similar for storable and non-storable
products. Third, our main analysis treats demand as separable across products. Cross-product
substitution could lead us to over-state the relevant elasticities as consumers substitute among
products, or under-state them as consumers substitute on the store-choice margin as in Thommasen
et al. (2017). To partially address this concern we show that estimated elasticities are similar when
we aggregate prices and quantities to the product category level. Finally, prices and promotions are
often determined jointly by retailers and manufacturers (Anderson et al., 2017). The fact that our
results are similar for store brands suggests that constraints imposed by manufacturers are unlikely
to be a key driver of our results.

The third section of our analysis considers potential explanations for uniform pricing. Menu
costs (Mankiw, 1985) are unlikely to provide a convincing explanation, since stores change prices
frequently over time. Price advertising is also unlikely to be an explanation, as prices are nearly as
similar between local advertising markets (DMAs) as within them, and most grocery chains do not
post prices online. Three other explanations seem to us potentially more plausible.

The first is that committing to uniform or zone pricing benefits chains by allowing them to soften
price competition. Dobson and Waterson (2008) present a model of this phenomenon, and Adams and Williams (2017) find mixed support for it using data from the hardware industry. As one piece of evidence pointing against this hypothesis in our setting, we show that the extent of price uniformity does not differ for chains that face few competitors in their typical market as opposed to those that face many competitors.

A second explanation is fairness concerns. Such concerns are often cited as a possible explanation for uniform pricing across products such as movie tickets sold by a single seller (e.g., Orbach and Einav, 2007), and we show examples below of grocery chains citing fairness as a concern. However, several facts point away from fairness as a main driver here: few consumers would know if a grocery chain charged different prices at geographically distant stores, it is not obvious how fairness concerns would explain zone pricing, chains in other markets such as gasoline do vary prices substantially without provoking any fairness outcry, and at optimal prices firms would be reducing prices for poorer customers and raising them for the rich—not an obviously objectionable practice.

The explanation we find the most support for is managerial decision-making costs (Bloom and Van Reenen, 2007)\(^2\). Implementing more flexible pricing policies may impose costs such as up-front managerial effort in policy design or investments in more sophisticated information technology. Inertial managers may also perceive a cost in deviating from the traditional pricing approach in the industry. A stylized model of such costs would require the chain to pay fixed costs at the chain and/or store level to implement flexible pricing. We find some limited support for these costs in the data. We find no evidence of deviations from (near) uniform pricing for stores with more extreme elasticity (within a chain), suggesting that store-level fixed costs are not a key driver. There is, however, a weak positive association across chains between measures of the loss from uniform pricing— influenced by the number of stores and the variation in the demand elasticities they face—and the extent of uniform pricing, consistent with chain-level fixed costs playing a role.

In the final section of the paper, we turn to the implications of uniform pricing for the broader economy. We first show that uniform pricing exacerbates inequality, increasing prices posted to consumers in the poorest decile of zip codes by 9.4 percent relative to the prices posted to consumers in the richest decile for food stores, 8.0 percent in drugstores, and 3.9 percent in mass-merchandise stores. We then show that uniform pricing substantially dampens the response of prices to local demand shocks. This significantly shifts the incidence of these shocks – for example, exacerbating the negative effects of the great recession on markets with larger declines in housing values. Finally, we show that it changes the incidence of trade costs, benefiting more remote areas that otherwise would pay significantly higher prices, and that it can also bias estimates of these costs that use spatial price gaps as a key input.

\(^2\)A different version of this explanation is that managers are simply unaware of the income differences across their stores, or that they lack the information to recognize its implications for optimal prices. This seems unlikely to us. There is also no evidence of firm learning, as the observed patterns are at least as strong in the most recent three years of data than in the first three years.
We are not the first to document uniform pricing policies in retailing. Reports from UK regulators show that roughly half of UK supermarket chains charge uniform prices across stores (Competition Commission, 2003, 2005) as do the main UK electronics retailers (MMC, 1997a,b). Allain et al. (2015) document national pricing in the French supermarket industry. Retailers such as IKEA are known to honor online prices in their brick and mortar stores (Dobson and Waterson, 2008). Cavallo, Nieman, and Rigobon (2014) show that Apple, IKEA, H&M, and Zara charge nearly uniform prices across the Euro zone in their online stores, though they charge different (real) prices across countries with different currencies. Early studies of the Dominicks chain in the Chicago market including Hoch, Kim, Montgomery, and Rossi (1995), Montgomery (1997), and Chintagunta, Dubé, and Singh (2003) show that Dominicks varies prices across several zones defined “almost entirely by the extent of local competition,” holding prices constant across stores within a zone, and estimate the potential gains to more flexible pricing.

Two recent papers are more closely related. Recent work by Adams and Williams (2017) is particularly closely related. These authors show that the Home Depot and Lowe’s US hardware chains use a zone pricing strategy, with different degrees of price flexibility for different products. They then estimate a structural model of demand and oligopoly pricing for a single product, drywall, and use it to evaluate how profits would change under more flexible pricing for this product. Their analysis differs from ours in focusing on cost differences across stores as a source of variation in optimal prices—a factor that turns out to be important in their setting—but ruling out differences in price sensitivity of consumers across markets—a factor that plays a key role in ours.

A contemporaneous paper by Hitsch, Hortacsu, and Lin (2017) uses the same Nielsen data set to to decompose the source of variation in prices among the retails chains, and finds, like we do, that prices vary substantially more across chains than they vary within chain. Their paper is focused on a detailed decomposition in and frequency depth of sales which we do not consider in our paper. Our paper differs in relating the differences in within-chain and between-chain prices to a simple model of optimal pricing, considering different explanations for the observed within-chain price uniformity, and the implications of dampened response to local demand and cost differences.

Our paper relates to a broad range of work studying the extent and implications of local retail price variation. Examples beyond those cited above include Broda and Weinstein (2008), Gopinath, Gourinchas, Hsieh, and Li (2011), Coibion, Gorodnichenko, and Hong (2015), Fitzgerald and Nicolini (2014), Handbury and Weinstein (2015), and Kaplan and Menzio (2015). Our work also speaks to the wider literature tracing out the implications of retail firms’ price setting strategies for macroeconomic outcomes. This includes influential early work using scanner data by Bils and Klenow (2004) and Nakamura and Steinsson (2008), as well as recent contributions such as Anderson et al. (2017).

More broadly, our paper also relates to the work in behavioral industrial organization (for a review, see Heidhues and Koszegi, 2018). Most of the work in this area in the last 15 years has focused
on firms optimally responding to behavioral consumers (DellaVigna and Malmendier, 2004; Gabaix and Laibson, 2006). Our paper is part of a smaller literature which considers instead behavioral firms, that is, instances and ways in which firms deviate substantially from profit maximization (Goldfarb and Xiao, 2011; Romer, 2006; Massey and Thaler, 2013; Hortaçsu and Puller, 2008; Hortaçsu, Luco, Puller, and Zhu, 2017; Ellison, Snyder, and Zhang, 2017). Among the patterns documented so far, there appears to be wide variation in the firm’s ability to maximized profits, itself tied to managerial ability (Bloom and Van Reenen, 2007). Firms also appear to respond well to some variables, but largely neglect other determinants of profitability (Hanna, Mullainathan, and Schwartzstein, 2014).

2 Data

Our primary data sources are the Nielsen Retail Scanner (RMS) and Consumer Panel (Homescan, HMS) data provided by the Kilts Center at the University of Chicago. The retailer scanner panel records the average weekly revenue and quantity sold for over 35,000 stores in the US over the 2006-2014 period, covering about a million different unique products (UPCs). We use this data set to extract the information on weekly price and quantity. We also use some information from the consumer panel which is based on following the purchase of 60,000+ consumers across different stores. We present the main information in this Data section, with additional detail in the Appendix.

Stores. We focus the analysis on three store types, or channels: food (i.e., grocery), drug, and mass-merchandise. Table 1, Panel A shows that the initial Nielsen sample includes 38,539 stores for a total average yearly revenue (as recorded in the RMS data) of $224 billion.

We define a chain to be a unique combination of two identifiers in the Nielsen data: ‘parent_code’ and ‘retailer_code.’ The former generally indicates the company that owns a store and the latter indicates the chain itself. Nielsen does not disclose the names of the chains in the data, but a general example would be the Albertson’s LLC parent company which owns chains such as Safeway, Shaw’s, and Jewel-Osco. Sometimes, a single ‘retailer_code’ appears under multiple ‘parent_codes’, possibly for reasons related to mergers. We introduce additional restrictions detailed below to exclude cases like these where chain identity is unclear.

We first introduce set of sample restrictions at the store level. We exclude stores that switch chains over time, stores that are in the sample for fewer than two years, and stores without any consumer purchases in the Homescan data. This reduces the sample to 22,985 stores in 113 chains.
We next introduce restrictions at the chain level. We require that the chains are present in the sample for at least 8 of the 9 years; this eliminates a few chains with typically only a small number of stores each with inconsistent presence in the data. Next, we resolve cases where the mapping of stores to chains is not sufficiently clear. A first concern occurs when the same retailer_code identifier appears for stores with different parent_codes. It is unclear whether the use of the same retailer_code in this case indicates that these stores belong to one chain, or perhaps they belong to a subchain that changed owner, or something else. Thus, for each retailer_code, we only keep the parent_code associated with the majority of its stores, and then further exclude cases in which this retailer_code-parent_code combination accounts for less than 80% of the stores with a given retailer_code. A second concern is for chains in which a number of stores switch chain, given that this may indicate a change in ownership of the entire chain. We thus exclude chains in which 60% or more of stores belonging to the retailer_code-parent_code change either parent_code or retailer_code in our sample.

To define the demographics of the stores, we use the Homescan data, which includes all shopping trips for the consumers in the Nielsen HMS panel. The median store has 21 Nielsen consumers ever purchasing at the store who make a total of 502 trips (Panel B of Table 1). We use demographic variables like income and education from the 2008-2012 5-year ACS for the 5-digit zip code of residence of the consumers shopping in each store, and then compute the weighted average across the consumers, weighting by the number of trips that they take to the store. We let $y_s$ denote this measure of income for store $s$.

Table 1 provides summary statistics for our main sample. Panel A summarizes the sample restrictions, which leave 22,680 stores from 73 chains, covering a total of $191 billion of average yearly revenue. These include 9,415 stores from 64 food store chains ($136 billion average yearly revenue), 9,977 stores from 4 drugstore chains ($21 billion), and 3,288 stores from 5 mass-merchandise chains ($34 billion). Panel B summarizes these stores’ demographics. The median store has an average per-capita income of $26,900, with sizable variation across stores; for example, the 75th percentile is at $33,750. Panel C-E provide chain-level summary statistics for food, drug, and mass merchandise stores respectively. The median food chain (Panel C of Table 1) has 66 stores, and has locations in 4 DMAs and 2.5 states. Drugstore and mass-merchandise chains are significantly larger and span significantly more states, with the vast majority of stores in both cases belonging to 2 chains. Given this high concentration, our between-chain analyses below are limited to food chains.

Our store sample covers the entire continental US (see map in Appendix Figure 1), and the number of stores and chains in the sample remains fairly constant between 2007 and 2013 (Online Appendix Table 1).

**Products.** We focus most of our analysis on a set of products that are both frequently sold and
widely available. This guarantees clean comparisons both within and between chains, and avoids
problems with the fact that the price measures is missing in weeks with zero sales. For food stores we
focus on one UPC from each of 10 product categories (“modules”): canned soup, cat food, chocolate,
coffee, cookies, soda, bleach, toilet paper, yogurt and orange juice.\footnote{These modules have a large overlap with ones used in previous analyses, e.g., Hoch, Kim, Montgomery, and Rossi (1995)} We define the first eight to be storable products and the last two to be non-storable products. These modules together account for
an average yearly revenue of $13.7 billion across the 9,415 stores in our food store sample, or 10.1
percent of total revenue. For drug and mass merchandise stores, we focus on the subset of these
modules in which some UPC is available in at least 90 percent of stores: soda and chocolate for
drug, and soda, chocolate, cookies, bleach, and toilet paper for mass merchandise. We choose the
specific UPCs to maximize sales and availability across our sample of stores.\footnote{See Appendix SectionA.1.2 for more details} In most cases, these
UPCs remain the same across years; in all cases, the UPC is the same across stores within a channel
and year.

Table 2 details our sample of products. Examples include a 12-can package of Coca-Cola, a single
14.5 oz can of Campbell’s Cream of Mushroom soup, and a 59 oz. bottle of pulp-free Simply Orange
juice.

In our robustness analysis, we consider larger sets of products. To avoid availability issues, we
construct these larger product samples only for food stores. They include less commonly sold items
(the 20th highest-availability product across chains for each module), high-quality items (chosen
to have a high-unit-price) product, the top-selling generic product within each chain, and a subset
of generic products comparable across chains, and a large basket of products we use to construct
module-level price and quantity indices.\footnote{See Appendix SectionA.1.2 for more details}

To define the module-level baskets, we select all UPCs in each module such that the average
share of weeks with non-zero sales is at least 95 percent, where the average is taken across stores.\footnote{We omit weeks from this calculation in which the store has zero recorded sales in all ten modules.} For some modules such as soda and orange juice, products meeting this criterion cover 50-60 percent
of the total module revenue, while for other modules like chocolate or coffee, they cover just 15-20
percent. (see Online Appendix Table 1, Panel B). Summing over the 10 modules, these products
cover an average annual revenue of $6bn.

\textbf{Prices.} As is standard in the literature, we define the price $P_{sjt}$ in store $s$ of product $j$ in week
$t$ to be the ratio of the weekly revenue to weekly units sold. We let $p_{sjt}$ denote the log of the price.
The price is not defined if no units are sold in a UPC-store-week. We define the average log price of
store $s$, $\bar{p}_{s}$, to be the average across products and weeks of $p_{sjt}$.

Table 2 summarizes prices and availability for the products in our main sample. The average
price varies from $0.49 for cat food in food stores to $8.70 for toilet paper in mass merchandise stores
(Column 3). The products have at least one recorded sale in the large majority of store-weeks, for example in 99.7% of store-week-UPC observations for chocolate in food stores (Column 4). Cat food, coffee, and toilet paper have somewhat lower availability in food stores, as do most of the products sold in drugstores and mass-merchandise stores, but are still in the range around or above 95%. We also compute the average yearly revenue per store that these products generate, with the highest number associated with the soda product in food stores, $34,100.

To compute the module-level price and quantity index for store $s$ we start from the weekly log price $p_{sjt}$ and weekly log units sold $q_{sjt}$, then average across all products $j$ included in the basket for that module-chain-year. As weights, we use the total quantity sold for product $j$ in a chain-year. If a product $j$ has no sales in a particular store $s$ and week $t$, product $j$ is omitted for that store-week cell, and the other weights are scaled up accordingly.\footnote{We use the same weights for the price variable and the quantity variable so that, under the assumption that all products within a module have a constant-elasticity demand with the same elasticity $\eta$, we can recover the elasticity $\eta$ regressing the index quantity on the index price. We use quantity weights so that our price index resembles a geometric modified Laspeyres Index, similar for example to Beraja, Hurst, and Ospina (2016) and to how the BLS builds category-level price indices. Note that our index is not exactly a geometric Laspeyres Index because the weights are not week 1 weights but instead the average quantities sold in year $y$.}

**Major Grocer Data.** We use supplemental scanner data from a single major grocer ('parent_code') studied in Gopinath, Gourinchas, Hsieh, and Li (2011). These data contain the same variables as the Nielsen data, plus gross revenue (defined to be the total revenue had all transactions occurred at the non-sale posted price), wholesale prices paid, and gross profits. The definition of weeks in these data also differs from Nielsen, and is aligned with the timing of the retailer's weekly promotional price changes. The data cover 250 stores belonging to twelve chains ('retailer_codes') beginning in 2004 and ending in mid-2007. We focus on the largest retailer, which has 134 stores. We match 133 of these 134 stores to stores in the Nielsen data set following a procedure detailed in Appendix Section A.1.7.

### 3 Descriptive evidence

#### 3.1 Example

We begin with a visualization of pricing by a single chain (chain 128), which we choose to be representative of the typical patterns observed in our data. Figure 1a shows prices of the orange juice product. The 250 rows in the figure correspond to stores, and are sorted by income. The columns correspond to weeks from January 2006 to December 2014. The color of each store-week indicates the demeaned log price, $\log(P_{sjt}) - \log(P_j)$, where $P_j$ is the average price for product $j$ across weeks, stores, and chains. Darker colors correspond to higher prices, and white indicates missing values due to zero sales.

The figure shows substantial variation of prices across weeks, corresponding to frequent sales...
as large as 30 log points, but virtually no variation across stores within a week. To the extent that prices do vary across stores, this variation is uncorrelated with store income—i.e., the vertical position of stores in the chart. This is despite the fact that store income ranges from about $13,000 at the bottom of the chart to about $50,000 at the top of the chart. Figure 1b shows a similar pattern for five other products: cat food, cookies, soda, chocolate, and yogurt. Here we display just 50 of the 250 stores shown in Figure 1a, with the same 50 stores shown for the 5 products, and still ordered by income. We see variation across products in the depth and frequency of sales, but again no systematic variation of prices across stores. The pricing patterns of this chain are representative of the large majority of chains in our sample. Online Appendix Figures 1a and 1b show two other similar examples.

While patterns like these are typical of the majority of chains, a few other chains follow a different pattern, which we will call zone pricing. Figure 2a displays an example for chain 130, returning to the orange juice product. Figure 2a follows the same design as Figure 1a, except that we group stores geographically by sorting them by 3-digit zip codes within states. This chain operates in 12 different states. Prices are essentially uniform within horizontal bands, but then differ for different bands. For example, stores in Georgia and Kentucky share the same pricing patterns, which are different in Illinois and most of Indiana. Note that the pricing zones are strongly correlated with state borders but do not follow them perfectly.

### 3.2 Measures of Pricing Similarity

To describe chain pricing patterns more systematically, we introduce three measures of the extent of uniform pricing. Each measure defines the similarity of prices of a pair of stores $s$ and $s'$. To compute a chain-level measure of uniformity, we average the raw measure across pairs within each chain.

The first measure is the **quarterly absolute log price difference**. We denote the average unweighted weekly log price in store $s$ of product $j$ in quarter $q$ by $p_{sjq}$. We compute for each pair of stores $s$ and $s'$ the absolute difference in this average log price, and average it across the quarters in the data, and across the 10 products in our main sample: $a_{s,s'} = \frac{1}{N_q N_j} \sum_{q,j} |p_{sjq} - p_{sj'q}|$, where $N_q$ and $N_j$ denote the number of non-missing quarters and products, respectively.

The second measure is the **weekly correlation in prices**. We first demean the log price $p_{sjt}$ at the store-year-product level to obtain $\tilde{p}_{sjt}$. Then we compute the correlation of $\tilde{p}_{s;jt}$ and $\tilde{p}_{s';jt}$, including all weeks $t$ and over all products $j$ which are non-missing in both store $s$ and store $s'$.

The two measures capture, by design, two orthogonal aspects of similarity: differences in average prices between the stores, and correlation of price changes over time. Two stores with the same timing and depth of sales, but different regular prices would have high weekly correlation but also a high quarterly difference. Conversely, two stores with similar average prices at the quarterly level,
but different timing of sales would have a low quarterly difference, but also low weekly correlation.

The third measure is the share of (nearly) identical prices. This is defined as price differences smaller than 1 percent, i.e. the share of observations across products $j$ and weeks $t$ for which $|P_{sjt} - P'_{s'jt}|/((P_{sjt} + P'_{s'jt})/2) < .01$.

Figures 3a-b display the distribution of the first two measures for a sample of store pairs. The solid blue bars indicate pairs that belong to the same chain, while the hollow red bars indicate pairs that belong to different chains. To define the set of pairs for the former, we keep all stores for chains with fewer than 200 stores, and a random sample of 200 stores from larger chains, and then compute similarity for all pairs within the resulting set of stores. Prices for same-chain pairs are far more similar on both measures than for different-chain pairs. The absolute log price difference (Figure 3a) is typically below 5 log points for the former, and typically above 10 log points for the latter. The weekly correlation (Figure 3b) is typically above 0.8 for the former and below 0.2 for the latter.

Table 3 summarizes a number of variants of these measures. The first row summarizes the same information shown in Figure 3, reporting the mean and standard deviation of absolute log price difference and weekly correlation for our full set of same-chain and different-chain store pairs, as well as the share of identical prices, which also reveals much more similarity within than between chains. The second row shows that the patterns are essentially unchanged if we restrict attention to cases where stores $s$ and $s'$ are in the same geographic market (Designated Market Area, or DMA). The third row shows the same for cases where $s$ and $s'$ are in different DMAs and also face very different income levels (with one store in the pair in the top third of the income distribution and the other in the bottom third). These results provide initial evidence against the possibility that the observed uniformity just reflects same-chain store pairs serving more homogeneous consumers in terms of either geography or demographics. They also suggest that it does not result from constraints specific to pairs of stores operating in the same geographic market, for example because price advertising is determined by newspaper or television market. The remaining rows of Table 3 show that these pricing patterns are not an artifact of focusing on our set of widely-available products. Focusing on food stores, the table shows similar patterns for: (i) the 20th-highest-selling product within a category; (ii) the top-selling store-brand product, and (iii) products with high unit-prices.\footnote{In Online Appendix Figure 7, we show that chains with uniform prices for our benchmark products also tend to have uniform prices for these alternative products.}

Figure 4 summarizes pricing uniformity at the chain level.\footnote{For computational reasons, we use a maximum of 400 stores per chain} In Figure 4a, weekly correlation is on the vertical axis, absolute log price difference is on the horizontal axis, and each point indicates the average value for a single chain. The vast majority of chains cluster in the upper-left of the figure, with low price differences and high correlation. Out of 73 chains, 58 have both an average correlation of weekly prices above 80 percent and an absolute quarterly distance in prices below 4
percent. The two measures of pricing similarity are also highly correlated: chains that are similar in one dimension are also similar in the other dimension. Deviations from this one might have expected to see ex ante—for example having highly correlated sales but varying the level of regular prices across stores—does not appear to a substantial degree in the data.

Figure 4b returns to the phenomenon of zone pricing. We decompose the measures of pricing similarity into similarity for pairs of stores within a state, versus across state boundaries. We focus on chains that operate at least three stores in each of two or more states. We plot the within-state log price difference on the x axis, and the between-state log price difference on the y axis. To the extent that zone pricing follows state boundaries, it should show up in this figure as low differences within and larger differences between, i.e., points above the 45-degree line in the figure. We see that between differences are indeed larger in almost all cases, but for the majority of chains only slightly so; these chains do not appear to determine prices by state to a significant extent. A minority of chains do have clearer zone pricing patterns, however. Most notable is chain 9, which has an average within-state difference of roughly 2 log points but an average between-state difference of more than 9 log points.

3.3 Price Response to Consumer Income

We now turn to the relationship of prices to income. High-income areas have less elastic consumers (as we confirm below), so all else equal we would expect stores in high-income areas to charge higher prices. Though we argue that variation in marginal costs across stores is likely to be small, any such variation would likely be positively correlated with income, and so tend to strengthen this relationship.

Figure 5 shows the relationship of log income to price within and between chains.\(^\text{16}\) We first regress both store average log price \(p_s\) and store income \(y_s\) on chain-product fixed effects. Figure 5a shows a binned scatterplot of the residuals, illustrating the within-chain relationship. The relationship is positive and highly significant, but the magnitude is very small economically: an increase in per-capita income of $10,000, equivalent to a move from the 30th to the 75th percentile, is associated with an increase in prices of only 0.72 percent. Figure 5b shows a scatterplot of the chain averages, illustrating the between-chain relationship.\(^\text{17}\) This is also highly significant, and its magnitude is more than five times larger: a $10,000 increase is associated with a price increase of 4.5 percent.

We view this sharp contrast between the within and between chain results as one of our key findings. It suggests that chains are either varying their prices far too little across stores in response to income, or varying their prices at the overall chain level far too much. Our model below separates

\(^{16}\)In Online Appendix Figure 11, we show that results are similar when we replace income with the fraction of college graduates.

\(^{17}\)Here we omit drug and mass merchandise chains, since comparing across formats may be less informative and the number of chains for these channels is small. Online Appendix Figure 10 shows the plot including these chains. The overall pattern remains unchanged.
these two hypotheses, providing strong support for the former.

The online appendix shows the distribution of within-chain coefficients separately by chain (Online Appendix Figures 8a-c). The majority of chains have small, positive coefficients in the range between 0 and 0.01, with 27 coefficients positive and significantly different from zero. Only five chains have coefficients above 0.01. We also show in the online appendix that the pattern of tiny within-chain response and large between-chain response is robust to dropping the two outlier chains 98 and 124 (Online Appendix Table 2). It also holds for lower-selling and high price products, as well as for all but one module separately (Online Appendix Figure 9a).

Figure 5c-d examines the role of zone pricing in these relationships. As we documented in Figures 2 and 4b, some chains vary prices more between states than within them. In Figure 5c, we re-estimate the within-chain relationship, but now plot residuals after taking out chain-state-product fixed effects. This further reduces the slope of the price-income relationship to 0.56 percent per $10,000 of income, but it remains statistically significant. In Figure 5d, we show the complementary plot of chain-state mean prices after subtracting the overall chain mean. This thus shows the extent of variation across states within a chain. Here, a $10,000 income increase is associated with an increase in prices of 2.16 percent, a slope about half the size as in the between-chain analysis but much larger than for the within-chain analysis. These findings are largely due to chains 9, 32, 4901, and 4904, two large food chains that operate in a number of states with wide differences in income as well as the two largest drugstore chains. Figure 6 shows the zone pricing relationship separately by format. We see the largest between-state price response for drug stores, and a smaller response for both food and mass merchandise stores.

Finally, Table 4 presents an alternative view of the price-income relationship. We run a store-level regression of average log price $p_s$ on both store income $y_s$ and the average income of stores in the chain to which $s$ belongs. In some specifications, we include separately the average income in $s$’s chain-state. We separate food stores (Panel A) from the drug and mass merchandise stores (Panels B and C), since it is only for the food stores that we can do a meaningful between-chain comparison. The first column presents the regression including only own-store income as a benchmark.\(^\text{18}\) The second column adds chain average income for food stores. Consistent with the evidence in Figure 5, a store’s response to its own consumers’ income is an order of magnitude smaller than its response to the average income served by its chain. Another way to say this is that if we look at two stores both serving consumers of the same income, one of which is from a mainly high-income chain and one of which is from a mainly low income chain, the former will tend to charge much higher prices than the latter. The third and fourth columns add chain-state average income as a regressor. This response is larger than the own-store-income response but smaller (for food stores) than the response

\(^{18}\text{For mass merchandise stores, there is a negative relationship between prices and income when not including chain fixed effects because among the largest two mass merchandise chains, the one operating in, on average, higher income areas has lower prices (see Online Appendix Figure 10b).}\)
to overall chain average income, consistent with our other zone pricing results.

3.4 Composition Bias

The pattern of within-chain pricing in Figure 5a-c poses a puzzle. Why would chains exert the effort to vary their prices in a highly systematic way with consumer income, but then do so with an economically tiny magnitude far smaller than the one with which they respond to income at the chain level, and far smaller than the analysis below suggests would be profit maximizing? We show here that this small price-income relationship is likely to be mainly an artifact of composition bias, due to the fact that the standard Nielsen price measure is the weekly average price paid rather than the price the store posted at any given point in time.

If all consumers of a store in a given week paid the same prices, weekly average price paid and posted price would be equal. For them to diverge, prices paid must vary within a week. There are two main reasons why they are likely to do so. First, Nielsen’s weekly revenue and units sold are based on a week that runs from Sunday through Saturday. Although most retailers do not change prices at more than weekly frequency, they may institute their price changes on a different day of the week. If, for example, they change prices on Wednesdays, consumers who buy in the first half of Nielsen’s week will pay a different price from those who buy in the second half. Second, some but not all consumers may use store cards or other obtain other discounts that lead them to pay lower prices.

The following example highlights the bias that can arise, focusing on the first case. Consider a retailer that charges identical prices in all stores and that changes prices on Wednesdays. Suppose in a particular week they cut the price from $P_{\text{high}}$ to $P_{\text{low}}$. The measured weekly average price in the Nielsen data for store $s$ will be $P_{\text{RMS}}^{s} = \theta_{s}P_{\text{high}} + (1 - \theta_{s})P_{\text{low}}$, where $\theta_{s}$ is the share of purchases made in the first half of the week in store $s$. If the share $\theta_{s}$ varies across stores for any reason, this will obscure the fact that the chain is charging uniform prices. But it should not only vary, it should do so systematically: for stores facing elastic consumers, more will shift purchases to the low price, and $\theta_{s}$ will be low; for stores facing inelastic consumers, fewer will shift, and $\theta_{s}$ will be high. Measures prices $P_{\text{RMS}}^{s}$ will thus be higher for stores facing higher income or otherwise less elastic consumers, even if posted prices do not vary at all. A similar bias arises if the share of consumers who use store cards or other discounts is greater among consumers who are most price elastic.

A simple example suggests that this bias can explain the small price-income gradient we observe. Suppose that the income of store $s$ is $10,000 greater than the income of store $s'$, and that, consistent with our estimates of the price-elasticity relationship below, this translates into price elasticities among their respective consumers of $\eta_{s} = -2.5$ and $\eta_{s'} = -2.65$. Suppose that $P_{\text{low}}$ is 35 percent lower than $P_{\text{high}}$, and that the price change occurred exactly midway through the Nielsen week.
Consistent with our model below, assume a constant-elasticity demand function \( Q_s = kP_s^{\eta_s} \). Then it is straightforward to show that \((\theta_s, \theta_s') = (0.328, 0.318)\), and the difference in log prices is \( p_{s}^{RMS} - p_{s'}^{RMS} = 0.006.\) This example would thus imply a slope of 0.006 in the analogue of Figure 5c, the same as we observe in the data.

To provide direct evidence on the magnitude of this bias, we use the major grocer data described in Section 2. This grocer does, indeed, change prices every week on Wednesday, and the revenue and units sold reported in the grocer’s data are based on weeks defined Wednesday-Tuesday. We would therefore expect the bias arising from mid-week price changes to be present in the Nielsen data but not in the grocer’s data. Figure 7a shows a bin scatter of the within-chain relationship using the Nielsen price measure for the 133 stores in both data sets. We believe that this grocer uses geographic pricing zones, so we focus on the within-chain-state relationship as in Figure 5c. The slope of 0.0027 is similar to the one in Figure 5c and marginally significant. Figure 7b reproduces the same exact estimate, but using weekly price measure from the grocer’s data. The estimated slope falls to 0.0008 and is no longer significantly different from zero. We thus cannot reject the view that posted prices for this retailer do not vary at all with income, and that all of the within-chain-state slope for this retailer is an artifact of the weekly offset. Figure 7c shows the same slope when we replace the weekly average price with the posted non-sale price, which we observe in the data. This is not the object we would ideally like to measure—if stores vary the frequency or depth of their sales we would consider this real variation in posted prices—but it provides a benchmark. Here all remaining slope disappears, and we see that for non-sale prices at least this chain sets completely uniform prices with respect to income.

As an additional check about the importance of this bias, we use an algorithm described in Appendix Section A.1.8 to estimate non-sale prices in the Nielsen data and repeat the analysis of Figure 5. Online Appendix Figures 12a-d show that this flattens the within-chain price-income relationship but not the between-chain relationship.

Our conclusion is that a large part of the within-chain and within-chain-state slopes shown in Figure 5 are likely an artifact of composition bias. We suspect that a large majority of chains are in fact charging exactly the same prices in all of their stores, or in all stores within geographic zones. Moreover, we note that this bias will not only affect the cross-sectional relationship of prices and income, but also the apparent response of prices to income shocks observed in panel data. We discuss the implications of this bias for the literature on local price responses in Section 6 below.

### 3.5 Variation in Marginal Cost

Stroebel and Vavra (2014) provide a detailed analysis suggesting that variation in marginal costs

\[ \theta_s = \left( \frac{P_{s}^{high}}{P_{s}^{low}} \right)^{\eta_s} \]

Plugging in the values for \( P_{s}^{high}, P_{s}^{low}, \eta_s, \) and \( \eta_s \) yield the values of \((\theta_s, \theta_s')\) which in turn yield values of \( I_s^{RMS} \) and \( I_{s'}^{RMS} \).
among retailers such as those in our data is likely to be negligible. They first use novel data on wholesale costs to show that geographic variation in these costs is minimal. Since wholesale costs account for three-quarters of total costs, and a presumably much larger share of marginal costs, this significantly limits the scope for cost variation. They then go on to present further evidence suggesting that neither variation in labor costs nor variation in retail rents plays a significant role.

We can confirm the findings for wholesale costs in our large grocer’s data. Figure 7d plots a within-chain-state bin scatter of the wholesale cost variable for this grocer against store income. The figure displays no evidence of a positive relationship between the two variables. Taking this evidence together, we will assume for the remainder of our analysis that marginal costs are constant across stores within a chain.

4 Demand estimation and optimal prices

4.1 Model

We introduce a simple demand model to gauge the degree to which we would expect prices to vary within and between chains. The model makes strong assumptions, and we do not necessarily take deviations from the model predictions to imply a failure of profit maximization. It provides valuable benchmark, however, providing strong evidence on the extent to which short-run pricing incentives vary across stores.

We consider the pricing decisions of a monopolistically competitive chain that chooses a price \( p_{sj} \) for each product in each of its stores to maximize total profits. Each store’s residual demand for product \( j \) takes the constant elasticity form \( Q_{sj} = k_{sjw} P_{sj}^{\eta_s} \), where \( Q_{js} \) is the number of units sold, \( k_{sjw} \) is a scale term that may vary seasonally by week of year \( w \), and \( \eta_s \) is the store’s price elasticity. Total cost \( C_{sj}(q) = c_j q + C_s \) for a store consists of a constant marginal cost \( c_j \) and a store-level fixed cost \( C_s \). The chain solves,

\[
\max_{\{P_{s,j}\}} \sum_{s,j} (P_{sj} - c_j) Q_{sj}(P_{sj}) - C_s.
\]

The first order conditions yields for all \( j \),

\[
P^*_{sj} = \frac{\eta_s}{1 + \eta_s} c_j
\]

or in log terms

\[
p^*_{sj} = \log \left( \frac{\eta_s}{1 + \eta_s} c_j \right).
\]

There is thus a simple relationship between elasticities and optimal prices, and under optimal pricing a regression of log prices on \( \log \left( \frac{\eta_s}{1 + \eta_s} \right) \) within chains should yield a coefficient of one.
4.2 Elasticity estimates

The model above requires estimates of the price elasticity of demand at the store level. As our benchmark measure of elasticity, we estimate the response of log quantity at the weekly level to the weekly log price product-by-product, for each store \( s \). More precisely, letting \( q_{sjt} = \log(Q_{sjt}) \), we estimate separately for each store \( s \),

\[
q_{sjt} = \eta_{sp} + \alpha_{sjy} + \gamma_{sjw} + \epsilon_{sjt},
\]

(3)

where \( \alpha_{sjy} \) is a product-year fixed effect, \( \gamma_{sjw} \) is a product-week-of-year fixed effect, and \( \epsilon_{sjt} \) is an error term. The former controls for the fact that the exact UPC associated with a product varies in some cases across years, and the latter captures seasonal variation in \( k_{sjw} \). The coefficient on the log price is the estimated price elasticity, \( \hat{\eta}_s \). We use price variation for all 9 years and all 10 products in order to maximize precision. We cluster the standard errors by bi-monthly periods, thus allowing for correlation across products, as well as over time within a 2-month period.

This stylized demand structure abstracts away from two important margins: inter-temporal substitution and cross-product substitution. The former could lead quantities in week \( t \) to vary with prices in prior weeks. The latter could lead to demand for one product to depend on the price of other products. We revisit these assumptions below.

To adjust for sampling error in the elasticity estimates, we use a simple empirical shrinkage procedure. We re-estimate the elasticity separately using just the first 26 weeks of year year and again using the next 26 weeks of each year; label these elasticity estimates \( \hat{\eta}_{1,s} \) and \( \hat{\eta}_{2,s} \). We choose a shrinkage parameter \( \rho \) to minimize the mean squared difference between \( (1 - \rho) \hat{\eta}_{1,s} + \rho \bar{\eta}_1 \) and \( \hat{\eta}_{2,s} \), where \( \bar{\eta}_1 \) is the overall mean of \( \hat{\eta}_{1,s} \) across stores. We then adjust our overall estimates \( \hat{\eta}_s \) as \( \hat{\eta}_s = (1 - \rho) \hat{\eta}_s + \rho \bar{\eta}_s \), where \( \bar{\eta} \) is the mean of \( \hat{\eta}_s \). The estimated optimal shrinkage is just \( \hat{\rho} = .104 \) for food stores, though it is slightly larger at \( \hat{\rho} = .305 \) for drugstores and \( \hat{\rho} = .408 \) for mass-merchandise stores.

Figure 8a shows the distribution of the resulting elasticity estimates for food, drug, and mass merchandise stores. All are well-behaved, with all but a handful of values less than the theoretical maximum of \(-1\), and most of the mass falling between \(-2\) and \(-4\). Figure 8b shows the distribution of associated standard errors, which are mostly between 0.05 and 0.2 for food stores and between 0.2 and 0.4 for drugstores and mass-merchandise stores. The lower precision for the latter is expected given the smaller number of products in the drug and mass-merchandise samples.

Figure 8c provides evidence on the fit of the constant elasticity demand model. The figure shows a binned scatter plot of residuals of \( q_{sjt} \) against residuals of \( p_{sjt} \) after partialing out the fixed effects \( \alpha_{sjy} \) and \( \gamma_{sjw} \). The model predicts that this relationship should be linear, and the results suggest that it is to a remarkable degree. This plot aggregates across all products and tens of
thousands of stores of all types. Visual inspection of this relationship by product and store-by-store
generally yields similarly well-behaved linear relationships (with different slopes, as expected given
the different mean elasticity estimates for each store type and module); some additional examples
are in Online Appendix Figures 14a-b.

We provide two additional pieces of evidence validating the elasticity estimates for food stores in
Online Appendix Figures 14c-d. First, we document that the log price variable explains about half
of the remaining variation (in terms of $R^2$) after controlling for the fixed effects. Second, we run a
regression that pools across stores and augments equation (3) by including also the prices charged in
weeks $t - 2$ and $t - 4$, as well as in week $t + 4$. The coefficients on these variables, while statistically
significant and in line with the predictions of a model of stockpiling, are an order of magnitude or
more smaller than the coefficients on price in week $t$. Furthermore, they are not systematically larger
for storable products, like toilet paper and canned soup, than for non-storables, like orange juice
and yogurt.

Finally, we examine the correlates of our estimated elasticities. Figure 8d shows that the esti-
mated elasticities vary monotonically (and in fact linearly) as a function of store income. Table 5
presents store-level regressions of the estimated elasticities $\tilde{\eta}_s$ on a broader set of demographic and
competition measures. The results confirm the robust relationship between elasticity and income,
with an increase of $10,000 is associated with an increase of the elasticity of 0.140 (s.e. 0.014). This
estimate remains similar with the addition of chain fixed effects. In columns 3 and 4, we add as
determinants the share of college graduates, the median home price, and controls for the percent
urban share. We also add a simple measure of competition with other stores: indicators for the
number of other food stores within 5 kilometers of the store. The coefficients generally have the
expected sign, with income as the strongest determinant, and a weak, but correct-signed, effect of
the competition proxies.\textsuperscript{20}

The final four columns replace the estimated elasticity $\tilde{\eta}_s$ as the dependent variable with the log
elasticity term $\log\left(\frac{\bar{p}_s}{1+\tilde{\eta}_s}\right)$ suggested by equation (2). These regressions are the first-stage of the
instrumental variables regressions we estimate below. Income is a strong predictor of this term as
expected, with a coefficient that remains relatively similar across food, drug, and mass-merchandise
stores.

4.3 Comparing observed and optimal prices

In this section, we bring to the data the specification of equation (2), which optimal pricing as a
function of the store-level elasticity. In particular, we estimate

\textsuperscript{20}Column 5 in Online Appendix Table 3 shows that it is important to control for the percent urban variables, as
without those the competition variables have the opposite sign (though their effect is not significant).
\[ p_s = \alpha + \beta \log \left( \frac{\tilde{\eta}_s}{1 + \tilde{\eta}_s} \right) + \epsilon_s. \]  

Specification (4) follows from averaging equation (2) across products, and under the assumptions of the model the coefficient \( \beta \) on the log elasticity term is equal to 1. If the chains under-respond to the elasticity variation, instead, we will observe \( \beta < 1 \). For our benchmark specification, we instrument the log elasticity term with the store-level income to address remaining measurement error in these estimates.\(^{21}\) The standard errors are block bootstrapped, clustering by ‘parent_code’ in food stores and by ‘parent_code’*state in drugstores and mass-merchandise stores to allow for any within-chain correlation in errors. Figure 9 displays the first stage relationship between the log elasticity term and income within chain, between chains, and within and between chain-states. Unlike the analogous plots of the price-income relationship in Figure 5, the within and between relationships are remarkably similar, with a first stage coefficient varying between 0.03 and 0.055.

We estimate variants of this IV regression within and between chains and chain states. To compute within chain estimates we replace \( \alpha \) with chain fixed effects. To compute within-chain-state estimates we replace \( \alpha \) with chain-state fixed effects. To compute between-chain-state estimates we average \( p_s \) and the log elasticity term within chain states, and then run the regression including chain fixed effects. To compute between-chain estimates we average both terms within chains and then run the regression with no fixed effects. In all cases, we fix the first-stage coefficients at the values from the full sample shown in the final three columns of table 5. This is motivated by the similarity of the coefficients in Figure 9, and prevents us from losing first-stage power in the specifications where we aggregate the data.

Table 6 presents our main IV estimates. We begin with results for food stores. The first two columns show within-chain and within-chain-state results respectively. Both coefficients are statistically significant, but an order of magnitude smaller than the model prediction of \( \hat{\beta} = 1 \). This confirms that uniform prices do not simply arise because chains have no incentive to vary them.

The third column shows between-chain-state estimates. The results imply a substantial response of income to the elasticity term, though smaller than predicted by the model, \( \hat{\beta} = 0.351 \) (s.e. 0.193). Finally, the fourth column shows the between-chain estimates. The estimated coefficient on the log elasticity term in this between-chain regression, \( \hat{\beta} = 0.944 \) (s.e. 0.220), indicates that average pricing at the chain level is consistent with the model: we cannot reject a slope \( \beta = 1 \).

The second panel of Table 6 shows results for drug stores. They show a larger within-chain response, but still significantly smaller than predicted by the model: \( \hat{\beta} = 0.287 \) (s.e. 0.040). The between-chain-state relationship (zone pricing) is consistent with the model predictions: \( \hat{\beta} = 0.858 \) (s.e. 0.267). The results for the mass merchandise stores (Panel C) are intermediate between the ones for the

\(^{21}\) For this specification we winsorize the store elasticity \( \tilde{\eta}_s \) at -1.2. This happens very rarely in the case of our benchmark weekly elasticity estimates but more frequently for weekly index and quarterly top-product estimates.
food stores and those for the drug stores.

We present OLS estimates parallel to Table 6 in Online Appendix Table 4 and Online Appendix Figures 15a-d. We find qualitatively similar results, but the point estimates for the price-log elasticity relationship are about 3 times or more smaller. This may reflect measurement error in our estimated elasticities. It may also reflect a larger local average treatment effect due to variation in income being more salient to chains than variation in other determinants of elasticities. The OLS results reinforce the conclusion that the within-chain price-elasticity relationship is more than an order of magnitude too flat to be consistent with the model. However, the between-chain relationship in this case is clearly smaller than implied by the model.

4.4 Robustness

Table 7 presents a series of robustness checks, focusing on the results for food stores from the first panel of Table 6.

Larger Instrument Set. Panel A shows how the baseline results change when we instrument with the full set of demographic and competition variables shown in columns (3) and (4) of Table 5. Column (1) repeats the baseline within-chain specification. Columns (2) shows the results are similar with the larger instrument set. Column (3) shows this is true for the within-chain-state specification as well. Columns (4)-(5) repeat the baseline between-chain-state and between-chain specifications, and column (6) shows the between-chain specification results are similar with the larger instrument set.

Quarterly Elasticities. Our next set of results take one step toward addressing the fact that our short-run elasticities may differ from the longer-run elasticities that are relevant to the chains’ pricing problem, by using elasticities estimated at the quarterly level. Longer-run elasticities could be smaller due to stockpiling behavior, or larger if it takes consumers time to adjust to price changes—for example, if price increases cause them to gradually substitute to other stores. To address these concerns, we re-estimate all our elasticities at the quarterly level. That is, we average the weekly log price and log units sold across all weeks in a quarter, and then re-estimate our main equation (3). The controls in this case still include the year-product fixed effects as well as quarter-of-year*product fixed effects. The estimated quarterly elasticities are smaller (in absolute value) than the benchmark ones (Online Appendix Figure 17a), as expected, but the two measures are highly correlated (Online Appendix Figure 17b). Importantly, the quarterly elasticity measure passes the same validation exercises as our benchmark measure, as Online Appendix Figures 17c-e document: (i) the log-log specification is approximately linear; (ii) the standard errors of the estimated elasticity are still relatively small (at .15 to .4), even if clearly larger than in the benchmark elasticities, and (iii) the measure is still highly correlated with local income.

\[^{22}\text{We cluster the standard errors for the quarterly elasticities at the quarterly level, allowing for correlation across the 10 products.}\]
Panel B of Table 7 reports our main IV results using the quarterly elasticity measure. The finding that within-chain responses are an order of magnitude too small is robust to using the quarterly measure. In fact, the within-chain $\hat{\beta}$ coefficients become substantially smaller. This reflects two offsetting forces: the quarterly elasticities vary less across stores, which would tend to reduce the optimal price variation, but the fact that they are lower in magnitude increases the log elasticity term \( \log \left( \frac{\eta_s}{1 + \eta_s} \right) \) more responsive to a given change in elasticity. The smaller coefficient, and the consequently larger gap between actual and predicted price variation, means that the second effect dominates. The between-chain relationship is still an order of magnitude larger, but now significantly smaller than the model predicts ($\hat{\beta} = 0.340$).

**Module-Level Indices.** We next turn to another important limitation of our model, the fact that it ignores substitution between products. Firms care about the profits they earn from all products. If some of our response in our benchmark elasticities reflects within-store substitution, the optimal price response could be smaller than our model would predict. To partially address this issue, we re-estimate our elasticities using the module-level price and quantity indices described in Section 2.

As in the case of the quarterly elasticities, the module-level price elasticities are smaller (in absolute value) than the benchmark ones (Online Appendix Figure 18a), as expected, but highly correlated with the benchmark elasticity (Online Appendix Figure 18b). The index elasticity also passes the same validation tests (Online Appendix Figures 18c-e).

Panel C of Table 7 repeats our main results using the index elasticities. Here we continue to use the prices of our baseline products as the outcome; only the elasticity measure on the right-hand side is changed. As with the quarterly elasticities, this yields even smaller within-chain coefficients, meaning our main finding that chains vary prices too little from the model’s perspective is robust. Here we cannot re-estimate the between-chain specifications given that the price indices are not comparable across chains. In Online Appendix Table 5, Panel B we show that the within-chain results are similar using the price index as dependent variable.

**Other Products.** Panel D of Table 7, we use the 20th most-available good in each of the 10 product categories we use. There is no evidence that this different product makes a difference. Next, in Panel E, we consider the role of branding by a top-selling generic that is common to many chains within a subset of the modules considered. The within-chain relationship of pricing to income or elasticity remains very similar to the one for the top-selling branded good. In Online Appendix Table 5, we show that these patterns persist when using generic top sellers within chains (Panel C) and some high-quality (high-price) products (Panel D).

**Yearly Average Price Paid.** Our main question of interest is how the pricing decisions of firms compare to the benchmark of optimal pricing, and we are therefore interested mainly in the prices firms choose to post. As highlighted in the discussion in Section 3.4, variation in posted prices can
differ from variation in prices paid. If we are interested in the welfare effects on consumers, however, we may also want to consider the average price paid over longer time horizon. When prices vary over time, more elastic consumers could end up paying substantially lower prices on average than less elastic consumers even if the posted prices they face are the same.

To assess how large this force could be, we can aggregate the data further and look at variation in average prices paid at the yearly level. In Table 8 we present the regression results for our benchmark IV strategy, comparing the results for yearly average prices (Panel B) to our benchmark results on weekly average prices (Panel A). In particular, in Panel B, instead of using the log of the weekly average price, we use as the dependent variable the log of the yearly average price. The within-chain coefficient ($\hat{\beta} = 0.223$), while more than twice as large as the benchmark estimate in Panel A, is still 5 times smaller than the model prediction under our benchmark of optimal pricing ($\beta = 1$). Thus, even taking into account this margin of adjustment does not bring the level of prices up to what is expected in light of the model. Still, it is interesting to note how the presence of sales works as a kind of “automatic stabilizer,” guaranteeing that consumers in more-elastic stores pay lower prices over the year, even in presence of uniform pricing.

Online Appendix Figures 19a-d reproduce the key findings in Figure 5a-d, comparing the yearly average price to the weekly average price. As expected, the yearly average price is more responsive to within-chain differences in income than the weekly average price (Online Appendix Figures 19a and 19c), with a slope that is about twice as steep. Similarly, the between-state zone-pricing relationship is also stronger using the yearly average price (Online Appendix Figure 19d). The between-chain relationship for food stores, instead, is not much affected (Online Appendix Figure 19b).

### 4.5 Lost Profits

An important implication of the model is that it allows us to compute the profits firms sacrifice as a result of uniform pricing. More precisely, we estimate the profits under optimal pricing, under the observed pricing, and under (fully) uniform pricing. The profits in store $s$, summing over the products $j$, are

$$\Pi_s(P_{sj}) = \sum_j P_{sj}k_{sj}P_{sj}^{\eta_s} - c_{jc}k_{sj}P_{sj}^{\eta_s} - C_s, \quad (5)$$

Consistent with our previous assumptions, we let the marginal cost $c_{jc}$ vary by chain $c$, but assume it does not vary across stores within chain. Expression (5) also allows for a store-level fixed cost $C_s$.

To compute the optimal and actual profits, we need estimates for the demand term $k_{js}$ and for the marginal costs $c_{jc}$, in addition to the elasticities $\eta_s$ which we already estimated. To estimate the marginal costs $\hat{c}_{jc}$, we assume that chains set their average prices optimally, consistent with the findings above. This yields

$$\hat{c}_{jc} = \frac{\sum_{s(c)} P_{sj} \frac{\eta_s}{1+\eta_s}}{\sum_{s(c)} \frac{\eta_s}{1+\eta_s}}.$$
where \( s(c) \) is the set of stores \( s \) belonging to chain.\(^{23}\) To estimate the quantity term \( k_{sj} \), we use 
\[
\hat{k}_{sj} = Q_{sj} / P_{sj}^{\eta_s},
\]
where \( Q_{sj} \) is the average over all weeks \( t \) of the quantity sold \( Q_{sjt} \).

To compute the optimal profits \( \Pi^*_s \), we then assume that the stores charge the optimal price 
\[
P_{sj}^* = \hat{c}_{jc} \ast \hat{\eta}_c / (1 + \hat{\eta}_c).
\]
To compute the uniform-pricing profits \( \Pi_s \), we assume that the chain firms respond to the average elasticity in chain \( c \) \( \hat{\eta}_c \): 
\[
P_{j} = \hat{c}_j \ast \hat{\eta}_c / (1 + \hat{\eta}_c).^{24}\] Finally, for the actual profits \( \Pi_s \) we use the prices implied by our benchmark IV specification: 
\[
P_{sj} = \hat{c}_{jc} \ast [\hat{\eta}_c / (1 + \hat{\eta}_c)]^{\beta_{IV}},
\]
where \( \beta_{IV} \) is the estimate in Column 1 of Table 6. To be clear, \( \hat{\eta}_c \) is our shrunk elasticity estimate for store \( s \), not a predicted elasticity using income.

We then sum the profit expressions across all stores \( s(c) \) belonging to chain \( c \) and can compute the percentage loss in profit from uniform pricing as
\[
\frac{\Pi^*_c - \Pi_c}{\Pi^*_c} = \frac{\sum_j P_{sj}^* \hat{k}_{sj} P_{sj}^{\eta_s} - \hat{c}_{jc} \hat{k}_{js} P_{sj}^{\eta_s} - \sum_j \hat{P}_j \hat{k}_{sj} \hat{P}_j^{\eta_s} - \hat{c}_{jc} \hat{k}_{js} \hat{P}_j^{\eta_s} - C_s}{\sum_j P_{sj}^* \hat{k}_{sj} P_{sj}^{\eta_s} - \hat{c}_{jc} \hat{k}_{js} P_{sj}^{\eta_s} - C_s}.
\]

The percent change in profits is thus identified up to the fixed cost term \( C_s \). We follow Montgomery (1997) in assuming that the fixed costs are a fixed percentage of profits. Montgomery (1997) estimates that gross profit margins for supermarkets of 25 percent, and operating profit margins of 3 percent, implying that the share of fixed costs in gross profits is \( 22/25 = 0.88 \). We thus assume that fixed costs \( C \) are 88 percent of gross profits also in our setting, and thus multiply the profit loss by \( 1/(1-0.88) = 8.3 \).

In the first row of Panel A of Table 9 we display the distribution of the average percentage loss in profits across food chains. The mean loss from full uniform pricing, compared to optimal pricing, is quite large, at 10.3%. The mean loss for the actual price-elasticity slope is 7.8% on average across chains. The table also shows the loss of profits relative to state-zone optimal pricing, where prices are set optimally, but are uniform at the state level: this would reduce the losses, but not by much, reflecting the fact that most of the variation in elasticity occurs within state, not across states. The next two panels document the profit losses for the drugstores (Panel B) and the mass merchandise stores (Panel C), which show similar patterns.

## 5 Explanations

In the previous section we documented a set of findings about firm pricing in retail stores, and most importantly: (i) the large majority of chains charge largely uniform prices across all their stores, and thus do not respond to local income, or local demand elasticity; (ii) the chains do appear to instead respond to local income in setting the overall level of prices in their stores, with magnitudes
\(^{23}\)Notice that we are not assuming that each store \( s \) is maximizing profits, which would be contrary to our finding of uniform pricing. Rather, we only making the much weaker assumption that each chain sets on average the right prices chain-wide. The price \( P_{sj} \) in this expression is the average over all weeks \( t \) of the price \( p_{sjt} \).
\(^{24}\)While this is not the optimal uniform price, simulations suggest that it does not deviate much.
approximately consistent with what one would expect given a simple monopolistic competition model; (iii) for a small number of chains that do zone pricing, the pricing across the zones does respond to local income; (iv) the magnitude of the losses from price uniformity is sizable, on the order of 8 percent of profits at the chain level.

We now consider which explanations may make sense of these facts. Some traditional explanations do not appear to apply to this setting, among them menu costs (Mankiw, 1985). Grocery stores change prices regularly to implement sales. Thus, it is implausible that a menu cost limits the ability to set different prices at the store level, especially since store-level heterogeneity in income is persistent, and thus local prices would have to be updated only rarely.

A behavioral explanation that is also implausible in this setting is that firm managers have **limited attention** (e.g., Gabaix and Laibson 2006) with respect to the determinants of optimal pricing at the store level. It is hard to imagine that managers are literally not aware, or even optimally inattentive, with regards to the local incomes or price elasticities, given their access to data, and to consulting firms in this regard, and especially the fact that we examine the role of local income, averaged over several years. This is an obvious variable to observe.

A possibility is that the price uniformity may be due to a constraint posed by the advertising of coupons. Most likely, the advertising markets are the Nielsen DMAs. Thus, advertising constraints would tend to force price uniformity within a DMA, the relevant advertising zone, but not between DMAs. In Online Appendix Figures 20a-b we compare the zone pricing at the state level to the zone pricing at the DMA level (after taking residuals for state-chain fixed effects). We find less evidence of zone pricing at the DMA level than at the state level. Thus, it does not appear that firms are designing their pricing around advertising constraints.

Another possible explanation is that committing to uniform or zone pricing benefits chains by allowing them to soften price competition. Dobson and Waterson (2008) present a model of this **tacit collusion** explanation, and Adams and Williams (2017) find mixed support for it using data from the hardware industry. To test for it in our context, we compare the within-chain response of prices to income for stores with no competitors nearby, and for stores with 2+ competitors nearby (Online Appendix Figures 21a-b). If tacit collusion binds individual stores, we would expect more price response to income in the absence of local competitors. It is also possible that the pricing decisions are made at the chain level and thus we compare the extent of non-uniform pricing as a function of the stores in a chain that are isolated (that is, with no competitors nearby) (Online Appendix Figures 21c-d). Either way, we do not find much evidence supporting this model in our setting.

We discuss more in detail two remaining explanations. The first is one of managerial decision-making costs, or **managerial inertia**. Managers may perceive a cost in deviating from the traditional pricing in the industry, which has indeed been, it turns out, uniform pricing. The managers
may not be well incentivised to take the change, while fearing the cost in case a price change backfires.

A different explanation is that managers would like, per se, to price to the local demand elasticity, but they refrain from doing so because of fairness concerns among consumers. If consumers respond negatively to price differentiation across the stores, perhaps by boycotting a chain, tailoring prices to a store may not be worthwhile. There is certainly anecdotal evidence that fairness constraints may matter. In a report on the UK grocery pricing, the UK Competition Commission writes “Asda said that it would be commercial suicide for it to move away from its highly publicized national EDLP pricing strategy and a breach of its relationship of trust with its customers, and it would cause damage to its brand image, which was closely associated with a pricing policy that assured the lowest prices always” and “Morrisons stated that adopting a policy of local prices would be contrary to its long-standing marketing and pricing policy, it would damage its brand and reputation built up over many years and would adversely affect customer goodwill, as well as being costly to implement and manage.” (Competition Commission, 2003)

We test for it in our context in a way that mirrors our tests for tacit collusion: we compare the within-chain response of prices to income for stores with no stores belonging to the same chain nearby, and for stores with 2+ stores belonging to the same chain nearby (Online Appendix Figures 22a-b). If fairness binds individual stores, we would expect more price response to income in the absence of stores of the same chain. It is also possible that the pricing decisions are made at the chain level and thus we compare the extent of non-uniform pricing as a function of the stores in a chain that are isolated (that is, with no other stores belonging to the same chain nearby) (Online Appendix Figures 22c-d). Either way, we do not find much evidence supporting this model in our setting.

The two models—managerial inertia and consumer fairness—share some common components. In both cases, the model is consistent with the between-chain results, as firms can still set the right overall level of prices, even as they are concerned, or inertial, about store-specific pricing. In addition, we can model both explanations in terms of the firm facing a fixed cost in deciding whether to price flexibly (as opposed to uniformly). The fixed cost captures either the managerial cost or the expected fairness cost of pricing to market. More precisely, assume that for each store \( s \) the firm chooses to price to elasticity if

\[
\max_{p_{s,j}} \sum_j p_{s,j} q_{s,j} (p_{s,j}) - c_{s,j} q_{s,j} (p_{s,j}) - C_s - K \geq \max_{\bar{p}_{j}} \sum_j \bar{p}_{j} q_{s,j} (\bar{p}_{j}) - c_{s,j} q_{s,j} (\bar{p}_{j}) - C_s.
\]

That is, the firm decides whether to price to store \( s \), incurring a fixed cost \( K \), or instead set an overall uniform price \( \bar{p}_j \), which maximizes profits subject to uniform prices. To be more precise, the fixed costs could apply to two levels. First, the firm could decide store-by-store whether to price to elasticity in store \( s \); in this interpretation the fixed cost \( K \) is per store that is not priced uniformly.
Or the firm could decide at the chain level whether to price uniformly, or price to elasticity in every store; in this case, the fixed cost $K$ is firm-wide. Under either interpretation, the fixed cost captures the managerial costs or anticipated risk of negative publicity from consumers.

In the first version—that the fixed cost applies at the store level—we expect a threshold policy, in which firms will be more likely to price to store for stores with elasticities more substantially different from the average elasticity, since for these stores the average price $\bar{p}$ is more distant from the optimal prices, and thus the losses larger. Thus, if we rank stores within a chain by elasticity, or an elasticity determinant such as income, we should be more likely to see store-specific pricing for stores at the tails of the distribution. With this in mind, we revisit Figure 5a, which displays a bin scatter of within-chain prices as function of within-chain variation in income. The graph shows no evidence that the more extreme bins (for stores with about $15,000 higher, or lower, income than average for the chain) behave differently from the other stores. Rather, they are on the regression line. Thus, the evidence does not seem to support for this version of the fixed cost model, unless one assumes extremely high costs.

In the second version, the decision is considered at the chain level: the chain computes if the gain from targeted pricing in (6) is larger than the fixed cost $K$. For each chain, assuming constant marginal costs, we compute the optimal profit under flexible pricing versus with uniform pricing, as outlined in Section 4.5. Chains with a wider distribution of elasticities across their stores will have a larger estimated loss from uniform pricing. The x axis on Figure 10a shows the distribution across chains of this measure which varies from 2-3 percent of profits to over 20 percent of profits. On the y axis, this scatterplot displays for a chain the average quarterly absolute price difference, our measure of price dissimilarity across stores. In Figure 10b, on the y axis we show the chain-level price response to elasticity instrumented with income. Both figures show a weak, though, positive association between loss of profits and dissimilarity of pricing.

Overall, this evidence suggests that the the implicit costs of flexible pricing are large, in the range of 10-20 percent of profits. This suggests that firms believe in very large costs from consumers perceiving unfair pricing, or that managerial inertia has very sizable costs.

A final explanation that we consider is firm learning: firms may be learning to price to elasticity, especially as access to data increases. While learning is not an explanation of the average finding, it is interesting to ask whether firms are moving over time to flexible pricing from the first years in our sample (2006-08) to the most recent years (2012-14). Online Appendix Figures 23a provides no evidence that this is the case for food stores or mass-merchandise stores: the overall within-chain price-income relationship has remained about the same in the early versus later years. On the other hand, it does appear that drugstores may have gotten more responsive to income over time, as shown in Online Appendix Figure 23b. Online Appendix Figure 23c shows all of the price vs. income coefficients (non-instrumented) for each chain. Overall there is no trend but some individual chains
do better in the later period. Note that our income measure does not vary over time; it remains the 2008-2012 5-year ACS estimate regardless of the time period of prices.

6 Implications

In this Section, we consider the implications of our findings of price uniformity for a variety of economics contexts.

6.1 Inequality

Jaravel (2016) among others brings attention to the role of store pricing for the rise of inequality in the past decades, and shows that the introduction of novel products catering to higher-income consumers lowered the price for such goods, itself contributing to rising income inequality.

As we document now, price rigidity by retail stores has implications for inequality as well. In particular, we compare the observed average level of prices in areas with different income, with the counterfactual level of prices that one would expect if firms priced flexibly as in our benchmark model. We compute the observed level of prices at a particular income level by simply taking the average price charged by stores with local income in that range. For the counterfactual, we compute the optimal price under flexible pricing, taking the observed income of stores as a given. We do this for food stores (Figure 11a), drugstores (Figure 11b) and mass-merchandise stores (Figure 11c).

As the blue circles in Figure 11a show, areas with higher income have higher average prices: an extra $10,000 of local income increases prices in average by about 2 percent. This relationship is consistent with our between-chain relationship (e.g., Table 6 Column 4): chains operating in higher average income areas charge higher prices. Yet, this price-income slope is much flatter than expected if firms were pricing flexibly to the elasticity. Under flexible pricing (green points), the price increase associated with $10,000 higher local income would be about a 5 percent increase, more than twice as large. The difference occurs because of the lack of within-firm pricing variation, which thus flattens the response. The pattern is similar for drugstores (Figure 11b). For mass-merchandise stores, the observed price-income relationship is in fact negatively sloped, due to the fact that of the two major chains, the one operating in higher income areas has lower prices. Even there, the counterfactual price (green dots) has a more positive slope with respect to income.

These patterns have quantitatively important implications for inequality: by this calculation, low-income areas (average income of about $20,000) pay about 3 percent higher prices than they would pay under flexible pricing, and high-income areas (average income of about $60,000) pay about 8.5 percent lower prices than under flexible pricing. Thus, price rigidity contributes in a quantitatively important way to inequality. It is not obvious, though, that it would contribute to increases in inequality, as opposed to a level effect that is constant over time. Importantly,
consolidation between retailers could increase this pattern.

An interesting aspect of this finding is that it runs counter to the fairness explanation outlined above. Uniform pricing actually triggers “unfair” pricing in the sense of increasing inequality.

6.2 Response to local shocks

A second implication of our findings relates to the response of local prices to macroeconomics shocks (Beraja, Hurst, and Ospina, 2016; Stroebel and Vavra, 2014). Our results imply that the response of prices to demand shocks will be smaller for local shocks than for economy-wide shocks. This occurs because chains that charge uniform pricing will respond to economy-wide shocks in their overall price level, but they will respond to local shocks only to the extent that the local shocks affect a sizable fraction of their stores. Given that most chains span several states, a localized shock will induce a fairly small local response.

We provide a calibration of the size of the effects in Table 10 for food stores. We predict the response to a 1% income shock using the estimated store response to own and chain average income as in Table 4, Column 2. We do this separately for simulated shocks occurring at the county, DMA, state, and national level and for two different price variables: our benchmark price variable (the average weekly price), which is closest to the price posted by the stores, and the average yearly price, which more closely tracks the price paid by consumers taking into account the inter-temporal substitution. The percentages shown are the response to a 1% income shock in the indicated locality as a percent of the response of a 1% nationwide shock.

The table indicates that the response to a state-level shock would be only 50 percent (Column 1) or 57 percent (Column 2) as large as the response to a nation-wide shock. This is because many chains are spread across state lines, and would thus respond imperfectly to a local shock. The response drops to 18 percent (Column 1) or 30 percent (Column 2) for shock that occurs at the county level. This exercise, thus, suggests that price uniformity can have first-order implications for the response of prices to macro shocks.

6.3 Incidence of trade costs and taxation

A third implication of uniform pricing relates to the estimation and incidence of trade costs. A large literature estimates trade costs by examining differences in the prices of specific products at geographically separated retail stores. Prior studies are surveyed by Fackler and Goodwin (2001) and Anderson and van Wincoop (2004). As a recent example, Atkin and Donaldson (2015) use prices in the Nielsen RMS data to estimate trade costs, accounting explicitly for the source locations of the products and the possibility of spatially varying markups.

Setting aside for a moment the adjustment for markups, this strategy will estimate trade costs to be larger the more prices vary across space. Uniform pricing would thus lead trade costs to be
underestimated. At an extreme, if all stores were owned by a single chain that practiced uniform pricing, the estimated trade costs would be zero. In the observed data, the extent to which they are underestimated will depend on the size and geographic distribution of chains.

How would uniform pricing affect adjustments for markups? Atkin and Donaldson (2015) propose an innovative strategy that infers the extent of market power from the observed passthrough of price shocks in origin locations to prices in stores further away. While they would ideally use the origin wholesale price, this is not available in the data so they use the origin retail price as a proxy. Uniform pricing will tend to increase the estimated passthrough, as it increases the correlation between changes in retail prices in the origin with prices in other markets. It will therefore tend to reduce the level of estimated markups, while (correctly) implying less variation in markups across space. The extent of these effects again depends on the size and distribution of chains.

Both of these points relate to the estimation of trade costs. Uniform pricing also affects the true incidence of these costs. Just as we noted above that uniform pricing tends to raise prices in high-income areas and lower them in low-income areas, so too here it will tend to raise prices in locations close to where products are produced and lower them in remote locations. It thus shifts the incidence of trade costs away from those who actually purchase transported goods and toward those whose goods travel shorter distances.

7 Conclusion

In this paper, we show that most large US grocery and drug-store chains in fact set uniform or nearly-uniform prices across their stores. We show that limiting price discrimination in this way costs firms significant short-term profits. We find managerial costs to be the most plausible explanation for this pattern, possibly along with consumer fairness concerns. We show that the result of nearly-uniform pricing is a significant dampening of price adjustment, and that this has important implications for the pass-through of local shocks, the incidence of trade costs, and the extent of inequality.
References


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A Appendix

A.1 Data

A.1.1 Store Selection.

In the RMS data, Nielsen provides a basic categorization of stores into five “Channel Codes”: Convenience, Food, Drug, mass-merchandiser, and Liquor. In the HMS 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 the food stores selected in the final sample fall into the “Grocery” store category in the HMS channel code categorization.

Store open and close. Our elasticity estimates are potentially biased by stores entering and leaving the Nielsen dataset (which could be due to things like especially low “closeout” prices or low quantities due to stockouts). We do the same pooled linearity plots (residuals of logP and logQ after removing seasonality and module FE) and look only at the residuals from the weeks one month after entering and prior to leaving the sample. These points are not concentrated in any particular region and still appear near the line of best fit for all store-weeks. We also plot price and quantity sold over time for individual entering and leaving stores. Although some stores have lower quantity sold prior to exiting the sample, overall there are no uniform patterns across stores.

A.1.2 Product selection

We select 10 modules (product categories) based on commonly available and highly-sold products. These products include five that belong to product groups used in Hoch, Kim, Montgomery, and Rossi (1995) (soup, cookies, OJ, soda, and toilet paper), as well as products used in Montgomery (1997) (OJ).

Within a module (e.g., soda), we select a high-selling product (e.g., 12-pack cans of Coke). The product choice aims to ensure that (i) the product is available across as many chains and stores as possible (to ensure comparability across stores and across chains), and that (ii) within a store, it is sold in as many weeks of the year as possible (since otherwise the price is not recorded). Formally, we select the top-availability UPC as the product within a module-year with the highest number of week-store observations with positive sales. We do this for each module, repeatedly year by year. For three modules, this determines the selected product, which thus varies across the years. For the remaining 7 modules, we modify this procedure to be able to keep a constant product across all years. Namely, we consider all products that are present in all nine years, and whose coverage is at most 10 percentage points below that of the top product in a given module and year. Among these, we select the product with the highest availability across years as defined above.

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

For the 3 other modules, it was not possible to find a constant product across the years without sacrificing too much the availability objective.

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For Drugstores, we replace the top-availability soda UPC with the fifth-availability soda UPC as the top four products go on temporary price reductions extremely rarely and thus bias our elasticity estimates towards zero.

The “generic top-seller within chain” selection is done at the chain level, considering only generic products. We use the Nielsen identifier “CTL BR” to identify (masked) store-brand products. The products that we select in each module across chains may not be comparable.

We choose a different set of generic products to make between-chain comparisons of generic product pricing possible. The procedure is identical to our product selection procedure for top products except that we consider only generic products instead of excluding them. This is possible because Nielsen assigns the same (masked) UPC to products it deems similar. We make a further refinement to ensure that they are products of similar quality: we require that the average price for each store-product is within 20% of each other for stores in the same DMA. However, many of our top branded products actually fail this test so we are erring on the side of being too strict with this requirement. Still, for many products we still have low availability. We consider only the four modules with the highest availability—all above 80%—across all stores (soup, cookies, soda, and yogurt) and construct a pooled price level including only these products.

A.1.3 Prices.

**Week offset.** To be more precise, prices and units are aggregated over the period Sunday to Saturday for most but not all retailers. According to Nielsen: “For scanning data, not all retailers provide weekly data using a Sunday to Saturday definition. Some retailers provide data based on their promotion week, which varies by retailer. Nielsen maps non-Saturday ending weeks received from retailers to the best fit Saturday.”

**Suspiciously low prices.** We noticed that there are 1,118 observations of price = .01 and units sold < 10 in the top products we select. Since most of the products have average prices above .50 (see Table 2), and because there is no associated spike in units sold, we believe that these observations are invalid. There are similar issues of lesser frequency with prices between .02 and .10. We decide to drop all prices ≤ .10 as our log-log elasticity estimation is very sensitive to these outliers.

A.1.4 Pairs Dataset for the Analysis of Store Pricing Similarity

We have a more stringent store selection criteria for the pairs data. Since the measures are pairwise at the weekly (or quarterly) level, we want to ensure a sufficient number of overlapping weeks in each pair. To do this, we define a valid module as a module with non missing observations for at least 60% of all possible weeks (quarters with at least 6 weeks of non missing data within each quarter) over the nine years of data. For a store from our sample of 9,415 stores to be eligible for the

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27Our understanding is that Nielsen only guarantees identically-sized products when assigning products the same UPC.

28Note that these are all possible weeks out of nine years, i.e. 468 weeks. This is different than our availability measure, where the denominator is the number of weeks where the store has nonzero sales in all products in the ten modules we select.
pairs data, we define stores with at least 7 out of the 10 modules valid by this definition to be “good stores.” For each chain, we first sample from the good stores. The remaining stores are sampled if necessary. We emphasize again that the average quarterly log price that we use is the unweighted average log weekly price.

In the within-chain pairs data, we limit the number of stores in each chain to 400 for computational reasons (since the number of pairs scales with the number of stores squared), and we further limit the number of stores per chain to 200 in the distributional histograms for weighting reasons. Out of the 64 chains we select, only five chains have more than 400 stores and only ten chains have more than 200 stores.

For the between-chain pairs, we begin with the set of stores that we sampled for the within-chain pairs. First, we sample one store per chain-DMA if there are multiple chains in the DMA. If only one chain operates in the DMA, we sample two stores. We then drop stores from oversampled chains to reduce the sample to a total of two stores per DMA, with one caveat: we do not drop any chain completely, so some DMAs do have more than two stores in the final between-chain sample.

A.1.5 Demographics

All demographics are zip-code level data from the 2008-2012 5-year ACS. These years represent the middle five years of the Nielsen sample (which covers 2006-2014). We explain how we aggregate this zip-code level demographics into store-level demographics in Section ??.

There is one store in our sample that has 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 percent urban) on our sample of 9,415 stores. There are three drugstores that are only visited by one household each which reports a PO Box zip code as its zip code. We use county-level demographics for these three stores.

A.1.6 Competition Measures

We use the HMS panel data to help us construct a measure of competition based on geodesic distance. First, we assume that each HMS household lives at the center of its zip code. For each of the stores in the HMS dataset\footnote{Since we are not concerned about ownership in this measurement, we use all food stores in the dataset, not just the 9,415 in our sample (that we are confident we can assign to a chain). On the other hand, we do not track store opening and closing so we are implicitly assuming that if the store is open at all within the nine years, it is open for the entirety of 2006-2014.}, we use a trip-weighted average of the coordinates of each household in order to arrive at an imputed location for the store. We then count the number of stores within various distances of each store by geodesic distance\footnote{i.e. distance as the crow flies}.

A.1.7 Matching Stores from Nielsen RMS to Major Grocer Data

We choose the retailer that has the most stores in the Major Grocer Data. The two datasets have about 1.5 years of overlap covering all of 2006 and part of 2007. While the data from the Major Grocer has 5-digit zip codes, Nielsen data only has 3-digit zip codes. We thus take the sum of units...
sold in 2006 for our top products in 10 modules in both the Major Grocer data and for all stores in the Nielsen sample. We then use the Stata user-defined function (.ado) reclink and perform a fuzzy match, requiring a match of 3-digit zip code and allowing the sum of units sold (in string form) to be slightly mismatched. This results in 134 matches belonging to a single Nielsen retailer_code and 1 match belonging to a different retailer_code. We then limit the set of stores in the Nielsen data to those from the majority retailer and perform the fuzzy match again, but we continue to fail to match the single store. To check the matches, we use a different “manual” matching method where we round each 2006 yearly units sold in both the Nielsen and Major Grocer datasets to the nearest 2% or 5, whichever is larger. We then examine the best matches belonging to each store-module. The modal store always matches the result we obtain using reclink.

### A.1.8 Imputing Nonsale Prices from Nielsen RMS Data

We attempt to extract nonsale prices from the average prices in the Nielsen RMS Dataset. First, we only want to consider prices that are “high enough.” For each store-year-module, define $p_{s,j,y}^{80}$ to be the 80% percentile price in store $s$, year $y$, and module $j$. Then, we want to ensure that there is only one unique price charged during the week by keeping week $t$ if and only if the same price is recorded for three weeks in a row (or two weeks in a row for the first and last weeks of each year): $p_{s,j,t} = p_{s,j,t-1} = p_{s,j,t+1}$ for $t \in \{2,51\}$, week 1 if $p_{s,j,1} = p_{s,j,2}$, and week 52 if $p_{j,52} = p_{j,51}$. From this set of “unique” price-weeks, we keep only those where $p_{s,j,t} \geq p_{s,j,y}^{80}$. We then calculate the price level as detailed in Section 3.3, with the one difference that we omit any years with missing prices from the average. The value that we demean each store-module-year’s price by remains the average of all prices, as opposed to the average of nonsale prices.\footnote{This is done both because not all store-years have valid nonsale prices and to facilitate comparisons between this price measure and our benchmark measure}

We compare the results we get using this algorithm with the data from the Major Grocer. We ignore the week offset and match the first week in the Nielsen data to the first week of the Major Grocer data, the second week to the second, and so on. Almost all store-product-weeks match the Major Grocer true price data exactly, and in fact the discrepancies seem to be an issue with the MG data (for example, yogurt price of .7945936). There are also a few cases where the MG nonsale price is .80, the MG true price is .75, and this is a “sale” that lasts longer than three weeks so we categorize .75 as a nonsale price as it is above the 80th percentile of yearly prices.\footnote{This should not matter because the weeks that we keep in the Nielsen nonsale price are in the middle of a period where the price does not change anyways}
Figure 1. Examples of Uniform Pricing
Figure 1a. Pricing for Chain 128, Orange Juice

Notes: Plots depict demeaned log prices. Darker colors indicate higher price and are blank if price is missing. Each column is a week. Each row is a store, and stores are sorted by measure of store-level income per capita. In Figure 1a, dividers are $10,000s. In Figure 1b, the same 50 stores appear for each product.
Figure 2. Example of Zone Pricing: Chain 130, Orange Juice

Notes: Plots depict demeaned log prices. Darker colors indicate higher price and are blank if price is missing. Each column is a week. Each row is a store, and stores are sorted by three-digit zip code within each state divider.
Figure 3. Similarity in Pricing Across Stores: Same-Chain comparisons versus Different-Chain Comparisons.
Figures 3a-b. All pairs. Quarterly absolute difference in log prices and weekly correlation of log prices

Notes: Each observation is a store-pair. "Same chain" means same retailer_code. "Different chain" means both different retailer_code and different parent_code. Figures 3a-b show the relationship for all store-pairs. Figures 3c-d restricts the sample to pairs in different DMAs and where one store is in the top 33% of nationwide income and the other is in the bottom 33%. Quarterly Absolute Log Price Difference is Winsorized at .3 and Weekly Correlation is Winsorized at 0. A maximum of 200 stores per chain are used in the same chain distributions to avoid overweighting the 10 largest chains. See Appendix Section A.1.4. for details on how we formed the different chain sample.
Figure 4. Similarity in pricing, Chain-Level Measure
Figure 4a. Quarterly Similarity in Pricing versus Weekly Correlation of Prices, by Chain

Figure 4b. Within-State Price vs Between-State Price Quarterly Absolute Log Price Difference by Chain

Notes: Circles represent food stores, diamonds represent drugstores, and squares represent mass-merchandise stores. In Figure 4b, each observation is a chain that operates at least three stores in multiple states. Chains that differentiate pricing geographically are labeled. For computational reasons, a maximum of 400 stores per chain are used, which affects only the largest nine chains.
Notes: Standard errors clustered by parent_code. Axes ranges have been chosen to make the slopes visually comparable. Analytic weights equal to the number of stores in each aggregation unit are used in Figures 5b and 5d. In Figure 5a, residuals are after removing Chain FE. In Figure 5c, residuals are after removing ChainXState FE. In Figure 5b, labels indicate Chain. If we exclude outlier Chains 98 and 124, the regression results become .0395 (.1119). In Figure 5d., each observation is one of 25 bins of chain-state averages.
Figure 6. Zone Pricing

Figure 6a. Food Stores (All Chains), State Zones

Figure 6b. Food Stores (Zone-Pricing Chains Only), State Zones

Figure 6c. Drug Stores, State Zones

Figure 6d. Mass Merchandise Stores, State Zones

Notes: Standard Errors are clustered by parent_code* state. In Figure 6a., each observation is one of 25 bins of chain-states. In Figures 6b., 6c., and 6d., each observation is an individual chain-state for the chain indicated.
Figure 7. Price Response to Income: Investigation using Major Grocer Data

Figure 7a. Nielsen Data: Average Weekly Price

Figure 7b. Data from Major Grocer: Average weekly price

Figure 7c. Data from Major Grocer: Nonsale Price

Figure 7d. Data from Major Grocer: Wholesale Cost

Notes: Stores were matched using 3-digit zip code and total 2006 yearly expenditure for the 10 products we selected (See Appendix Section A.1.7. for more details). In each figure, there are 20 quantiles representing 133 stores from the Major Grocer. Values plotted are the residuals after removing state fixed effects, and robust standard errors are used. Price levels are based on are 2006 top-product prices only and are thus not identical to our benchmark top-product price level. Wholesale Cost (Figure 7d) does not include transport or storage costs and is before supplier discounts.
Figure 8. Elasticity Estimates and Validation

Figure 8a. Elasticity Estimates

Figure 8b. Elasticity Estimates: Distribution of Standard Errors

Figure 8c. Validation I. Linearity of Log Q and Log P

Figure 8d. Validation II. Relationship with store-level income

Notes: Figure 8c. 50 quantiles representing 60,552,601 store-module-weeks. Residuals are after taking out module*week of year and module*year FE. Figure 8d. 50 quantiles representing 22,680 stores. Residuals are after removing Chain FE. Standard errors are clustered by parent_code.
Figure 9. Elasticity versus Price, Instrumenting with Income, First Stage

Figure 9a. First Stage, Income and Elasticity within chains

Figure 9c. First Stage, within chain-state

Figure 9d. First Stage, Income and Elasticity, Between Chain-State Averages

Notes: Axes ranges chosen to make slopes visually comparable. Standard errors are clustered by parent_code in Figures 9a, 9b, and 9c and are clustered by parent_code*state in Figure 9d. Figure 9a: 50 quantiles representing 22,680 stores. Residuals are after removing Chain FE. Figure 9b: The Chain-level average log(e/(e+1)) was calculated by Winsorizing elasticity first and then taking the average log(e/(e+1)). Figure 9c: 50 quantiles representing 22,680 stores. Residuals are after removing ChainXState FE. Figure 9d: 25 quantiles representing 396 chain-state means. Residuals are after removing Chain FE.
Figure 10. Profit Loss from Uniform Pricing Versus Price Uniformity at Chain Level.

Figure 10a. Quarterly Absolute Log Price Difference vs. Simulated Lost Profits

Figure 10b. Chain-Level Price Response to Elasticity (IV) vs. Simulated Lost Profits

Notes: We approximate Operating Margin as 8.333*(variable costs) based on estimates from Montgomery (1997). Elasticities are Winsorized at -1.2 prior to calculating theoretical lost profits. Dashed vertical line indicates median value of 7.88%. Chain 295 (simulated 84% lost profits) has been omitted from both the scatterplot and the regression line. Figure 10a. The coefficient including Chain 295 is .0020 (.0006). Figure 10b. The coefficient including Chain 295 is .0121 (.0046).
Figure 11. Price Rigidity and Inequality: Prices in Areas with Different Income.

Figure 11a. Food Stores

Figure 11b. Drugstores

Figure 11c. Mass Merchandise stores

Notes: Counterfactual Price uses flexible pricing, applying the model of monopolistic competition to each chain but fixing the average chain price level relative to other chains unchanged from observed relationships. See Online Appendix Figure 24 for versions that do not preserve the average chain price level and using predicted elasticities for food stores.
### Table 1. Sample Formation and Summary Statistics: Stores and Chains

<table>
<thead>
<tr>
<th>Panel A. Sample Formation</th>
<th>No. of Stores</th>
<th>No. of Chains</th>
<th>No. of States</th>
<th>Total Yearly Revenue</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial Sample of Stores</td>
<td>38,539</td>
<td>326</td>
<td>48+DC</td>
<td>$224 billion</td>
</tr>
<tr>
<td>Store Restriction 1. Stores do not Switch Chain, ( \geq 104 ) weeks</td>
<td>24,489</td>
<td>119</td>
<td>48+DC</td>
<td>$193 billion</td>
</tr>
<tr>
<td>Store Restriction 2. Store in HMS dataset</td>
<td>22,985</td>
<td>113</td>
<td>48+DC</td>
<td>$192 billion</td>
</tr>
<tr>
<td>Chain Restriction 1. Chain Present for ( \geq 8 ) years</td>
<td>22,771</td>
<td>83</td>
<td>48+DC</td>
<td>$191 billion</td>
</tr>
<tr>
<td>Chain Restriction 2. Valid Chain</td>
<td>22,680</td>
<td>73</td>
<td>48+DC</td>
<td>$191 billion</td>
</tr>
<tr>
<td>Final Sample, Food Stores</td>
<td>9,415</td>
<td>64</td>
<td>48+DC</td>
<td>$136 billion</td>
</tr>
<tr>
<td>Final Sample, Drug Stores</td>
<td>9,977</td>
<td>4</td>
<td>48+DC</td>
<td>$21 billion</td>
</tr>
<tr>
<td>Final Sample, Merchandise Stores</td>
<td>3,288</td>
<td>5</td>
<td>48+DC</td>
<td>$34 billion</td>
</tr>
</tbody>
</table>

### Panel B. Store Characteristics

<table>
<thead>
<tr>
<th>Mean</th>
<th>25th</th>
<th>Median</th>
<th>75th</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average per-capita Income</td>
<td>$29,000</td>
<td>$22,450</td>
<td>$26,900</td>
</tr>
<tr>
<td>Percent with at least bachelor degree</td>
<td>21.0%</td>
<td>9.3%</td>
<td>17.8%</td>
</tr>
<tr>
<td>Number of HMS Households</td>
<td>28.3</td>
<td>11</td>
<td>21</td>
</tr>
<tr>
<td>Number of Trips of HMS Households</td>
<td>862</td>
<td>196</td>
<td>502</td>
</tr>
<tr>
<td>Number of Competitors within 5 km</td>
<td>2.3</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Number of Competitors within 10 km</td>
<td>8.0</td>
<td>1</td>
<td>3</td>
</tr>
</tbody>
</table>

### Panel C. Chain Characteristics, Food Stores

<table>
<thead>
<tr>
<th>Mean</th>
<th>25th</th>
<th>Median</th>
<th>75th</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Stores</td>
<td>147</td>
<td>30</td>
<td>66</td>
</tr>
<tr>
<td>Number of DMAs</td>
<td>7.4</td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td>Number of States</td>
<td>3.4</td>
<td>1</td>
<td>2.5</td>
</tr>
</tbody>
</table>

### Panel D. Chain Characteristics, Drugstores

<table>
<thead>
<tr>
<th>Chain 4901</th>
<th>Chain 4904</th>
<th>Chain 4931</th>
<th>Chain 4954</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Stores</td>
<td>3000</td>
<td>6853</td>
<td>55</td>
</tr>
<tr>
<td>Number of DMAs</td>
<td>118</td>
<td>201</td>
<td>9</td>
</tr>
<tr>
<td>Number of States</td>
<td>32</td>
<td>48+DC</td>
<td>1</td>
</tr>
</tbody>
</table>

### Panel E. Chain Charact., Mass-Merchandise Stores

<table>
<thead>
<tr>
<th>Chain 6901</th>
<th>Chain 6904</th>
<th>Chain 6907</th>
<th>Chain 6919</th>
<th>Chain 6921</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Stores</td>
<td>1565</td>
<td>1311</td>
<td>138</td>
<td>30</td>
</tr>
<tr>
<td>Number of DMAs</td>
<td>190</td>
<td>189</td>
<td>36</td>
<td>13</td>
</tr>
<tr>
<td>Number of States</td>
<td>47+DC</td>
<td>48</td>
<td>13</td>
<td>11</td>
</tr>
</tbody>
</table>

**Notes:** Valid chains are those in which at least 80% of stores with that retailer_code have the same parent_code and in which at least 40% of stores never switch parent_code or retailer_code. Total Yearly Revenue is the yearly average total revenue recorded in the Nielsen RMS dataset.
### Table 2. Summary Statistics: Products

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant Product</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Canned Soup (Campbell's Cream of Mushroom 10.75 oz)</td>
<td>Y</td>
<td>$3,400</td>
<td>$1.18</td>
</tr>
<tr>
<td>Cat Food (Purina Friskies 5.5 oz)</td>
<td>Y</td>
<td>$450</td>
<td>$0.49</td>
</tr>
<tr>
<td>Chocolate (Hershey's Milk Chocolate Bar 1.55 oz)</td>
<td>Y</td>
<td>$1,650</td>
<td>$0.72</td>
</tr>
<tr>
<td>Coffee</td>
<td>N</td>
<td>$6,400</td>
<td>$8.45</td>
</tr>
<tr>
<td>Cookies (Little Debbie Nutty Bars 12 oz)</td>
<td>Y</td>
<td>$2,100</td>
<td>$1.51</td>
</tr>
<tr>
<td>Soda (Coca-Cola 12pk cans)</td>
<td>Y</td>
<td>$34,100</td>
<td>$3.99</td>
</tr>
<tr>
<td>Orange Juice (Simply Orange 59 oz)</td>
<td>Y</td>
<td>$5,400</td>
<td>$3.54</td>
</tr>
<tr>
<td>Yogurt (Yoplait Low Fat Strawberry 6 oz)</td>
<td>Y</td>
<td>$1,900</td>
<td>$0.64</td>
</tr>
<tr>
<td>Bleach</td>
<td>N</td>
<td>$1,950</td>
<td>$2.04</td>
</tr>
<tr>
<td>Toilet Paper</td>
<td>N</td>
<td>$7,000</td>
<td>$8.60</td>
</tr>
</tbody>
</table>

### Panel B. Product Characteristics, Drugstores

<table>
<thead>
<tr>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Soda (Coca-Cola 12pk cans)</td>
<td>Y</td>
<td>$3,600</td>
<td>$4.30</td>
</tr>
<tr>
<td>Chocolate (Hershey's Milk Chocolate Bar 1.5 oz)</td>
<td>Y</td>
<td>$625</td>
<td>$0.72</td>
</tr>
</tbody>
</table>

### Panel C. Product Characteristics, Mass-Merchandise Stores

<table>
<thead>
<tr>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Soda (Coca-Cola 12pk cans)</td>
<td>Y</td>
<td>$13,300</td>
<td>$4.12</td>
</tr>
<tr>
<td>Chocolate (Hershey's Milk Chocolate Bar 1.55 oz)</td>
<td>Y</td>
<td>$725</td>
<td>$0.70</td>
</tr>
<tr>
<td>Cookies</td>
<td>N</td>
<td>$2,150</td>
<td>$2.57</td>
</tr>
<tr>
<td>Bleach</td>
<td>N</td>
<td>$2,700</td>
<td>$2.23</td>
</tr>
<tr>
<td>Toilet Paper</td>
<td>N</td>
<td>$7,600</td>
<td>$8.70</td>
</tr>
</tbody>
</table>

**Notes:** Constant Product indicates whether the top selling product changes over the 9-year sample. Weekly Average Price is the unweighted average of weekly price observations in all stores. Weekly Availability is number of store-weeks with nonzero sales divided by number of store-weeks in which stores in our sample have positive sales in all products belonging to the 10 modules.
<table>
<thead>
<tr>
<th>Measure of Similarity:</th>
<th>Absolute Difference in Log Quarterly Prices</th>
<th>Correlation in (De-meaned) Weekly Prices</th>
<th>Share of Identical Prices (Up to 1 Percent)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Same Chain</td>
<td>Different Chain</td>
<td>Same Chain</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
</tbody>
</table>

**Panel A. Benchmark UPCs, All Store Pairs**

Mean

|          | 0.034 | 0.117 | 0.836 | 0.128 | 0.529 | 0.107 |

Standard Deviation

|          | (0.023) | (0.034) | (0.127) | (0.106) | (0.189) | (0.048) |

Number of Pairs

|          | 491,941 | 2,620,810 | 490,077 | 2,616,142 | 489,901 | 2,614,537 |

**Panel B. Benchmark UPCs, Store Pairs Within a DMA**

Mean

|          | 0.022 | 0.115 | 0.902 | 0.135 | 0.619 | 0.117 |

Standard Deviation

|          | (0.014) | (0.039) | (0.057) | (0.152) | (0.152) | (0.091) |

Number of Pairs

|          | 140,989 | 10,361 | 140,648 | 10,369 | 140,644 | 10,360 |

**Panel C. Benchmark UPCs, Store Pairs Across DMA, Top 33% income vs Bottom 33% Income Only**

Mean

|          | 0.042 | 0.118 | 0.808 | 0.124 | 0.457 | 0.106 |

Standard Deviation

|          | (0.027) | (0.037) | (0.140) | (0.100) | (0.193) | (0.047) |

Number of Pairs

|          | 60,673 | 589,645 | 59,529 | 588,625 | 59,496 | 588,170 |

**Panel D. Generic Product UPCs, All Store Pairs**

Mean

|          | 0.032 | NA | 0.647 | NA | 0.611 | NA |

Standard Deviation

|          | (0.026) | NA | (0.193) | NA | (0.201) | NA |

Number of Pairs

|          | 377,225 | NA | 373,008 | NA | 373,008 | NA |

**Panel E. Non-Top Selling UPCs, All Store Pairs**

Mean

|          | 0.034 | 0.117 | 0.805 | 0.095 | 0.578 | 0.101 |

Standard Deviation

|          | (0.020) | (0.024) | (0.130) | (0.116) | (0.182) | (0.050) |

Number of Pairs

|          | 332,195 | 1,930,054 | 309,550 | 1,783,377 | 309,550 | 1,783,377 |

**Panel F. Higher Unit Price Items, 8 products in 3 modules only, All Store Pairs**

Mean

|          | 0.028 | 0.152 | 0.788 | 0.118 | 0.642 | 0.132 |

Standard Deviation

|          | (0.016) | (0.051) | (0.135) | (0.120) | (0.178) | (0.066) |

Number of Pairs

|          | 327,457 | 1,938,276 | 274,555 | 1,551,106 | 274,555 | 1,551,106 |

Notes: See Appendix for details on the store sample. The pool that stores are selected from consists of stores that meet our other selection criteria and also have for at least 7 modules nonmissing data for at least 60% of all quarters with minimum six weeks of nonmissing data (columns (1) and (2)) or 60% of all weeks (Columns (3) - (6)). A maximum of 200 stores per chain are used to avoid overweighting the five largest chains. Generic Between-Chain Store Pair Comparisons are not possible because we have selected different products for each chain-module.
### Table 4. Determinants of Pricing

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Log Prices in Store s</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
</tbody>
</table>

#### Panel A. Food Stores

<p>| | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Own Store Income</td>
<td>0.0175***</td>
<td>0.0044***</td>
<td>0.0029***</td>
<td>0.0029***</td>
</tr>
<tr>
<td></td>
<td>(0.0047)</td>
<td>(0.0013)</td>
<td>(0.0003)</td>
<td>(0.0003)</td>
</tr>
<tr>
<td>Chain Average Income</td>
<td>0.0404***</td>
<td>0.0284**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0101)</td>
<td>(0.0129)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Chain-State Average Income</td>
<td>0.0136*</td>
<td>0.0136*</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>(0.0069)</td>
<td>(0.0069)</td>
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<td></td>
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<tr>
<td>Fixed Effects</td>
<td>Chain</td>
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<tr>
<td>Observations</td>
<td>9,415</td>
<td>9,415</td>
<td>9,415</td>
<td>9,415</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.134</td>
<td>0.290</td>
<td>0.296</td>
<td>0.925</td>
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</table>

#### Panel B. Drugstores

<p>| | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Own Store Income</td>
<td>0.0084***</td>
<td>0.0075***</td>
<td>0.0075***</td>
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</tr>
<tr>
<td></td>
<td>(0.0012)</td>
<td>(0.0008)</td>
<td>(0.0008)</td>
<td></td>
</tr>
<tr>
<td>Chain-State Average Income</td>
<td>0.0103</td>
<td>0.0203***</td>
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<td></td>
<td>(0.0107)</td>
<td>(0.0074)</td>
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<tr>
<td>Fixed Effects</td>
<td>Chain</td>
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<tr>
<td>R-squared</td>
<td>0.056</td>
<td>0.063</td>
<td>0.470</td>
<td></td>
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#### Panel C. Mass-Merchandise Stores

<p>| | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Own Store Income</td>
<td>-0.0126***</td>
<td>0.0029***</td>
<td>0.0029***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0031)</td>
<td>(0.0010)</td>
<td>(0.0010)</td>
<td></td>
</tr>
<tr>
<td>Chain-State Average Income</td>
<td>-0.0699***</td>
<td>0.0076***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0099)</td>
<td>(0.0019)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fixed Effects</td>
<td>Chain</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>3,288</td>
<td>3,288</td>
<td>3,288</td>
<td></td>
</tr>
<tr>
<td>R-squared</td>
<td>0.043</td>
<td>0.272</td>
<td>0.916</td>
<td></td>
</tr>
</tbody>
</table>

**Notes:** In Panel A, standard errors are clustered by parent_code. In Panels B and C, standard errors are clustered by parent_code*state. There are insufficient chains to estimate a regression including chain average income for Drugstores (Panel B) or Mass-Merchandise Stores (Panel C).
Table 5. Determinants of Store-Level Price Elasticity

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Store s Shrunk Estimated Price Elasticity</th>
<th>Store s Log((elasticity/(1+elasticity))</th>
<th>First Stage</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td><strong>Demographic Controls</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Income Per Capita (in $10,000)</td>
<td>0.140***</td>
<td>0.143***</td>
<td>0.0722***</td>
</tr>
<tr>
<td>(0.0137)</td>
<td>(0.0087)</td>
<td>(0.0201)  </td>
<td>(0.0212)  </td>
</tr>
<tr>
<td>Fraction with College Degree (or higher)</td>
<td>0.458***</td>
<td>0.485***</td>
<td></td>
</tr>
<tr>
<td>(0.1136)</td>
<td>(0.1309)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Median Home Price (in $100,000)</td>
<td>0.0037*</td>
<td>0.0049***</td>
<td></td>
</tr>
<tr>
<td>(0.0020)</td>
<td>(0.0018)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Controls for Urban Share</td>
<td></td>
<td></td>
<td>X</td>
</tr>
<tr>
<td><strong>Controls for Number of Competitors w/in 5km</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1-4 Other Grocery Stores</td>
<td>-0.0119</td>
<td>0.0040</td>
<td></td>
</tr>
<tr>
<td>(0.0174)</td>
<td>(0.0142)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5-9 Other Grocery Stores</td>
<td>-0.0167</td>
<td>-0.0022</td>
<td></td>
</tr>
<tr>
<td>(0.0226)</td>
<td>(0.0215)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>10+ Other Grocery Stores</td>
<td>-0.0690*</td>
<td>-0.0544</td>
<td></td>
</tr>
<tr>
<td>(0.0393)</td>
<td>(0.0433)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fixed Effect for Chain</td>
<td>X</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Fixed Effect for Chain*State</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sample:</td>
<td>All Stores</td>
<td>All Stores</td>
<td>Food Stores</td>
</tr>
<tr>
<td>R Squared</td>
<td>0.083</td>
<td>0.652</td>
<td>0.669</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>22,660</td>
<td>22,660</td>
<td>22,660</td>
</tr>
</tbody>
</table>

Notes: Standard errors are clustered by parent_code for all columns except for columns (7) and (8), where they are clustered by parent_code*state. 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].
### Table 6. Responsiveness of Log Prices to Store-Level Log Elasticity

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Log Prices in Store s</th>
<th>Average Price for Chain-State</th>
<th>Avg. Log Prices for Chain ( c )</th>
<th>Between-Chain-</th>
<th>Between-Chain,</th>
</tr>
</thead>
<tbody>
<tr>
<td>Specification:</td>
<td>Within-Chain, IV</td>
<td>State, IV</td>
<td>IV</td>
<td>IV</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td></td>
</tr>
</tbody>
</table>

**Panel A. Food Stores**

Log (Elast. / (Elast.+1) ) in Store s: 
0.0919*** 0.0605***  
(0.0339) (0.0100)

Mean Log (Elast. / (Elast.+1) ) in State-Chain Combination: 
0.351**
(0.193)

Mean Log (Elast. / (Elast.+1) ) in Chain \( c \): 
0.944***
(0.220)

Fixed Effect for Chain: X
Fixed Effect for Chain-State: X

Number of Observations: 9,415 9,415 171 64

**Panel B. Drug Stores**

Log (Elast. / (Elast.+1) ) in Store s: 
0.287*** 0.231***  
(0.0400) (0.0293)

Mean Log (Elast. / (Elast.+1) ) in State-Chain Combination: 
0.858****  NA
(0.267)

Fixed Effect for Chain: X
Fixed Effect for Chain-State: X

Number of Observations: 9,972 9,972 83

**Panel C. Mass Merchandise Stores**

Log (Elast. / (Elast.+1) ) in Store s: 
0.187*** 0.134***  
(0.0492) (0.0436)

Mean Log (Elast. / (Elast.+1) ) in State-Chain Combination: 
0.478***  NA
(0.112)

Fixed Effect for Chain: X
Fixed Effect for Chain-State: X

Number of Observations: 3,288 3,288 142

**Notes:** In Panel A, bootstrap clusters are parent_codes. In Panels B and C, bootstrap clusters are parent_code*state. Elasticities are Winsorized to -1.2. Means are average Log Model (not Log Model of average elasticity).
Table 7. Log Prices and Store-Level Log Elasticity, Robustness (Food Stores)

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Log Prices in Store s</th>
<th>Average Price for Chain State</th>
<th>Average Log Prices for Chain c</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td><strong>Panel A. Benchmark Product</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log (Elast./ (Elast.+1) ) in Store s</td>
<td>0.0919*** (0.0339)</td>
<td>0.101*** (0.0349)</td>
<td>0.0643*** (0.0105)</td>
</tr>
<tr>
<td>Mean Log (Elast./ (Elast.+1) ) in Chain c</td>
<td>0.351* (0.202)</td>
<td>0.936*** (0.196)</td>
<td>0.915*** (0.187)</td>
</tr>
<tr>
<td>Fixed Effect for Chain</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Fixed Effect for Chain*State</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>9,415</td>
<td>9,415</td>
<td>9,415</td>
</tr>
</tbody>
</table>

| **Panel B. Elasticity Computed at Quarterly Horizon** |                       |                               |                               |
| Log (Elast./ (Elast.+1) ) in Store s | 0.0396** (0.0161) | 0.0389*** (0.0097) | 0.0253*** (0.0032) |
| Mean Log (Elast./ (Elast.+1) ) in Chain c | 0.151** (0.0591) | 0.409*** (0.0933) | 0.410*** (0.102) |
| Fixed Effect for Chain | X | X | X |
| Fixed Effect for Chain*State | X | X | X |
| Number of Observations | 9,403 | 9,403 | 9,403 |

| **Panel C. Elasticity Computed with Indices** |                       |                               |                               |
| Log (Elast./ (Elast.+1) ) in Store s | 0.0388*** (0.0141) | 0.0367*** (0.0116) | 0.0253*** (0.0038) |
| Mean Log (Elast./ (Elast.+1) ) in Chain c | 0.149** (0.0600) | NA | NA |
| Fixed Effect for Chain | X | X | X |
| Fixed Effect for Chain*State | X | X | X |
| Number of Observations | 9,258 | 9,258 | 9,258 |

| **Panel D. 20th-top selling product** |                       |                               |                               |
| Log (Elast./ (Elast.+1) ) in Store s | 0.0960*** (0.0251) | 0.105*** (0.0266) | 0.0749*** (0.0101) |
| Mean Log (Elast./ (Elast.+1) ) in Chain c | 0.299** (0.146) | 0.936*** (0.196) | 0.915*** (0.187) |
| Fixed Effect for Chain | X | X | X |
| Fixed Effect for Chain*State | X | X | X |
| Number of Observations | 9,415 | 9,415 | 9,415 |

| **Panel E. Generic, comparable across chains** |                       |                               |                               |
| Log (Elast./ (Elast.+1) ) in Store s | 0.0835** (0.0408) | 0.0975** (0.0466) | 0.0532*** (0.0204) |
| Mean Log (Elast./ (Elast.+1) ) in Chain c | 0.345 (0.454) | 1.486*** (0.383) | 1.481*** (0.350) |
| Fixed Effect for Chain | X | X | X |
| Fixed Effect for Chain*State | X | X | X |
| Number of Observations | 9,296 | 9,296 | 9,296 |

Notes: Standard errors are bootstrapped. Bootstrap samples are clustered at the parent_code level. 100 replications are used. Elasticities are Winsorized at -1.2. Panels B and C do not have the full sample of 9,415 stores because we excluded elasticity estimates with large standard errors. Generic Products in Panel E meet criteria where we think they are likely to be similar products. However, only four modules have sufficient availability and even those products are not sold in all stores. See Appendix Section A.1.2. for more details.
<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Log Prices in Store $s$</th>
<th>Average Price for Chain-State</th>
<th>Average Log Prices for Chain $c$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Specification:</td>
<td>Within-Chain, IV w/ income</td>
<td>Within-Chain, IV w/ All Variables</td>
<td>Between-Chain-State, IV w/ Income</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td><strong>Panel A. Price Variable is Average Weekly Log Price (Benchmark)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log (Elast. / (Elast.+1) ) in Store $s$</td>
<td>0.0919***</td>
<td>0.101***</td>
<td>0.0643***</td>
</tr>
<tr>
<td>Mean Log (Elast. / (Elast.+1) ) in Chain $c$</td>
<td>0.0339</td>
<td>0.0349</td>
<td>0.0105</td>
</tr>
<tr>
<td>Fixed Effect for Chain</td>
<td>X</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Fixed Effect for Chain*State</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of Observations</td>
<td>9,415</td>
<td>9,415</td>
<td>9,415</td>
</tr>
<tr>
<td><strong>Panel B. Price Variable is Log of Average Yearly Price</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log (Elast. / (Elast.+1) ) in Store $s$</td>
<td>0.223***</td>
<td>0.231***</td>
<td>0.197***</td>
</tr>
<tr>
<td>Mean Log (Elast. / (Elast.+1) ) in Chain $c$</td>
<td>0.0316</td>
<td>0.0326</td>
<td>0.0149</td>
</tr>
<tr>
<td>Fixed Effect for Chain</td>
<td>X</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Fixed Effect for Chain*State</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of Observations</td>
<td>9,415</td>
<td>9,415</td>
<td>9,415</td>
</tr>
</tbody>
</table>

**Notes:** Standard errors are bootstrapped. Bootstrap samples are clustered at the parent_code level. 100 replications are used. Elasticities are Winsorized at -1.2.
### Table 9. Estimated Loss of Profits at Chain Level

<table>
<thead>
<tr>
<th>Panel A. Food Stores</th>
<th>Mean</th>
<th>25th</th>
<th>Median</th>
<th>75th</th>
</tr>
</thead>
<tbody>
<tr>
<td>Loss of Profits Comparing Optimal Pricing to Uniform Pricing</td>
<td>10.30%</td>
<td>6.14%</td>
<td>7.96%</td>
<td>10.81%</td>
</tr>
<tr>
<td>Loss of Profits Comparing Optimal Pricing to Actual Price-Elasticity Slope</td>
<td>7.80%</td>
<td>4.79%</td>
<td>6.09%</td>
<td>8.26%</td>
</tr>
<tr>
<td>Loss of Profits Comparing Optimal Pricing to State-Zone Optimal Pricing</td>
<td>7.85%</td>
<td>4.64%</td>
<td>6.72%</td>
<td>9.23%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B. Drugstores</th>
<th>Chain 4901</th>
<th>Chain 4904</th>
<th>Chain 4931</th>
<th>Chain 4954</th>
</tr>
</thead>
<tbody>
<tr>
<td>Loss of Profits Comparing Optimal Pricing to Uniform Pricing</td>
<td>17.53%</td>
<td>13.54%</td>
<td>18.56%</td>
<td>10.91%</td>
</tr>
<tr>
<td>Loss of Profits Comparing Optimal Pricing to Actual Price-Elasticity Slope</td>
<td>7.41%</td>
<td>5.97%</td>
<td>8.75%</td>
<td>5.15%</td>
</tr>
<tr>
<td>Loss of Profits Comparing Optimal Pricing to State-Zone Optimal Pricing</td>
<td>11.65%</td>
<td>9.79%</td>
<td>18.56%</td>
<td>10.67%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel C. Mass Merchandise Stores</th>
<th>Chain 6901</th>
<th>Chain 6904</th>
<th>Chain 6907</th>
<th>Chain 6919</th>
<th>Chain 6921</th>
</tr>
</thead>
<tbody>
<tr>
<td>Loss of Profits Comparing Optimal Pricing to Uniform Pricing</td>
<td>8.70%</td>
<td>6.28%</td>
<td>3.46%</td>
<td>3.34%</td>
<td>5.08%</td>
</tr>
<tr>
<td>Loss of Profits Comparing Optimal Pricing to Actual Price-Elasticity Slope</td>
<td>4.73%</td>
<td>3.60%</td>
<td>2.07%</td>
<td>1.94%</td>
<td>3.02%</td>
</tr>
<tr>
<td>Loss of Profits Comparing Optimal Pricing to State-Zone Optimal Pricing</td>
<td>5.57%</td>
<td>4.67%</td>
<td>2.31%</td>
<td>0.88%</td>
<td>1.91%</td>
</tr>
</tbody>
</table>

Notes: Elasticities are Winsorized at -1.2. "Actual Pricing" is within-chain price-level predicted with elasticity by store type using shrunk elasticities and the IV coefficient from Table 6 Column 1 along with the observed chain average prices. Uniform Pricing and State-Zone Optimal Pricing assume that the chain prices to the mean elasticity in the chain or in the chain-state.
Table 10. Macro Shocks Under Uniform Pricing

<table>
<thead>
<tr>
<th>Locality of the Shock</th>
<th>Average Weekly Price</th>
<th>Average Yearly Price</th>
</tr>
</thead>
<tbody>
<tr>
<td>National Shock</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>State-Level Shock</td>
<td>50%</td>
<td>57%</td>
</tr>
<tr>
<td>DMA-Level Shock</td>
<td>37%</td>
<td>46%</td>
</tr>
<tr>
<td>County-Level Shock</td>
<td>18%</td>
<td>30%</td>
</tr>
</tbody>
</table>

Notes: Displayed are the estimated response to a permanent 1% shock in income in each locality as a percent of the response to a nationwide shock. Since the base (price response for a 1% national shock) is different, the percentages are not comparable across columns.
Appendix Figure 1. Store Locations

Note: Stores are placed at the midpoint of the county given in the RMS dataset, but locations are jittered so that stores do not overlap. In some cases, this may cause stores near state borders to be placed in the wrong state. This was a tradeoff we made to show more accurately the number of stores located in very large counties in Arizona and Southern California.
Online Appendix Figure 1a. Additional Examples of Chains with Uniform Pricing: Chain 2

Online Appendix Figure 1b. Additional Examples of Chains with Uniform Pricing: Chain 79

Notes: Plots depict demeaned log prices. Darker colors indicate higher price and are blank if price is missing. Each column is a week. Each row is a store, and stores are sorted within products by measure of store-level income per capita. The same 50 stores appear for each product.
Online Appendix Figure 2. Additional Examples of Chains with Geographic Pricing Blocks

Online Appendix Figure 2a. Example of Chain with Geographic Pricing Blocks: Chain 9, Orange Juice

Online Appendix Figure 2b. Example of Chain with Geographic Pricing Blocks: Chain 32, Orange Juice

Notes: Plots depict demeaned log prices. Darker colors indicate higher price and are blank if price is missing. Each column is a week. Each row is a store, and stores are sorted by three-digit zip code within each state divider.
Online Appendix Figure 2c. Example of Individualized Pricing: Chain 868, Orange Juice

Notes: Plots depict demeaned log prices. Darker colors indicate higher price and are blank if price is missing. Each column is a week. Each row is a store, and stores are sorted by measure of store-level income per capita.
Online Appendix Figure 3. Same as Figure 3 but one including store pairs located in the same DMA

Notes: Each observation is a store-pair where both stores are located in the same DMA. “Same chain” means same retailer_code. “Different chain” means both different retailer_code and different parent_code. Quarterly Absolute Log Price Difference is Winsorized at .3 and Weekly Correlation is Winsorized at 0. A maximum of 200 stores per chain are used in the same chain distributions to avoid overweighting the 10 largest chains. See Appendix Section A.1.4. for details on how we formed the different chain sample.
Online Appendix Figure 4: Pairs, Alternative Measure of Price Similarity: Weekly Absolute log price difference and Share Identical

Notes: Each observation is a store-pair. “Same chain” means same retailer_code. “Different chain” means both different retailer_code and different parent_code. Figures 3a-b show the relationship for all store-pairs. Figures 3c-d restricts the sample to pairs in different DMAs and where one store is in the top 33% of nationwide income and the other is in the bottom 33%. Quarterly Absolute Log Price Difference is Winsorized at .3 and Weekly Correlation is Winsorized at 0. A maximum of 200 stores per chain are used in the same chain distributions to avoid overweighting the 10 largest chains. See Appendix Section A.1.4. for details on how we formed the different chain sample.
Online Appendix Figure 5. Probability of Being in Same Chain as Function of Pricing Distance

Online Appendix Figure 5a. By Quarterly Absolute Log Price Difference

Online Appendix Figure 5b. By Correlation of Weekly Log Prices

Notes: Empirically observed probability of being in the same retailer is plotted with the distribution of all pairs in the background (grey histogram). A maximum of 200 stores are used for within-chain pairs. The base rate of two stores belonging to the same chain is .1628 for both measures.
Online Appendix Figure 6. Between and Within-State Weekly Correlation of Log Prices

Notes: Each observation is a chain that operates at least three stores in multiple states. Chains of note are labeled.
Online Appendix Figure 7. Robustness of Key Fact, by Retailer. Quarterly Absolute Log Price Difference (Food stores only)

Onl. App. Fig. 7a. Vs. 20th Availability Items

Onl. App. Fig. 7b. Vs. Top Selling Generic

Onl. App. Fig. 7c. Vs. High Quality Unit-Price Items

Notes: 20th Availability and Top Generic products contain ten products, one from each module. High Quality products contain eight products, three each from Coffee and Cookies and two from Chocolate. A maximum of 400 stores are used per retailer.
Online Appendix Figure 8. Within-Chain Response of Prices to Income, By Chain

Online Appendix Figure 8a. Food Stores

Notes: Plotted are the coefficients for independent store-level regressions of price on income (in $10,000s) for each chain and 95% confidence intervals based on robust standard errors. 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. Two chains with SE > .02 are omitted (one, Retailer 295, has coefficient (Robust SE) 0.015 (.0254)).
Notes: Plotted are the coefficients for independent store-level regressions of price on income (in $10,000s) for each chain and 95% confidence intervals based on robust standard errors. A coefficient of 0.01 means that within chain \( \text{c} \), prices are set 1 log point (1%) higher for an increase in income of $10,000.
Online Appendix Figure 9. Price vs. Income by module/product group (Food stores only)

Online Appendix Figure 9a. Within-chain Price vs. Income Regression

Notes: Figure 9a plots the coefficients for independent store-level regressions of price on income (in $10,000s) with chain fixed effects for the top-seller in each module (or the pooled price level for the product group) and 95% confidence intervals based on standard errors clustered by parent_code. Figure 9b plots the same relationships but for chain averages using analytic weights equal to number of stores with standard errors again clustered by parent_code. A coefficient of 0.01 for module m means that chains set average prices for module m 1 log point (1%) higher for an increase in average income of $10,000. Squares indicate pooled price levels (averages of multiple products), while circles indicate individual products.
Online Appendix Figure 10. Between-Chain Relationship of Price to Income, Drug and Mass Merchandise Chains

Online Appendix Figure 10a. Drugstore Chains

Online Appendix Figure 10b. Mass-Merchandise Chains

Notes: Hollow circles represent food store chains.
Online Appendix Figure 11. Price Response to Demographics, Results with Store-Level Education

O. A. Figure 11a. Price versus Education: Within-Chain

O. A. Figure 11b. Price versus Education: Between Chains (F only)

O. A. Figure 11c. Price versus Education: Within-Chain-State

O. A. Figure 11d. Price versus Education: Between Chain-State

Notes: Standard errors clustered by parent_code. Axes ranges have been chosen to make the slopes visually comparable. Analytic weights equal to the number of stores in each aggregation unit are used in Figures 10b. and 10d. In Figure 10a, residuals are after removing Chain FE. In Figure 10c, residuals are after removing ChainState FE. In Figure 10b, labels indicate Chain. In Figure 10d., each observation is one of 25 bins representing 396 chain-states.
Online Appendix Figure 12. Price Response to Income: Estimated Nonsale Price Levels using Nielsen Data

Onl. App. Fig. 12a. Nonsale Prices: Within-Chain

Onl. App. Fig. 12b. Between-Chain Relationship (Food stores only)

Onl. App. Fig. 12c. Nonsale Prices: Within-Chain-State

Onl. App. Fig. 12d. Nonsale Prices: Between-Zones Relationship

Notes: Standard errors clustered by parent_code. Axes ranges have been chosen to make the slopes visually comparable. Analytic weights equal to the number of stores in each aggregation unit are used in Figures 12b and 12d. In Figure 12a, residuals are after removing Chain FE. In Figure 12c, residuals are after removing ChainXState FE. In Figure 12b, labels indicate Chain. In Figure 12d, each observation is a bin of chain-states.
Notes: For each store type, pooled elasticities estimated using prices and quantities from the first half of each year only are shrunk to the mean and compared to pooled elasticities estimated using only the prices and quantities from the second half of each year. A value of zero indicates that no shrinkage is performed and raw estimates are being compared, and a value of one indicates that all estimated elasticities are replaced by the mean elasticity for the first half of the year.
Online Appendix Figure 14. Additional Validation for Elasticity
Online Appendix Figure 14a. Test of Linearity: Pooled, Decomposed
Online Appendix Figure 14b. Test of Linearity: Soda, Decomposed
Online App. Figure 14c. Food Store Incremental R-squared
Online App. Figure 14d. Food Store Stockpiling Evidence: Lags and Leads

Notes: Figure 14a shows the residuals after removing year*module and {week of year}* module FE for all products. Figure 14b shows the residuals after removing year and week of year FE for soda only. Each observation is a store-week of the product indicated. Figure 14c shows the distribution of R-squared using the pooled regression of all 10 products in food stores only. In Figure 14d, all food stores are regressed together with store, year*module, and week-of-year*module fixed effects, unlike our main specification (which consists a separate regression for each store).
Notes: “Log Elasticity” is \( \log(\text{Elasticity}/(1+\text{Elasticity})) \). Standard errors are clustered by parent_code. Elasticities are Winsorized at -1.2. In Figures 15b and 15d, the values are the average \( \log(\text{Elasticity}/(1+\text{Elasticity})) \). Axis ranges were chosen so that slopes are visually comparable.
Online Appendix Figure 16. Robustness of Result on Price vs. Income, Different Products (Food Stores only)

Online Appendix Figure 16a-b. Top product relationships in Food Stores

Top Seller Price vs. Income, within chain

Top Seller Price vs. Income, between chain

Online Appendix Figure 16c-d. Lower-Selling Products (20th Highest Selling)

20th Seller Price vs. Income, within chain

20th Seller Price vs. Income, between chain

Notes: These robustness checks use the price level for the alternate products indicated. Residuals are after removing Chain FE. Standard errors are clustered by parent_code.
Online Appendix Figure 16e. Top-Selling Generic Product
Top Generic Product vs Income, within chain

Online Appendix Figure 16f-g. Similar Generic Product Across Chains
Similar Generic Product, within chain

Similar Generic Product, between chain

Notes: Residuals are after removing Chain FE. Standard errors are clustered by parent_code except for Figure 16g., where they are robust. Figures 16f. and 16g. do not impose any module-level availability minimums for a store to be included. Changing this does not affect the within-chain relationship much but steepens the between-chain relationship.
Online Appendix Figure 16h. Index Price Level

Index Price Level, within chain

Notes: Residuals are after removing Chain FE. Standard errors are clustered by parent_code. The mean index price level is used in Figure 16h and this is the only robustness specification that uses more than one product per module. Since module-level indices are constructed at the chain level, between-chain comparisons are not possible.
Notes: In Figure 17a, elasticities are Winsorized at 0 and -5. In Figure 17b, there are 50 bins representing 9,415 stores. Standard errors are clustered by parent_code. In Figure 17c, there are 50 bins representing 3,488,542 store-quarter-modules. Residuals are after removing module*quarter-of-year and module*year fixed effects. In Figure 17d, standard errors are clustered by quarter and are Winsorized at .8.
Online Appendix Figure 17e. Correlation with Income

Notes: Standard errors are clustered by parent_code.
Notes: In Figure 18a., elasticities are Winsorized at 0. In Figure 18b., there are 50 bins representing 9,415 stores. Standard errors are clustered by parent_code. In Figure 18c., there are 50 bins representing 39,778,208 store-week-modules. Residuals are after removing module*quarter-of-year and module*year fixed effects. In Figure 18d., standard errors are clustered bimonthly and are Winsorized at .4.

82
Online Appendix Figure 18e. Index Elasticity

Elasticity vs. Income

Notes: Standard errors are clustered by parent_code.
Online Appendix Figure 19. Weekly Average Price versus Yearly Average Price

Online Appendix Figure 19a. Within-Chain

Online Appendix Figure 19b. Between-Chain (Food Stores only)

Online Appendix Figure 19c. Within-Chain-State

Online Appendix Figure 19d. Between Chain-State

Notes: Residuals are after removing Chain FE. Standard errors are clustered by parent_code. Yearly average price paid is normalized such that the average store yearly average price = 0. This level is on average 6.3% lower than the weekly average price. Figures 19a. and 19c. have 50 bins representing 22,680 stores. Figure 19d. has 25 bins representing 396 chain-states. Weekly Average Price is our best approximation of the price that stores post to consumers, while Yearly Average Price represents the average price that the stores sell their goods at.
Notes: Analytic weights equal to the number of stores in each chain-geography are used. Residuals are after removing Chain FE for the Chain-State Zones (Figure 20a) and after removing Chain-State FE for the Chain-DMA Zones (Figure 20b).
Online Appendix Figure 21. Evidence on Tacit Collusion: Within-Chain-State Price vs. Elasticity by Number of Competitors’ Stores within 10 km

Online Appendix Figure 21a. Within-Chain, Food and Mass-Merchandise Stores

Online Appendix Figure 21b. Within-Chain, Drugstores

Online Appendix Figure 21c. Between-Chain Average Quarterly Absolute Log Price Difference vs. Fraction of Stores with zero competitors within 10 km

Online Appendix Figure 21d. Chain-Level Price Response to Elasticity (IV) vs. vs. Fraction of Stores with zero competitors within 10 km

Notes: Throughout, only stores of the same type are counted, so for example drugstores are not included in the count of stores within 10 km for food stores. In Figure 21a-b, residuals are after removing Chain-State FE. Number of competitors is number of other stores of the same type within 10 km, excluding stores in the same chain. Standard Errors are clustered by parent_code in Figure 20a. and are clustered by parent_code*state in Figure 21b. In Figures 21c. and 21d. The regression line fits only the food stores (solid circles). In Figure 20d., a separate first stage using all stores of the appropriate type is used, just like in the first stage of our benchmark IV estimation.
Online Appendix Figure 22: Fairness

Online Appendix Figure 22a. Within-Chain, Food and Mass-Merchandise Stores

![Within-Chain, Food and Mass-Merchandise Stores](image)

Online Appendix Figure 22b. Within-Chain, Drugstores

![Within-Chain, Drugstores](image)

Online Appendix Figure 22c. Between-Chain Average Quarterly Absolute Log Price Difference vs. Fraction of Stores with zero branches within 10 km

![Between-Chain Average Quarterly Absolute Log Price Difference](image)

Online Appendix Figure 22d. Chain-Level Price Response to Elasticity (IV) vs. Fraction of Stores with zero branches within 10 km

![Chain-Level Price Response to Elasticity (IV)](image)

**Notes:** In Figures 22d-e, Fraction is fraction of stores without another store of the same chain within 10 km. The regression line and coefficient only include food stores (solid circles).
Online Appendix Figure 23: Learning Over Time in Food Stores

Online Appendix Figure 23a. Within-Chain, Food and Mass-Merchandise Stores

Online Appendix Figure 23b. Within-Chain, Drugstores

Online App. Fig. 23c. Price versus Income Within-Firm Coefficients

Notes: The same nine-year average income (2006-2014) is used for all figures so only price levels differ. In Figures 23a-b, Residuals are after removing Chain-State Fixed Effects. Standard Errors are clustered by parent_code (23a) and parent_code*state (23b). In Figure 23c., only stores in both periods are included. Chains with robust SE greater than .01 in either period are omitted.
Online Appendix Figure 24. Implications of Price Rigidity for Grocery Prices in Areas with Different Characteristics, Robustness

Online Appendix Figure 24a. Force Marginal Cost to be the same across all stores, benchmark elasticity

Notes: These are variations of Figure 11a. Figure 24a. forces the marginal cost to be the same across all stores regardless of chain, while Figure 24b. allows marginal cost to vary but uses elasticities predicted with income in a manner identical to the first stage of our IV estimation.
### Online Appendix Table 1. Additional Summary Statistics

<table>
<thead>
<tr>
<th></th>
<th>No. of Stores</th>
<th>No. of Chains</th>
<th>No. of States</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A. Main Sample by Year</strong></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>2006</td>
<td>19,252</td>
<td>64</td>
<td>48+DC</td>
</tr>
<tr>
<td>2007</td>
<td>20,311</td>
<td>73</td>
<td>48+DC</td>
</tr>
<tr>
<td>2008</td>
<td>21,164</td>
<td>73</td>
<td>48+DC</td>
</tr>
<tr>
<td>2009</td>
<td>21,564</td>
<td>73</td>
<td>48+DC</td>
</tr>
<tr>
<td>2010</td>
<td>21,663</td>
<td>73</td>
<td>48+DC</td>
</tr>
<tr>
<td>2011</td>
<td>21,666</td>
<td>73</td>
<td>48+DC</td>
</tr>
<tr>
<td>2012</td>
<td>21,669</td>
<td>73</td>
<td>48+DC</td>
</tr>
<tr>
<td>2013</td>
<td>21,331</td>
<td>73</td>
<td>48+DC</td>
</tr>
<tr>
<td>2014</td>
<td>20,666</td>
<td>70</td>
<td>48+DC</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Yearly Module Revenue by Store (in $)</th>
<th>% of Module Revenue Captured</th>
<th>Average Price</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel B. Index Characteristics, Food Stores</strong></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Canned Soup</td>
<td>$55,500</td>
<td>34.0%</td>
<td>$1.15</td>
</tr>
<tr>
<td>Cat Food</td>
<td>$11,000</td>
<td>19.8%</td>
<td>$0.49</td>
</tr>
<tr>
<td>Chocolate</td>
<td>$41,500</td>
<td>21.3%</td>
<td>$0.87</td>
</tr>
<tr>
<td>Coffee</td>
<td>$30,000</td>
<td>15.5%</td>
<td>$5.80</td>
</tr>
<tr>
<td>Cookies</td>
<td>$50,500</td>
<td>24.5%</td>
<td>$2.33</td>
</tr>
<tr>
<td>Soda</td>
<td>$240,500</td>
<td>53.1%</td>
<td>$1.98</td>
</tr>
<tr>
<td>Orange Juice</td>
<td>$77,500</td>
<td>62.2%</td>
<td>$3.09</td>
</tr>
<tr>
<td>Yogurt</td>
<td>$80,500</td>
<td>41.6%</td>
<td>$0.82</td>
</tr>
<tr>
<td>Bleach</td>
<td>$7,500</td>
<td>41.2%</td>
<td>$1.84</td>
</tr>
<tr>
<td>Toilet Paper</td>
<td>$75,500</td>
<td>32.2%</td>
<td>$4.42</td>
</tr>
</tbody>
</table>

**Notes:** Panel A reports the number of stores and chains in our main sample for each year. In Panel B, we present summary statistics on the price index computed aggregating within each module all products (UPCs) available in at least 95% of week-store observations for that chain (details in the text). We report the average yearly revenue at the store level for all the products included in the index (Column 1), the percent of module revenue covered by the basket (Column 2) and the average price of the products included in our index (Column 3).
Online Appendix Table 2. Price versus Income, Within Chain and Between Chain

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Price for Stores</th>
<th>Average Price for Chain-State</th>
<th>Average Price for Chain c</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
<td></td>
</tr>
</tbody>
</table>

### Panel A: Food Stores

<table>
<thead>
<tr>
<th></th>
<th>Income Per Capita</th>
<th>Fixed Effects</th>
<th>Weighted by number of stores</th>
<th>Drop Two Outlier Chains</th>
<th>R Squared</th>
<th>Number of Observations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(in $10,000)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.0044***</td>
<td>Chain</td>
<td>X</td>
<td>X</td>
<td>0.920</td>
<td>9,415</td>
</tr>
<tr>
<td></td>
<td>(0.0013)</td>
<td>Chain*State</td>
<td>X</td>
<td>X</td>
<td>0.958</td>
<td>9,415</td>
</tr>
<tr>
<td></td>
<td>0.0029***</td>
<td></td>
<td></td>
<td></td>
<td>0.948</td>
<td>171</td>
</tr>
<tr>
<td></td>
<td>(0.0003)</td>
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<td></td>
<td>0.312</td>
<td>64</td>
</tr>
<tr>
<td></td>
<td>0.0166***</td>
<td></td>
<td></td>
<td></td>
<td>0.542</td>
<td>64</td>
</tr>
<tr>
<td></td>
<td>(0.0079)</td>
<td></td>
<td></td>
<td></td>
<td>0.209</td>
<td>62</td>
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<tr>
<td></td>
<td>0.0448***</td>
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<td></td>
<td>(0.0101)</td>
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<tr>
<td></td>
<td>0.0505***</td>
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<tr>
<td></td>
<td>(0.0060)</td>
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<tr>
<td></td>
<td>0.0395***</td>
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<tr>
<td></td>
<td>(0.0119)</td>
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### Panel B: Drugstores

<table>
<thead>
<tr>
<th></th>
<th>Income Per Capita</th>
<th>Fixed Effects</th>
<th>Weighted by number of stores</th>
<th>R Squared</th>
<th>Number of Observations</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>(in $10,000)</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>0.0093***</td>
<td>Chain</td>
<td>X</td>
<td>0.443</td>
<td>9,973</td>
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<tr>
<td></td>
<td>(0.0011)</td>
<td>Chain*State</td>
<td>X</td>
<td>0.684</td>
<td>9,973</td>
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<tr>
<td></td>
<td>0.0075***</td>
<td></td>
<td></td>
<td>0.660</td>
<td>83</td>
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<tr>
<td></td>
<td>(0.0008)</td>
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<td></td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>0.0278***</td>
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<tr>
<td></td>
<td>(0.0077)</td>
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<td></td>
<td>NA</td>
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### Panel C: Mass-Merchandise Stores

<table>
<thead>
<tr>
<th></th>
<th>Income Per Capita</th>
<th>Fixed Effects</th>
<th>Weighted by number of stores</th>
<th>R Squared</th>
<th>Number of Observations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(in $10,000)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.0041***</td>
<td>Chain</td>
<td>X</td>
<td>0.914</td>
<td>3,288</td>
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<tr>
<td></td>
<td>(0.0011)</td>
<td>Chain*State</td>
<td>X</td>
<td>0.945</td>
<td>3,288</td>
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<td></td>
<td>0.0029***</td>
<td></td>
<td></td>
<td>0.969</td>
<td>142</td>
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<td></td>
<td>(0.0010)</td>
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<tr>
<td></td>
<td>NA</td>
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</tr>
</tbody>
</table>

**Notes:** Standard errors are clustered by parent_code in Panel A and are clustered by parent_code*state in Panels B and C.
## Online App. Table 3. Determinants of Price Elasticity, Robustness

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Store's Shrunk Estimated Price Elasticity</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td><strong>Demographic Controls</strong></td>
<td></td>
</tr>
<tr>
<td>Benchmark Income</td>
<td>0.143***</td>
</tr>
<tr>
<td>(in $10,000)</td>
<td>(0.0087)</td>
</tr>
<tr>
<td>County Income</td>
<td></td>
</tr>
<tr>
<td>(in $10,000)</td>
<td></td>
</tr>
<tr>
<td>HMS Range Midpoints</td>
<td></td>
</tr>
<tr>
<td>(in $10,000)</td>
<td></td>
</tr>
<tr>
<td>Fraction with College Degree (or higher)</td>
<td></td>
</tr>
<tr>
<td>Controls for Urban Share</td>
<td></td>
</tr>
<tr>
<td>Median Home Price</td>
<td></td>
</tr>
<tr>
<td>(in $100,000)</td>
<td></td>
</tr>
<tr>
<td><strong>Controls for Number of Competitors w/in 5km</strong></td>
<td></td>
</tr>
<tr>
<td>1-4 Other Grocery Stores</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
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<tr>
<td>5-9 Other Grocery Stores</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>10+ Other Grocery Stores</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>Fixed Effect for Chain</td>
<td>X</td>
</tr>
<tr>
<td>R Squared</td>
<td>0.652</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>22,660</td>
</tr>
</tbody>
</table>

**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. Number of observations differ due to data availability. 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).
### Online Appendix Table 4. Log Prices and Store-Level Log Elasticity, OLS

<table>
<thead>
<tr>
<th>Specification:</th>
<th>Dependent Variable:</th>
<th>Log Prices in Stores</th>
<th>Average Price for Chain-State</th>
<th>Avg. Log Prices for Chain c</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Within-Chain, OLS</td>
<td>Between-Chain, State, OLS</td>
<td>Between-Chain, OLS</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3) OLS</td>
</tr>
<tr>
<td><strong>Panel A. Food Stores</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Log (Elast. / (Elast.+1) ) in Store s</td>
<td>0.0326***</td>
<td>0.0262***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Mean Log (Elast. / (Elast.+1) ) in State-Chain Combination</td>
<td>0.0859</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Mean Log (Elast. / (Elast.+1) ) in Chain c</td>
<td></td>
<td>0.102*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Fixed Effect for Chain</td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Fixed Effect for Chain-State</td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Number of Observations</td>
<td>9,415</td>
<td>9,415</td>
<td>171</td>
</tr>
<tr>
<td><strong>Panel B. Drug Stores</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Log (Elast. / (Elast.+1) ) in Store s</td>
<td>0.158***</td>
<td>0.108***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Mean Log (Elast. / (Elast.+1) ) in State-Chain Combination</td>
<td>0.324***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Fixed Effect for Chain</td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Fixed Effect for Chain-State</td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Number of Observations</td>
<td>9,975</td>
<td>9,975</td>
<td>83</td>
</tr>
<tr>
<td><strong>Panel C. Mass Merchandise Stores</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Log (Elast. / (Elast.+1) ) in Store s</td>
<td>0.0563***</td>
<td>0.0252</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Mean Log (Elast. / (Elast.+1) ) in State-Chain Combination</td>
<td>0.138***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Fixed Effect for Chain</td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Fixed Effect for Chain-State</td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Number of Observations</td>
<td>3,288</td>
<td>3,288</td>
<td>142</td>
</tr>
</tbody>
</table>

**Notes:** For Panel A, standard errors are clustered by parent_code. For Panels B and C, they are clustered by parent_code*state. Elasticities above -1.2 are Winsorized. Retailer means for the Between-Chain specification are average Log(Elasticity/(Elasticity+1). Analytic weights equal to the number of stores in each group are used in columns (3) and (4).
Online App. Table 5. Log Price and Log Elasticity, Robustness II (Food Stores)

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Log Prices in Stores</th>
<th>Average Price for Chain-State</th>
<th>Average Log Prices for Chain c</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Within-Chain, IV w/ income</td>
<td>Within-Chain, IV w/ All Variables</td>
<td>Between-Chain-State, IV w/ income</td>
</tr>
<tr>
<td>Specification:</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
</tbody>
</table>

**Panel A. Benchmark Product**

Log (Elast. / (Elast.+1) ) in Store s

<table>
<thead>
<tr>
<th></th>
<th>0.0919***</th>
<th>0.101***</th>
<th>0.0643***</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(0.0339)</td>
<td>(0.0349)</td>
<td>(0.0105)</td>
</tr>
</tbody>
</table>

Mean Log (Elast. / (Elast.+1) ) in Chain c

<table>
<thead>
<tr>
<th></th>
<th>0.351*</th>
<th>0.936***</th>
<th>0.915***</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(0.202)</td>
<td>(0.196)</td>
<td>(0.187)</td>
</tr>
</tbody>
</table>

Fixed Effect for Chain

| X                  | X         | X         |

Fixed Effect for Chain*State

| X                  | X         | X         |

Number of Observations

| 9,415              | 9,415     | 9,415     |

**Panel B. Price Index as Dependent Variables**

Log (Elast. / (Elast.+1) ) in Store s

<table>
<thead>
<tr>
<th></th>
<th>0.102***</th>
<th>0.112***</th>
<th>0.0749***</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(0.0301)</td>
<td>(0.0311)</td>
<td>(0.0093)</td>
</tr>
</tbody>
</table>

Mean Log (Elast. / (Elast.+1) ) in Chain c

<table>
<thead>
<tr>
<th></th>
<th>0.356**</th>
<th>NA</th>
<th>NA</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(0.181)</td>
<td>NA</td>
<td>NA</td>
</tr>
</tbody>
</table>

Fixed Effect for Chain

| X                  | X         | X         |

Fixed Effect for Chain*State

| X                  | X         | X         |

Number of Observations

| 9,415              | 9,415     | 9,415     |

**Panel C. Generic top-seller within chain**

Log (Elast. / (Elast.+1) ) in Store s

<table>
<thead>
<tr>
<th></th>
<th>0.0594***</th>
<th>0.0676***</th>
<th>0.0414***</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(0.0223)</td>
<td>(0.0239)</td>
<td>(0.0051)</td>
</tr>
</tbody>
</table>

Mean Log (Elast. / (Elast.+1) ) in Chain c

<table>
<thead>
<tr>
<th></th>
<th>0.225</th>
<th>NA</th>
<th>NA</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(0.178)</td>
<td>NA</td>
<td>NA</td>
</tr>
</tbody>
</table>

Fixed Effect for Chain

| X                  | X         | X         |

Fixed Effect for Chain*State

| X                  | X         | X         |

Number of Observations

| 9,415              | 9,415     | 9,415     |

**Panel D. High Quality Items**

Log (Elast. / (Elast.+1) ) in Store s

<table>
<thead>
<tr>
<th></th>
<th>0.0985***</th>
<th>0.107***</th>
<th>0.0921***</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(0.0112)</td>
<td>(0.0127)</td>
<td>(0.0096)</td>
</tr>
</tbody>
</table>

Mean Log (Elast. / (Elast.+1) ) in Chain c

<table>
<thead>
<tr>
<th></th>
<th>0.184**</th>
<th>0.848***</th>
<th>0.850***</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(0.0870)</td>
<td>(0.207)</td>
<td>(0.189)</td>
</tr>
</tbody>
</table>

Fixed Effect for Chain

| X                  | X         | X         |

Fixed Effect for Chain*MSA

| X                  | X         | X         |

Number of Observations

| 9,395              | 9,395     | 9,395     |

| 170                | 63        | 63        |

Notes: The same first stage (benchmark weekly elasticity on income) is used for all panels; only the second stage differs. Standard errors are bootstrapped. Bootstrap samples are clustered at the parent_code level. 100 replications are used. Elasticities are Winsorized at -1.2. Generic Products in Panel C are chosen by chain so between-chain comparisons are not possible. For Panel D., twenty stores do not sell sufficient quantities of our high-quality items.
### Online Appendix Table 6. Estimated Loss of Profits at Chain Level, Robustness

<table>
<thead>
<tr>
<th>Panel A. Food Stores</th>
<th>Mean</th>
<th>25th</th>
<th>Median</th>
<th>75th</th>
</tr>
</thead>
<tbody>
<tr>
<td>Loss of Profits Comparing Optimal Pricing to Actual Pricing (Raw Prices)</td>
<td>11.56%</td>
<td>5.76%</td>
<td>8.38%</td>
<td>12.85%</td>
</tr>
<tr>
<td>Loss of Profits Comparing Optimal Pricing to Actual Pricing (Chain-State Means)</td>
<td>10.75%</td>
<td>5.75%</td>
<td>7.90%</td>
<td>10.45%</td>
</tr>
<tr>
<td>Loss of Profits Comparing Optimal Pricing to Actual Pricing (Raw Average Yearly Prices)</td>
<td>9.53%</td>
<td>4.34%</td>
<td>6.63%</td>
<td>10.54%</td>
</tr>
<tr>
<td>Loss of Profits Comparing Optimal Pricing to Actual Yearly Price-Elasticity Slope</td>
<td>5.59%</td>
<td>3.50%</td>
<td>4.45%</td>
<td>6.01%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B. Drugstores</th>
<th>Chain 4901</th>
<th>Chain 4904</th>
<th>Chain 4931</th>
<th>Chain 4954</th>
</tr>
</thead>
<tbody>
<tr>
<td>Loss of Profits Comparing Optimal Pricing to Actual Pricing (Raw Prices)</td>
<td>15.83%</td>
<td>11.88%</td>
<td>21.79%</td>
<td>9.89%</td>
</tr>
<tr>
<td>Loss of Profits Comparing Optimal Pricing to Actual Pricing (Chain-State Means)</td>
<td>13.98%</td>
<td>12.08%</td>
<td>17.46%</td>
<td>10.56%</td>
</tr>
<tr>
<td>Loss of Profits Comparing Optimal Pricing to Actual Pricing (Raw Average Yearly Prices)</td>
<td>11.98%</td>
<td>6.37%</td>
<td>17.60%</td>
<td>9.44%</td>
</tr>
<tr>
<td>Loss of Profits Comparing Optimal Pricing to Actual Yearly Price-Elasticity Slope</td>
<td>2.24%</td>
<td>1.85%</td>
<td>2.80%</td>
<td>1.61%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel C. Mass Merchandise Stores</th>
<th>Chain 6901</th>
<th>Chain 6904</th>
<th>Chain 6907</th>
<th>Chain 6919</th>
<th>Chain 6921</th>
</tr>
</thead>
<tbody>
<tr>
<td>Loss of Profits Comparing Optimal Pricing to Actual Pricing (Raw Prices)</td>
<td>12.72%</td>
<td>15.94%</td>
<td>5.12%</td>
<td>16.04%</td>
<td>9.98%</td>
</tr>
<tr>
<td>Loss of Profits Comparing Optimal Pricing to Actual Pricing (Chain-State Means)</td>
<td>8.82%</td>
<td>5.91%</td>
<td>3.84%</td>
<td>13.34%</td>
<td>7.70%</td>
</tr>
<tr>
<td>Loss of Profits Comparing Optimal Pricing to Actual Pricing (Raw Average Yearly Prices)</td>
<td>10.43%</td>
<td>12.18%</td>
<td>10.98%</td>
<td>9.15%</td>
<td>7.88%</td>
</tr>
<tr>
<td>Loss of Profits Comparing Optimal Pricing to Actual Yearly Price-Elasticity Slope</td>
<td>2.22%</td>
<td>1.78%</td>
<td>1.02%</td>
<td>1.01%</td>
<td>1.51%</td>
</tr>
</tbody>
</table>

Notes: Elasticities are Winsorized at -1.2. Raw prices are unadjusted observed prices. Chain-State Mean Prices use chain-state means in place of observed prices for every store within a chain-state, effectively enforcing chain-state zone pricing.
Online Appendix Table 7. Evidence for Tacit Collusion and Fairness Explanations

<table>
<thead>
<tr>
<th>Specification:</th>
<th>Within-Chain, IV</th>
<th>Between-Chain</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent Variable:</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Log Prices in Stores</td>
<td>Chain Price Response to Income (IV)</td>
</tr>
<tr>
<td></td>
<td>Food Stores</td>
<td>Drugstores</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Panel A. Within-Chain</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log (Elast. / (Elast.+1) ) in Store s</td>
<td>0.0853***</td>
<td>0.253***</td>
</tr>
<tr>
<td></td>
<td>(0.0275)</td>
<td>(0.0545)</td>
</tr>
<tr>
<td>Log (Elast. / (Elast.+1) ) in Store s * (Zero competitors stores within 10 km) (Tacit Collusion)</td>
<td>0.0154</td>
<td>-0.0458</td>
</tr>
<tr>
<td></td>
<td>(0.0194)</td>
<td>(0.0548)</td>
</tr>
<tr>
<td>Log (Elast. / (Elast.+1) ) in Store s * (Zero same-chain stores within 10 km) (Fairness)</td>
<td>0.0040</td>
<td>0.166***</td>
</tr>
<tr>
<td></td>
<td>(0.0142)</td>
<td>(0.0445)</td>
</tr>
<tr>
<td>Chain Fixed Effects</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Number of observations</td>
<td>9,415</td>
<td>9,976</td>
</tr>
</tbody>
</table>

Panel B. Between Chain

| Percent of Stores in Chain with zero competitors stores within 10 km (Tacit Collusion) | -0.147 | -0.0455 |
| | (0.1308) | (0.0594) |
| Percent of Stores in Chain with zero same-chain stores within 10 km (Fairness) | 0.172 | -0.0367 |
| | (0.1367) | (0.0596) |
| Analytic Weights = number of stores in chain | X |
| Number of observations | 73 | 73 |
| R-squared | 0.126 | 0.019 |

Notes: In columns 1-3, standard errors are bootstrapped. In Column 1, bootstrap clusters are parent_codes, while in columns 2-3, bootstrap clusters are parent_code*chain. These coefficients do not match what is showed in Figures 21a-b and 22a-b because the figures leave out stores with one competitor for tacit collusion tests (one store of the same chain for fairness tests) within 10 km. In Columns 5-6, standard errors are clustered by parent_code. The dependent variable is the chain-level price response to elasticity, instrumented with income.
## Online Appendix Table 8. Test of Firm Learning: Comparing 2006-08 to 2012-14

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Log Prices in Store $s$</th>
<th>Average Price for Chain-State Within-Chain, IV</th>
<th>Average Log Prices for Chain $c$ Between-Chain, IV</th>
<th>Log Prices in Store $s$</th>
<th>Average Price for Chain-State Within-Chain, IV</th>
<th>Average Log Prices for Chain $c$ Between-Chain, IV</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Specification:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Years:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Panel A. Food Stores</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log (Elast. / (Elast.+1)) in Store $s$</td>
<td>0.116*** (0.0349)</td>
<td>0.0676*** (0.0104)</td>
<td>0.0912** (0.0361)</td>
<td>0.0624*** (0.0110)</td>
<td>0.515*** (0.189)</td>
<td>0.977*** (0.197)</td>
</tr>
<tr>
<td>Mean Log (Elast. / (Elast.+1)) in Chain $c$</td>
<td>0.458 (0.3646)</td>
<td>NA</td>
<td>1.250*** (0.328)</td>
<td>NA</td>
<td>0.416*** (0.0647)</td>
<td>0.339*** (0.0513)</td>
</tr>
<tr>
<td>Fixed Effect for Chain</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fixed Effect for Chain-State</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of Observations</td>
<td>8,642</td>
<td>8,642</td>
<td>167</td>
<td>64</td>
<td>8,642</td>
<td>8,642</td>
</tr>
<tr>
<td><strong>Panel B. Drug Stores</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log (Elast. / (Elast.+1)) in Store $s$</td>
<td>0.192*** (0.0487)</td>
<td>0.167*** (0.0318)</td>
<td>0.416*** (0.0647)</td>
<td>0.339*** (0.0513)</td>
<td>0.515*** (0.189)</td>
<td>0.977*** (0.197)</td>
</tr>
<tr>
<td>Mean Log (Elast. / (Elast.+1)) in Chain $c$</td>
<td>0.458 (0.3646)</td>
<td>NA</td>
<td>1.250*** (0.328)</td>
<td>NA</td>
<td>0.416*** (0.0647)</td>
<td>0.339*** (0.0513)</td>
</tr>
<tr>
<td>Fixed Effect for Chain</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of Observations</td>
<td>8,553</td>
<td>8,553</td>
<td>80</td>
<td>80</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Panel C. Mass Merchandise Stores</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log (Elast. / (Elast.+1)) in Store $s$</td>
<td>0.127** (0.0558)</td>
<td>0.0899 (0.0576)</td>
<td>0.241*** (0.0762)</td>
<td>0.128** (0.0559)</td>
<td>0.315 (0.264)</td>
<td>NA</td>
</tr>
<tr>
<td>Mean Log (Elast. / (Elast.+1)) in Chain $c$</td>
<td>0.315 (0.264)</td>
<td>NA</td>
<td>0.820*** (0.238)</td>
<td>NA</td>
<td>0.241*** (0.0762)</td>
<td>0.128** (0.0559)</td>
</tr>
<tr>
<td>Fixed Effect for Chain</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of Observations</td>
<td>3,012</td>
<td>3,012</td>
<td>139</td>
<td>139</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Notes:** Standard errors are bootstrapped. Bootstrap clusters are by parent_code in Panel A and by parent_code*state in Panels B and C. Elasticities above -1.2 are Winsorized. Retailer means for the Between-Chain specification are average Log(Elasticity/(Elasticity+1)). The same first stage including all stores of the same type using nine-year elasticities and incomes are used within each panel. Stores must be present in both the early and late periods in order to be included in the second stage.