An Empirical Study of National vs. Local Pricing under Multimarket Competition

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Abstract

Geographic price discrimination is generally considered beneficial to firm profitability. Firms can extract higher rents by varying prices across markets to match consumers’ preferences. This paper empirically demonstrates, however, that a firm may prefer to forego the flexibility to customize prices and instead employ a national pricing policy that fixes prices across geographic markets. Under appropriate conditions, a national pricing policy helps avoid intense local competition due to targeted prices. We examine the choice of national versus local pricing under multimarket electronics retail chain competition using extensive data from the digital camera market. We estimate a flexible model of aggregate demand that incorporates additional micro purchase moments and semi-parametric heterogeneity. Counterfactual analyses show that the major retail firms should employ a national pricing policy to maximize profits, rather than target prices in each local market. Fixing prices across markets allows the retailers to soften otherwise intense local competition by subsidizing competitive markets with profits from less competitive markets. Additional results explore how market factors could affect the pricing policy decision and assist retail managers in choosing their geographic pricing policies.

Keywords: pricing, retailing, competitive strategy, spatial targeting, national pricing policy.

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1 Introduction

Geographic price discrimination is generally considered beneficial to firm profitability. Varying prices across markets with different consumer preferences and socio-economic characteristics allows a firm to extract more surplus by matching prices to consumers’ local willingness to pay. Prior empirical work on geographic price discrimination documents such profit-enhancing effects (Chintagunta, Dubé, and Singh 2003). Many large retail chains, such as Walmart, Starbucks, and McDonald’s, implement a form of region-based pricing that permits them to target prices to local market conditions.¹ In this study, we argue, and empirically demonstrate, that in competitive settings, retailers may be better off forsaking the flexibility of local pricing in favor of a national pricing policy that fixes prices across geographic markets.²

The rationale behind such a national pricing policy is that in competitive settings targeted prices intensify local competition and increase the risk of a price war (Wells and Haglock 2007). To illustrate the intuition underlying a national pricing policy, consider a simple example with two retail chains and three independent markets. Chains A and B operate as monopolists in the first two markets, respectively, and compete as a duopoly in the third market. Under general conditions, a local pricing policy yields higher prices in the monopoly markets compared to lower prices in the duopoly market. However, if the duopoly market is relatively large compared to the monopoly markets, a chain can increase its profits by charging a uniform price across markets. The optimal national price falls between the (local) high monopoly price and low duopoly price, thus softening the duopoly market competition (Dobson and Waterson 2005). National pricing is optimal if the profit gain from softened competition in the duopoly market exceeds the profit loss sacrificed in the monopoly markets.³

This paper’s objective is to empirically examine a firm’s choice of national versus local

¹Evidence can be found at, for example, http://walmartstores.com/317.aspx, and “Coffee talk: Starbucks chief on prices, McDonald’s rivalry,” The Wall Street Journal, March 7, 2011.
²In the remainder of the paper, we use the terms national, uniform, and fixed interchangeably to refer to the policy of fixing prices across geographic regions.
³Web Appendix A provides an analytical model in which we formalize this intuition.
pricing in a multimarket competitive setting. We examine this decision in the context of the U.S. digital camera market, which generated $5.8 billion in sales in 2012. Our paper focuses on the competitive rationale that underlies a national pricing policy, in terms of how a chain’s choice of pricing policy depends on balancing profits with competitive pressures across markets. A key determinant of a chain’s decision is the relationship between the joint distribution of market structure and consumer preferences. While our empirical application focuses on electronics retailers and digital cameras, the insights from this investigation could generalize to other industries evaluating chain-level pricing policies. Firms may, of course, have other reasons to pursue national pricing over local pricing, such as minimizing organizational costs or maintaining consistent prices offline and online, which we view as beyond the study’s scope.

Our analysis uses point-of-sales data from the NPD Group to provide a near census of U.S. retail sales of digital cameras, including multiple large chains and rich geographic variation in market conditions. We use these data to recover preferences flexibly using an aggregate model of demand with random coefficients estimated separately in each of more than 1,500 markets. Estimating the demand model separately by market results in significantly more variation in elasticity estimates compared to estimates from pooling the data. To improve the estimation, we modify the model in Berry, Levinsohn, and Pakes (1995) by including micro moments based on survey data that relate purchase behavior with consumer income levels (Petrin 2002). Including the micro moments improves the estimated substitution patterns and attenuates the price elasticities. Because product assortment varies substantially across markets and over time, we account for product congestion bias due to unbalanced choice sets using a congestion term (Ackerberg and Rysman 2005).

In our model, retail chains set an overall pricing policy and then compete in a Bertrand-Nash equilibrium in choosing product-level prices. In effect, the national pricing policy constrains the pricing decisions to identical prices across geographic markets whereas a local policy provides the chain with complete flexibility.\footnote{Two points about the game are worth mentioning. First, we assume firms can credibly commit to these policies before engaging in Bertrand-Nash competition. In practice, as we discuss in Section 2.3, the chains} Although consumer preferences are
estimated without any equilibrium assumptions, we require an equilibrium assumption on
the product-level pricing problem to recover the retailers’ marginal costs. This equilibrium
assumption only applies to the product-level pricing game and not to the chains’ choice of
overall pricing policy (e.g., national vs. local). Thus, we take the chain’s pricing policy as
given and use the product-level pricing game to recover marginal costs conditional on the
demand estimates. One benefit of considering the electronics retail chains’ market is that
two of the three largest chains primarily employ national pricing policies.\(^5\) In calculating
margins we use the firms’ actual pricing policies. For robustness, we repeat the analysis
assuming local pricing policies.

Given the marginal cost estimates, we conduct several counterfactuals to assess the prof-
itability of national and local pricing policies. First, a simulation demonstrates that the
two major electronics retail chains should employ national pricing policies to maximize prof-
its. Uniform prices across markets allow the retailers to subsidize more competitive markets
with profits from less competitive markets to soften the otherwise intense local competition.
Compared to a situation in which both chains use local pricing policies, national pricing
results in profit increases of 5.3% to 8.4% across chains.

Second, we investigate the boundary conditions under which a firm would prefer to employ
a national pricing policy. As the number of competitive markets decreases, the firms begin to
prefer local pricing to recap the benefits in their monopoly markets. We find that the leading
retailer would prefer local pricing if it closed at least 29% of its stores in the competitive
markets. Moreover, we leverage a unique feature of our data to examine the impact of local
competitive intensity on the choice of pricing policies. That is, at the end of the second
year of the data period, one major retailer exited from the industry, thereby significantly
changing the competitive landscape. We find that although the dominant retailer is still

\(^5\)Due to a data confidentiality requirement, we are prohibited from disclosing the names of retailers and
camera brands. Throughout the paper, we denote chains and brands by generic letters and numbers.
weakly better off by employing national pricing (because of the existence of a large discount retailer), the benefit from national pricing is nearly gone compared to the situation when its major rival was competing in the markets. The counterfactual exercises imply that if national pricing provides an advantage then it must be a competitive advantage. Sufficient competition is needed in order for national pricing to be the optimal strategy.

Third, we explore the possibility that chains may adopt a hybrid pricing policy across geographic markets, by employing uniform pricing for most markets, but allowing targeted pricing for selected markets. Specifically, based on the intuition that national chains may adopt special policies in large metropolitan markets, we test the outcome as if the two leading chains customize prices in the five largest metropolitan areas of the U.S. The result is that profits at both chains decreases because competition in these large markets is especially intense, and thus the counterfactual local prices further intensify competition and reduce profits. Moreover, we consider the possibility that the leading chains convert a portion (the top 10% or 20%) of their largest monopolist markets into local pricing zones, while maintaining uniform pricing elsewhere. The results indicate that such a hybrid strategy favors the leading chain, but not the second largest chain.

This paper broadly relates to the literature on retail pricing (Rao 1984; Eliashberg and Chatterjee 1985; Besanko, Gupta, and Jain 1998; Shankar and Bolton 2004), and in particular, on geographic price discrimination (Sheppard 1991; Hoch et al. 1995; Duan and Mela 2009). Previous studies on geographic price discrimination, however, generally neglect the effect of pricing competition in the multimarket context. The closest paper to the present study is Chintagunta, Dubé, and Singh (2003), who study a single chain’s zone-pricing policy across different neighborhoods in Chicago. The authors find that, by further localizing prices, a chain could substantially increase its profit without adversely affecting consumer welfare. Data limitations prevent the authors from incorporating information on competitors other than a distance-based proxy. Therefore, the counterfactual results do not account for competitive responses, whereas we explicitly model the interaction between retailers following a policy change. The intuition behind our main result is similar to ideas discussed in the context of targeting individual consumers in Chen, Narasimhan, and Zhang (2001).
Our findings provide further empirical support to the theoretical literature on multimarket contact, such as Bernheim and Whinston (1990), Bronnenberg (2008), and Dobson and Waterson (2005). Our results also broadly relate to work on the coordination of retailer pricing strategies across channels (Zettelmeyer 2000) and choice of pricing formats across markets (Lal and Rao 1997; Ellickson and Misra 2008).

The rest of the paper is organized as follows. Section 2 introduces the data and overviews the market structure and pricing policies observed in the data. Section 3 describes the demand model and the chain pricing model. Section 4 details model estimation and reports results of parameter estimates. Section 5 presents counterfactual experiments of various pricing policy changes and checks the robustness of local market definition. Section 6 concludes the paper with a discussion of its limitations, and highlights areas of future research. All other details of the analysis are located in the Web Appendix.

2 Data and Industry Facts

In this section, we discuss the data sets and the industry, and document the current market structure and pricing policies.

2.1 Data

The data in this paper come from a variety of sources: (1) store-level sales and price data on digital cameras from the NPD Group, (2) two sets of consumer survey statistics from PMA, (3) online vs. offline shopping statistics from Mintel, (4) digital camera sales across channels from Euromonitor, and (5) consumer demographics from the U.S. Census. Next, we describe each of these data sets.

First, the NPD data contains approximately 10 million monthly point-of-sales observations between January 2007 and April 2010. The data cover most stores in the United States that sell digital cameras. Each observation is at the month-store-camera model level, providing a highly granular picture of product-level sales across a large number of stores and
Table 1: Annual Market Shares (%) of Top Camera Brands

<table>
<thead>
<tr>
<th></th>
<th>2007</th>
<th>2008</th>
<th>2009</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brand 1</td>
<td>21.4</td>
<td>21.5</td>
<td>21.6</td>
</tr>
<tr>
<td>Brand 2</td>
<td>17.0</td>
<td>19.1</td>
<td>20.6</td>
</tr>
<tr>
<td>Brand 3</td>
<td>7.3</td>
<td>11.1</td>
<td>12.8</td>
</tr>
<tr>
<td>Brand 4</td>
<td>16.4</td>
<td>13.7</td>
<td>12.2</td>
</tr>
<tr>
<td>Brand 5</td>
<td>6.4</td>
<td>6.1</td>
<td>5.6</td>
</tr>
<tr>
<td>Brand 6</td>
<td>5.5</td>
<td>5.4</td>
<td>5.2</td>
</tr>
<tr>
<td>Brand 7</td>
<td>3.8</td>
<td>4.5</td>
<td>5.2</td>
</tr>
<tr>
<td>Total</td>
<td>77.8</td>
<td>81.4</td>
<td>83.2</td>
</tr>
</tbody>
</table>

time periods. The data set contains nearly 60 unique camera brands. We focus our analysis on the largest seven brands, which account for approximately 80% of sales, as reported in Table 1. The NPD data also contain a detailed description of the product characteristics for each camera model, such as mega-pixels, optical zoom, thickness, weight, and display size. For market definition, NPD splits the United States into 2,100 distinct geographic markets called store selling areas (SSAs), which define close competitive markets. Ninety-five percent of SSAs contain only one store of each major retailer. We rely on this market definition for our analysis and consider the robustness of this definition in Section 5.4.

Second, we use consumer survey data from the market research firm PMA to augment the estimation with micro moments, which relate digital camera purchases with household income. PMA conducts an annual survey each January on consumer purchasing and usage of digital cameras. The respondents consist of a rotating representative panel of 10,000 randomly selected U.S. households. From the survey responses we obtain the proportion of households at different income levels that bought a new digital camera. We apply these proportions to construct the micro moments for demand estimation. Also, we use the Mintel report on the shares of offline versus online purchases by household income across categories to scale the PMA survey data to obtain the shares of offline camera purchases at different income levels.

Third, we use the channel sales data from Euromonitor to construct an appropriate market size definition. A proper measure of market size is important to accurately recover
firms’ mark-ups. Common measures are population size, number of households (e.g., Berry et al. 1995), or total category demand (e.g., Song 2007). The use of population size as a proxy for potential demand can be problematic because in any given month, only a fraction of all consumers considered purchasing digital cameras. To correctly specify market size, we attempt to quantify all potential consumers including (1) those who bought cameras in the stores under investigation, (2) those who bought cameras through other channels (e.g., online), and (3) those who considered buying but chose not to. The first group of consumers directly corresponds to the NPD store data assuming single-unit purchases per trip. For the second group, we estimate the share of consumers who purchased cameras outside of the retail chains, using data on camera sales by distribution channel from Euromonitor International (2010) for all income levels. Based on the Euromonitor data in 2009 only 9.2% of digital cameras were purchased online and 1.8% through other channels not reported in our data, thus the NPD data covers the vast majority of digital cameras sales in the U.S. The third group represents consumers who are in the market but eventually choose not to purchase a camera. To estimate this group, we obtain another set of survey data on camera purchase intentions from PMA. The annual survey asked households about their purchase intentions in the next three-, six-, or twelve-month periods. These percentages less the actual purchase probabilities from the PMA report of the following year yields a rough measure of the share of non-purchasers. In the demand model, we combine the second and third groups as the composite outside good.

2.2 Market Structure and Major Retailers

The relative advantage between national and local pricing relies on two key characteristics of market structure: (i) the size of competitive markets versus monopoly markets and (ii) the degree of local competition, in terms of the elasticity of substitution across chains in a market. Next, we describe some model free evidence for the competitive market structure

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6 For example, in a homogeneous logit model, the mark-up across all products of a firm is a constant and it is negatively related to market size.

7 A simple analytical model in Web Appendix A illustrates the intuition behind how these features of market structure determine the relative advantage of national and local pricing policies.
The retail digital camera market is concentrated with three national chains, A, B, and D, accounting for 70% of the total sales in our data. Other retailers had shares below 3% each. Chains A and B are specialty retailers of consumer electronics, whereas Chain D is a discount retail chain. Figure 1 depicts the market shares of the three chains, which shows that before 2009, A and B accounted for approximately 40% and 16% of the shares of the U.S. market, respectively. At the end of 2008, chain B terminated operations and liquidated all stores within three months (for reasons mostly independent of camera sales). The market share B left was immediately taken up by A, making A the dominant national player with almost 60% of the entire U.S. digital camera market. Chain D maintained an approximate 9% share throughout the period. As a result of the concentrated market structure, in the current study, we focus on the competition between these three big-box retail chains. Accordingly, we remove the local markets in which none of the three firms exist (about 24% reduction in the number of SSAs), thereby leading to the three major chains accounting for almost 90% of the market share in the areas in which they operate. We group all small sellers in these areas into a single chain L.

Table 2 presents the distribution of competitive market structures across SSAs before and after Chain B exited, and the associated average annual sales. All three chains operated in a mixture of monopolist-like markets and oligopoly markets. The leading chain, A, had approximately 800 stores in 2007 and expanded to around 1,000 stores by early 2010. The second-largest chain, B, operated approximately 600 stores until its bankruptcy. Before Chain B’s exit, Chains A and B competed in more than half the markets in which they operated. At the same time, in many markets, Chains A and B did not coexist and only faced competition either from Chain D or those small retailers, which are not shown in this table.

Given these market conditions, whether a firm would prefer a national or local pricing policy is unclear. On the one hand, the retailer could leverage its power in the monopoly or low-competition markets by employing a local pricing policy. On the other hand, the
relatively large proportion of duopoly and triopoly markets may push the retailer to use a national pricing policy to ease the competition. Both the distributions of market sizes and structures determine the optimal chain-level policy. After Chain B’s exit, the number of monopoly markets for Chain A increased by approximately 65% and the sales in these markets went up by over 100%. Again, whether Chain A would find switching to local pricing following Chain B’s exit optimal depends on the relative size of these markets and the intensity of competition in its other markets. Although it gained monopoly markets, Chain A still faces competition from Chain D in most of the markets Chain A operates in. Thus a firm’s choice of pricing policy is an empirical question, which we investigate in the next section using a structural empirical model of chain competition and a set of counterfactual analyses.
<table>
<thead>
<tr>
<th>Market Type</th>
<th>Before B Left</th>
<th>After B Left</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td># SSAs</td>
<td>Sales</td>
</tr>
<tr>
<td>A-only</td>
<td>101</td>
<td>0.62</td>
</tr>
<tr>
<td>A-D</td>
<td>315</td>
<td>2.51</td>
</tr>
<tr>
<td>B-only</td>
<td>79</td>
<td>0.33</td>
</tr>
<tr>
<td>B-D</td>
<td>118</td>
<td>0.71</td>
</tr>
<tr>
<td>A-B</td>
<td>59</td>
<td>0.76</td>
</tr>
<tr>
<td>A-B-D</td>
<td>402</td>
<td>5.60</td>
</tr>
<tr>
<td>D-only</td>
<td>525</td>
<td>0.85</td>
</tr>
</tbody>
</table>

Note: Sales are in million units.

### 2.3 Pricing Policies

Both retailers A and B used nearly national pricing policies: prices for each product are almost identical across geographic locations until the product reaches approximately 80% of its cumulative lifetime sales. For the remaining lifetime of the product sales, the products often go on clearance and each local store can decide on price promotions. In contrast, Chain D implemented localized pricing throughout the life of the product.

To investigate the pricing policies of three retailers, Figure 2 presents the coefficients of variation in the sales-weighted price across stores for all products relative to their cumulative share of lifetime sales. Each dot in the figure is a product-month observation. For Chains A and B, before the cumulative share reaches approximately 80%, a product’s price exhibits little to no variation across stores. In contrast, for Chain D, the price variation across stores is much higher and relatively constant over a product’s lifecycle.

Even though Chains A and B employ national pricing, there are several reasons for the small variation observed in price across stores for these chains. First, we must derive unit prices by dividing the monthly sales data containing product-level revenue by volume in each store. This aggregation leads to small differences in monthly average product price across stores. Second, some sales are made using store-level coupons, open-box sales, or other local

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8To determine the cumulative sales of the products that entered prior to January 2007, we use national sales data from NPD aggregated over stores from January 2000 to March 2010.
promotions that are independent of a chain’s national pricing policy. Third, measurement error in either the revenue or volume would generate apparent price variation. All these errors will be absorbed into an unobservable demand shock term in the model.

In addition to these descriptive patterns in the data, discussions with a senior pricing director at one of the chains confirmed that Chains A and B both follow national pricing policies for most of a product’s lifecycle, and then transition to local (clearance) pricing when they predict the product has reached a considerable portion (e.g., 80%) of its cumulative lifetime sales. Furthermore, Chains A and B state on their websites that company policy dictates that online and offline prices should generally match. These chains offered price-match guarantees to compensate price difference for the sales from their own stores. In contrast, Chain D, employing a local pricing policy, made no claims regarding price uniformity, and explicitly states that online prices are excluded from their companies’ price-matching guarantees. Chain D is not oriented towards consumer electronics, selling many categories beyond those sold by Chains A and B. Given this, our analysis in Section 5.1 focuses on evaluating counterfactual pricing policies for Chains A and B, although we also consider alternative policies for Chain D.

3 Model

This section provides a market-specific aggregate demand model to estimate consumer preferences. We then compute marginal costs for the counterfactual simulations using a supply-side model. To facilitate demand estimation, we incorporate a set of micro moments that relate income to digital camera purchasing patterns.

3.1 Aggregate Demand

We model consumer demand for digital cameras using an aggregate discrete choice model (Berry 1994; Berry et al. 1995). To incorporate demographic variation in income, we model consumer utility through a Cobb-Douglas function. The utility household $i$ extracts from
Figure 2: Price Dispersion in Chain A (top), B (middle), and D (bottom)
choosing product $j$ at month $t$ is

$$U_{ijt} = (y_i - p_{jt})^\alpha G(x_{jt}, \xi_{jt}, \beta_i) e^{\epsilon_{ijt}},$$

(1)

where $t=1, ..., T$ is the index for month and $j=1, ..., J_t$ denotes the set of products available at month $t$. A product $j$ is defined as a particular camera sold in a particular store. $x_{jt}$ are observed product characteristics with coefficients $\beta_i$. $\xi_{jt}$ represent unobservable shocks common to all households. These shocks may include missing product attributes, unquantifiable factors such as camera design and style, and measurement errors due to aggregation or sampling. $y_i$ is the income of household $i$, $p_{jt}$ is the price of product $j$ at month $t$, and $\alpha$ is the price coefficient indicating the marginal utility of expenditures. For the income distribution $y_i$, we use zip-code-level demographics from the U.S. Census adjusted by the CPI inflation data from the U.S. Bureau of Labor Statistics to match the periods under investigation.

$G(\cdot)$ is assumed to be linear in logs, and the transformed utility for $j=1, ..., J_t$ is

$$u_{ijt} = x'_{jt} \beta_i + \alpha \log (y_i - p_{jt}) + \xi_{jt} + \epsilon_{ijt}.$$  

(2)

Accordingly, the utility for the outside option $j=0$ is

$$u_{i0t} = \alpha \log (y_i) + \epsilon_{i0t}.$$  

(3)

Assuming $\epsilon$'s are distributed type-I extreme value, the market share of product $j$ in

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9The fact that our data are available at the store level and the lack of information on store characteristics make it difficult to model store choice via a nested choice model. It is also unclear if consumers actually choose a store before selecting among the products. Moreover, Berry (1994) shows that with aggregate demand, a nested logit is a special case of a random coefficients model, and the latter allows for more complicated correlation patterns between products. Thus we treat store affiliation as an additional product attribute that additively enters into consumer utility function.

10One issue with using a Cobb-Douglas utility is that income must be larger than price before taking logs. With simulated income draws, some of these draws could fall below price and violate this condition. In the current study, digital camera price is much smaller than household monthly income on average, so the estimation bias resulted from the sample selection on income should be negligible.
Table 3: Percent of Households that Purchased a New Digital Camera

<table>
<thead>
<tr>
<th>Year</th>
<th>&lt; $29,999</th>
<th>$30,000–$49,999</th>
<th>$50,000–$74,999</th>
<th>&gt; $75,000</th>
</tr>
</thead>
<tbody>
<tr>
<td>2007</td>
<td>8%</td>
<td>16%</td>
<td>20%</td>
<td>20%</td>
</tr>
<tr>
<td>2008</td>
<td>8%</td>
<td>12%</td>
<td>14%</td>
<td>18%</td>
</tr>
<tr>
<td>2009</td>
<td>7%</td>
<td>11%</td>
<td>14%</td>
<td>15%</td>
</tr>
</tbody>
</table>

month $t$ is simply the logit choice probabilities aggregated over all households in the market

$$s_{jt} = \int \frac{\exp[\mathbf{x}'_{jt}\beta + \alpha \log(1 - p_{jt}/y_{ij}) + \xi_{jt}]}{1 + \sum_{k=1}^{J_{jt}} \exp[\mathbf{x}'_{kt}\beta + \alpha \log(1 - p_{kt}/y_{ik}) + \xi_{kt}]} dP(\beta_{i})dP(y_{i}),$$

where $P(\beta_{i})$ and $P(y_{i})$ are probability density functions of heterogeneous tastes and household income, respectively. We use the U.S. Census data to recover the distribution of $y_{i}$ under the assumption of log-normality, whereas $\beta_{i}$ is normally distributed and we estimate the parameters of this distribution as part of the structural estimation.\(^{11}\)

The set of observed camera attributes includes price and five key attributes: camera brand, mega-pixels, optical zoom, thickness, and display size (the last four attributes and price are models as linear variables.). Given that the sale observations in each market may not be sufficient to robustly estimate a full set of random coefficients, we further decompose $\mathbf{x}_{jt}$ into $\mathbf{x}^{fc}_{jt}$ and $\mathbf{x}^{rc}_{jt}$, and assign random coefficients only to $\mathbf{x}^{rc}_{jt}$. $\mathbf{x}^{rc}_{jt}$ includes mega-pixels, store affiliation, and camera brand. The other three non-price attributes are included in $\mathbf{x}^{fc}_{jt}$. As the industry exhibits strong seasonality, we include “November-December” and “June” dummies in $\mathbf{x}^{fc}_{jt}$.

### 3.2 Micro Moments

Leveraging information that links average consumer demographics to consumers’ purchase behavior can improve estimates of aggregate models (Petrin 2002). We divide each

\(^{11}\)The normality assumption on consumer heterogeneity may cause estimation bias if the actual distribution is heavily tailed or multi-mode, as demonstrated by Li and Ansari (2013). To allow for flexible heterogeneity distribution, we estimate the demand model separately for each local market, leading to a semi-parametric estimation of national-level consumer heterogeneity.
market into $R$ distinct income tiers, with varying price coefficients across these tiers:

$$\alpha_r = \begin{cases} 
\alpha_1, & \text{if } y_i < \bar{y}_1 \\
\alpha_2, & \text{if } \bar{y}_1 \leq y_i < \bar{y}_2 \\
\vdots \\
\alpha_R, & \text{if } y_i \geq \bar{y}_{R-1},
\end{cases} \quad (5)$$

where $\bar{y}_1, \bar{y}_2, \ldots, \bar{y}_{R-1}$ are the cutoffs on income. PMA defined four income tiers from its consumer surveys and reports average purchase probabilities of households at these tiers (Table 3). In demand estimation, we construct additional micro moments according to

$$E[\{\text{household } i \text{ bought a new camera at } t}\} \mid \{i \text{ belongs to income tier } r \text{ at } t\}],$$

where $r=1, \ldots, R$, and match these moments to the variation of purchase probabilities across income groups in the PMA data. The function of micro moments is different from hierarchically adding demographics via parameter heterogeneity. The latter approach only provides extra flexibility in the model, whereas the micro moments entail a process that restricts the GMM estimator to match additional statistics, making the estimated substitution pattern directly reflect demographic-driven differences in choice probability. Also, the variation in purchase probabilities across income groups provides new information that facilitates parameter identification.

To apply the PMA data, three modifications are necessary before constructing the micro moments. First, the PMA survey adds up both online and offline sales; therefore, it is inconsistent with the NPD data and the store demand model. We use additional statistics from Mintel regarding online versus offline shares by household income to calibrate the PMA survey responses. Second, the PMA data provide digital camera purchase likelihood by income tier at the national level, whereas our analysis is at the local market level. Thus we scale the PMA data to make them consistent with the geographic differences in demographics and with the actual market size underlying the demand model. We discuss the details of the scaling procedure in Web Appendix D. Third, given the store data are at the monthly level, we linearly interpolate the PMA yearly data to convert them to monthly observations.
3.3 Product Congestion

According to Ackerberg and Rysman (2005), logit models impose restrictions on how the dimensionality of the unobserved characteristics space (the $\epsilon$’s) changes with the number of choice alternatives. That is, logit models do not allow “congestion” in the unobservable characteristics space. Therefore, price sensitivity may be estimated without price variation, but solely with variation in the number of products across choice scenarios. In our data, the camera market exhibited significant geographic differences and underwent frequent product entry and exit. For example, the average number of products across geographic markets varies from 25 to 64, and the within-market coefficient of variation across time is about 23%. Such variation in the size of choice sets can lead to biased elasticity estimates.

To accommodate congestion for unobserved characteristics in logit models, Ackerberg and Rysman (2005) propose a modified specification that imposes a bound on the space of unobserved characteristics. The bound is a function of the number of products in a market, and the products are considered equally differentiated along unobserved characteristics but constrained by the bound. The bound is implemented as a congestion term $\log(R_{jt})$, where $R_{jt} = J_t^j$, and $\gamma$ is a parameter to estimate. We add the congestion term to the model and report the comparison with and without this correction in Section 4.3. We refer readers interested in the product congestion bias to Ackerberg and Rysman (2005) for more details.

3.4 Chain-Level Pricing Model

In this subsection we present the supply-side model of chains engaged in multimarket price competition. To obtain estimates of marginal costs for subsequent counterfactual analyses, we assume a chain operates under either a national pricing policy that fixes prices across markets, or a local pricing policy that customizes prices in every market. In each month, conditional on its chosen pricing policy, the chain sets prices in a Bertrand-Nash fashion.

It should be noted that the equilibrium assumption only applies to the period price-setting game and not to each chain’s overall choice of spatial pricing policy (national vs. local). This assumption is reasonable given that the choice of overall spatial pricing policy is a much more
long-term decision. Not assuming equilibrium on overall spatial pricing policy permits us to evaluate a chain’s pricing-policy choice in a set of counterfactual analyses. Further, we estimate marginal costs under both national and local pricing for the firms and test the robustness of the recovered marginal cost and counterfactual results regarding the assumed pricing policy.

Each chain $f$ sells some subset of $J_{ft}$ of the total $J_t$ products. With a national pricing policy, a chain has a profit function that sums up local profits with uniform prices ($t$ is suppressed in the rest of this section):

$$\Pi_f = \sum_{j=1}^{J_f} (p_j - c_j) \sum_{m} s_{jm} M_m, \quad (6)$$

where $m$ denotes a local market in which the chain operates. $M_m$ represents the size of market $m$ and $s_{jm}$ is the share of product $j$ in market $m$.

Given that $s_{jm}$ is a function of price $p_j$, the first-order condition with respect to $p_j$ is

$$\sum_{m} s_{jm} M_m + \sum_{r=1}^{J_f} (p_r - c_r) \sum_{m} \frac{\partial s_{rm}}{\partial p_j} M_m = 0, \quad \text{for } j = 1, ..., J_f . \quad (7)$$

Stacking prices and costs and aligning simulated shares across markets, the pricing equation (7) can be written in matrix notation for all competing chains:

$$c = p - \Delta^{-1} q, \quad (8)$$

where $q = \sum_{m} M_m \int_{i \in m} s_i$, is a vector of total unit sales of each product, and $\Delta$ is a block diagonal matrix in which each block, $\Delta_f$, corresponds to a chain. Let $\mu_i(p) = \alpha, \log(1-p/y_i)$, so $\partial \mu_i(p)/\partial p$ is a diagonal matrix. Then,

$$\Delta_f = - \sum_{m} M_m \int_{i \in m} \left[ \frac{\partial \mu_i(p)}{\partial p} (\text{diag}(s_i) - s_i s_i') \right]. \quad (9)$$

Here the integration is specific to the demographic distribution in market $m$.  


Under local pricing, the profit in one market is independent of another market. The summation over \( m \) in (9) drops out, and market size cancels out as well. That is,

\[
c = p - \Delta^{-1}s,
\]

(10)

where \( s = \int_{i \in m} s_i \) is a vector of product shares, and

\[
\Delta_f = -\int_{i \in m} \left[ \frac{\partial \mu_i(p)}{\partial p} \left( \text{diag}(s_i) - s_i s_i' \right) \right].
\]

(11)

Using (8) and (10), we compute the marginal costs with the demand estimates as input. Then in the counterfactual simulation, we use the same formulas to calculate the new equilibrium prices under alternative pricing policies.\(^{12}\) Based on the pricing patterns observed in the data section, we assume A and B fixed price across markets for each camera before sales of the camera hit the 80% threshold of its lifetime sales. In calculating marginal costs, we combine (8) and (10) to capture this transition. The marginal costs in the last 20% of sales are solved by constrained optimization on Equation (10), constraining the cost to be the same across markets for each product. Constant marginal costs for a given product across markets and independent of the chain-level pricing policy seem reasonable because of the efficient distribution of consumer electronics and the chain-controlled sales force compensation schemes. In addition, we calculate two sets of costs (i.e., the uniform costs under national pricing and the constrained costs under local pricing), and find significant similarity between them. The relative difference between the two sets of costs averaged across products is merely 0.81%. Thus, assuming local or national pricing to derive marginal costs should not affect the results of the counterfactual analyses reported later.

\(^{12}\)Uniqueness and existence of equilibrium have been shown under certain conditions for homogeneous logit demand models (Caplin and Nalebuff 1991). These properties of equilibrium in models such as ours with multiproduct firms and heterogeneous preferences are not yet well understood (Konovalov and Sandor 2010).
4 Estimation

In this section, we discuss our estimation approach and the estimates of the demand parameters, elasticities and margins under alternative model specifications. Note that the demand estimation is free of equilibrium assumptions in order to accurately recover consumer preferences. Furthermore, the digital cameras market is characterized by rich geographic variation in market structure, product mix, and consumer demographics. Thus the method of estimating demand needs to take into account the local variation in market conditions. To this end, we estimate the demand model separately for each of the more than 1,500 markets in which A, B, and/or D operated.

Because a market contains approximately 1,200 observations on average, separate estimation for each market permits the inclusion of heterogeneity within a market, but does not constrain the shape of preference heterogeneity across markets. For comparison purposes, we also estimate a single model that pools the data across markets.

4.1 Moments

In each market, the demand system has the following two components:

\[
\begin{align*}
    s_{jt} &= \int \frac{\exp(V_{ijt})}{\exp(V_{ijt}) + \sum_{k=1}^{J} \exp(V_{ikt})} dP(\beta_i) dP(y_i) \\
    \tilde{s}_{rt} &= \int \sum_{j=1}^{J_t} s_{ijt}
\end{align*}
\]

where (12) is a market share equation with the systematic utility

\[
V_{ijt} = \mathbf{x}_{jt}^f \beta_f c + \mathbf{x}_{jt}^r \beta_i r + \alpha_r \log(1 - p_{jt}/y_i) + \rho \log(R_{jt}) + \xi_{jt},
\]

and (13) is implemented as micro moments with \( \tilde{s}_{rt} \) denoting the percentage of households at income tier \( r \) that purchased new cameras at month \( t \). The integrals in these equations are numerically computed through Monte-Carlo simulation. For each dimension, we use \( I = 2000 \) pseudo-random draws generated from Sobol sequence to approximate the integrals.
Append four identical terms, \( \log(1 - p_{jt}/y_i) \) to get \( x_{ijt}' \) that accounts for the \( R = 4 \) income tiers in the micro moments. Then stack observations \( \forall j \) and then \( \forall t \) as rows into matrices and rewrite the systematic utility \( V_{ijt} \) as

\[
V_i = X\theta_1 + X_{rc} \theta_2 v_i + \xi, \tag{14}
\]

where \( X \) is a stack of \( x_{jt}' \), \( x_{ijt}' \) and \( \log(R_{jt}) \), and \( X_{rc} \) is a stack of \( x_{ijt}' \). \( \theta_1 \) is a vector combining the fixed (non-random) coefficients \( \beta_{fc} \), the means of the random coefficients, \( \bar{\beta} = E[\beta_i] \), as well as the coefficient of the congestion term \( \rho \). \( \theta_2 \) is a diagonal matrix in which the diagonal contains the standard deviations of the random coefficients (we assume no correlation between the random coefficients) and the four \( \alpha_r \)'s. \( v_i \) is a vector consisting of random draws from a standard multivariate normal distribution associated with \( \beta_i \), as well as four binary indicators of household \( i \)'s income level. The mean utility invariant across households is therefore

\[
\delta = X\theta_1 + \xi. \tag{15}
\]

The demand system is estimated by GMM estimator. This estimation has two sets of moments: the demand-side orthogonality conditions, which we describe next, and the micro moments (13). Assuming \( \xi \) is mean independent of some set of exogenous instruments \( Z \), the demand-side moments are given by

\[
g(\delta, \theta_1) = \frac{1}{N_d} Z'\xi = \frac{1}{N_d} Z' (\delta - X\theta_1) = 0, \tag{16}
\]

where \( N_d \) denotes the number of sale observations.

We follow the approximation to optimal instruments in Berry et al. (1995) to construct a set of instruments to identify demand parameters. They include own product characteristics, the sum of the characteristics across other own-firm products, and the sum of the characteristics across competing firms. These instruments explain a relatively large portion of price variation. The \( R^2 \) in the regression of price on the instruments is about 0.72.
4.2 MPEC Approach

Following the work of Su and Judd (2012), Vitorino (2012), and Dubé et al. (2012), we formulate the aggregate demand estimation as a mathematical program with equilibrium constraints (MPEC). The GMM estimator minimizes the 2-norm of $g(\delta, \theta_1)$ in (16), subject to the constraints imposed by the share equations (12) and by the micro moments (13). Specifically, we treat the micro moments as additional nonlinear constraints to the estimation objective function, and solve the nested problems and the GMM minimization simultaneously by augmenting the Lagrangian. The constrained optimization can be written as

$$\min_{\phi} \quad F(\phi) = \eta' W \eta$$

s.t.  
$$s(\delta, \theta_2) = S$$
$$\eta_1 - g(\delta, \theta_1) = 0$$
$$\eta_2 - \tilde{s}(\delta, \theta_2) = -\tilde{S},$$

where $\phi = \{\theta_1, \theta_2, \delta, \eta_1, \eta_2\}$ contain optimization parameters. $W$ is the weighting matrix in the optimization. $S$ is a vector of actual shares. $\tilde{S}$ is a vector of the micro-data collected from the PMA consumer survey and scaled by the Mintel statistics and local demographic distributions. $\eta = (\eta_1; \eta_2)$ are auxiliary variables that yield extra sparsity to the Hessian of the Lagrangian (Dubé et al. 2012).

Web Appendix B provides additional details of the estimation procedure. In Web Appendix C, we derive closed-form Jacobian and Hessian formulas for the objective function, the demand moments, and the micro moments.

4.3 Parameter Estimates

This section discusses parameter estimates, elasticities, and margins across various model specifications. First, we present the parameter estimates from the pooled (across markets) demand model, which makes discussing the implications of each parameter easier. Second, we discuss the results from estimating the demand model separately across the 1,599 markets.
Table 4: Parameter Estimates of the Pooled Demand Model

<table>
<thead>
<tr>
<th>Variable</th>
<th>OLS</th>
<th>2SLS</th>
<th>Random Coefficients</th>
<th>Random Coefficients &amp; Microdata</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Price Coefficients (α’s)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\alpha_1$</td>
<td>5.014</td>
<td>18.162</td>
<td>32.005</td>
<td>8.318</td>
</tr>
<tr>
<td></td>
<td>(0.021)</td>
<td>(0.027)</td>
<td>(0.806)</td>
<td>(1.126)</td>
</tr>
<tr>
<td>$\alpha_2$</td>
<td></td>
<td></td>
<td>29.689</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(6.781)</td>
<td></td>
</tr>
<tr>
<td>$\alpha_3$</td>
<td></td>
<td></td>
<td>63.408</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(8.467)</td>
<td></td>
</tr>
<tr>
<td>$\alpha_4$</td>
<td></td>
<td></td>
<td>82.339</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(12.296)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Other Parameters</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mega-pixels</td>
<td>0.049</td>
<td>0.055</td>
<td>0.247</td>
<td>1.521</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.023)</td>
<td>(0.017)</td>
</tr>
<tr>
<td>Mega-pixels s.d.</td>
<td></td>
<td></td>
<td>0.119</td>
<td>0.996</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.005)</td>
<td>(0.068)</td>
</tr>
<tr>
<td>Optical Zoom</td>
<td>0.004</td>
<td>0.016</td>
<td>0.023</td>
<td>0.084</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.000)</td>
<td>(0.005)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Thickness</td>
<td>-0.159</td>
<td>-0.183</td>
<td>-0.177</td>
<td>-0.371</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.001)</td>
<td>(0.002)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Display Size</td>
<td>0.340</td>
<td>0.457</td>
<td>0.564</td>
<td>1.101</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.000)</td>
<td>(0.002)</td>
<td>(0.041)</td>
</tr>
<tr>
<td>Nov-Dec</td>
<td>-0.137</td>
<td>-0.159</td>
<td>-0.361</td>
<td>-0.114</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>June</td>
<td>0.100</td>
<td>0.117</td>
<td>0.056</td>
<td>0.035</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Congestion</td>
<td>-0.898</td>
<td>-1.002</td>
<td>-0.934</td>
<td>-1.520</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.000)</td>
<td>(0.021)</td>
<td>(0.013)</td>
</tr>
</tbody>
</table>

Note: The data contain about 1.78 million observations. Standard errors are put in round brackets. All specifications include year fixed effects and brand-chain interactions.
Table 5: Elasticity Estimates

<table>
<thead>
<tr>
<th>Elasticity</th>
<th>Separate Estimation</th>
<th>Pooled Estimation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2SLS &amp; Microdata</td>
<td>2SLS &amp; Microdata</td>
</tr>
<tr>
<td>Price</td>
<td>-1.496 [-0.248]</td>
<td>-1.245 [0.152]</td>
</tr>
<tr>
<td></td>
<td>-2.903 [0.773]</td>
<td>-2.184 [0.373]</td>
</tr>
<tr>
<td>Mega-pixels</td>
<td>0.390 [0.179]</td>
<td>0.460 [0.099]</td>
</tr>
<tr>
<td></td>
<td>0.434 [0.260]</td>
<td>0.576 [0.181]</td>
</tr>
<tr>
<td>Optical Zoom</td>
<td>0.080 [0.169]</td>
<td>0.051 [0.059]</td>
</tr>
<tr>
<td></td>
<td>0.067 [0.260]</td>
<td>0.064 [0.043]</td>
</tr>
<tr>
<td>Thickness</td>
<td>-0.206 [-0.270]</td>
<td>-0.228 [-0.126]</td>
</tr>
<tr>
<td></td>
<td>-0.305 [0.264]</td>
<td>-0.367 [0.132]</td>
</tr>
<tr>
<td>Display Size</td>
<td>0.212 [0.559]</td>
<td>0.118 [0.012]</td>
</tr>
<tr>
<td></td>
<td>0.179 [0.532]</td>
<td>0.253 [0.094]</td>
</tr>
</tbody>
</table>

Note: Standard deviations are computed across markets and put in square brackets.

Note that the parameter estimates are not directly comparable across markets, because the scale in utility is different (Swait and Louviere 1993). To facilitate comparison, we calculate elasticities in both the separate and the pooled estimation.

Table 4 reports parameter estimates from the pooled demand model. The price coefficient triples when moving from OLS to 2SLS with instrumental variables, suggesting price endogeneity is present in the demand specification. The random coefficients model with micro data shows the price coefficients vary substantially across income tiers. Similar to the findings in Petrin (2002), we find the marginal utility of expenditures on other goods and services increases with income. Consumers on average favor cameras with higher mega-pixels, longer optical zooms, and larger displays, and they dislike cameras that are thick in size. Yet the taste for mega-pixels is highly heterogeneous across consumers. Some consumers in the market appear to have little valuation for resolution, consistent with the industry trend that the pursuit of higher resolution in the compact point-and-shoot sector has declined since 2007 (Euromonitor 2010).

Table 5 reports the elasticities from estimating the model separately across markets,
and compares them to elasticities from the pooled estimation. Figure 3 plots the density of the price elasticity and mega-pixel elasticity under either the pooled or the separate estimation. From Table 5 and Figure 3, we see that for both homogeneous and random coefficients specifications, estimating demand separately for each market generates more dispersion in elasticities than the pooled estimation. The separate estimation relaxes the assumption made in the pooled estimation that coefficients across markets share a common heterogeneity distribution. Therefore, the estimates of the market-specific models should better reflect local market conditions and geographic variations embedded in the data. In addition, the congestion term leads to a decrease of approximately 10% in price elasticity due to the varying number of products rather than consumer substitution.

---

13Elasticities are only calculated for linear variables. In each separate model, we include year, brand, and chain dummies. We drop brand-chain interaction fixed effects due to data availability at the SSA level.
Table 6: Inferred Price Margin from Demand Estimates and Pricing Equilibrium

<table>
<thead>
<tr>
<th>Margin</th>
<th>Separate Estimation</th>
<th>Pooled Estimation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2SLS &amp; Microdata</td>
<td>2SLS &amp; Microdata</td>
</tr>
<tr>
<td>Mean</td>
<td>69.62%</td>
<td>82.05%</td>
</tr>
<tr>
<td>Median</td>
<td>63.19%</td>
<td>78.36%</td>
</tr>
<tr>
<td>10%-percentile</td>
<td>45.46%</td>
<td>74.42%</td>
</tr>
<tr>
<td>90%-percentile</td>
<td>93.82%</td>
<td>87.63%</td>
</tr>
</tbody>
</table>

Note: Margin is defined as $(p - c)/p$.

Table 6 compares the estimated price margins across alternative demand estimations. The 2SLS estimates imply average margins of approximately 70% and 82% in the separate and pooled estimations, respectively. These margins are unrealistic for the digital cameras retail industry, reflecting the underestimated price elasticities in the homogeneous models. The pooled estimation results in higher margins than the separate estimation. Overall, the random coefficients model with the micro moments and congestion leads to average price margins of approximately 35%, which are consistent with the reported margins in public reports. The correction for biases in demand estimates by incorporating micro moments and congestion helps the demand model better estimate consumer substitution patterns.

5 Counterfactual Simulations

We conduct a series of counterfactuals to assess the impact of alternative pricing policies on firm profitability. First, we consider how firms’ prices and profits would change if the chains considered either national or local pricing policies. Second, we examine the boundary conditions under which a chain will prefer a local pricing policy. Third, since the national and local pricing policies represent two possible extremes, we alternatively consider a pair of hybrid policies, in which the firms employ national pricing except for a few local markets. Finally, we present the results of several robustness checks.

14 According to industry reports, such as Euromonitor (2010), the average retail margin for point-and-shoot cameras usually ranges from 25% to 35%.
Table 7: Counterfactual Profits ($\pi_A, \pi_B$) under Alternative Pricing Policies before B Exits ($\text{millions}$)

<table>
<thead>
<tr>
<th>Chain A</th>
<th>Local</th>
<th>National</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chain B</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Local</td>
<td>(307.60, 104.06)</td>
<td>(320.58, 105.17)</td>
</tr>
<tr>
<td>National</td>
<td>(310.03, 110.47)</td>
<td>(323.91, 112.78)</td>
</tr>
</tbody>
</table>

5.1 National vs. Local Pricing

First, we evaluate the firms’ profit as if the two major chains were under alternative pricing policies. Specifically, using the demand and cost estimates obtained from the data period before B exits, we simulate equilibrium prices and profits when A and B choose between national and local pricing. Throughout the simulation, we assume Chain D, the large discount retailer, continues to use local pricing. Also, we assume the smallest Chain L, consisting of very small sellers, is passive and does not respond to any market changes.

In computing the counterfactual outcomes, one should note that this process uses parameter estimates based on the demand and supply models. In particular, the demand estimates are obtained from a structural model that yields standard errors. Sampling errors in the demand-side parameters propagate into the marginal costs and subsequently into the counterfactuals, leading to uncertainties in the counterfactual results. To assess the impact of demand parameter uncertainty, we take $I = 100$ random draws from the asymptotic (normal) distribution of the demand estimates. For each draw, we compute the marginal costs and the counterfactual outcomes. Thus, we obtain not only point estimates of the counterfactual outcomes but also the deviations around them.

Table 7 reports the total profits of Chains A and B prior to B’s exit under the four possible pricing-policy scenarios: Local-Local, Local-National, National-Local, and National-National. This table is the average of the 100 tables corresponding to the $I = 100$ random draws. The results show that under the existing market conditions, employing national pricing is optimal for both firms A and B. Consistent with Figure 2, which shows both Chains A and B used a nearly national pricing policy in the data, the profit increase between
Table 8: Decompose Profit Difference between (National, National) and (Local, Local)

<table>
<thead>
<tr>
<th>Chain</th>
<th>$\Delta \pi$ Overall</th>
<th>$\Delta \pi$ in markets where A and B do not compete</th>
<th>$\Delta \pi$ in markets where A and B compete</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$$ million</td>
<td>percent</td>
<td>$$ million</td>
</tr>
<tr>
<td>A</td>
<td>16.31</td>
<td>5.30%</td>
<td>-4.09</td>
</tr>
<tr>
<td>B</td>
<td>8.72</td>
<td>8.38%</td>
<td>-2.91</td>
</tr>
</tbody>
</table>

Note: $\Delta \pi = \pi(\text{National, National}) - \pi(\text{Local, Local})$

the purely national pricing in our counterfactual and the observed national pricing policy is small (less than 1%). The increase in profits between the purely national pricing and local pricing is 5.3% for Chain A and 8.4% for Chain B. Moreover, neither A nor B would find deviating unilaterally from a national pricing strategy profitable. Taking into account the uncertainty in the demand parameter estimates propagated into the supply side, we find that the National-National Nash equilibrium in Table 7 holds for 92 of the $I = 100$ random draws mentioned above. Therefore, in a game between A and B in which chains first choose a pricing policy and then set prices each period, the results in Table 7 constitute a sub-game perfect equilibrium with a national pricing policy.

Table 8 decomposes the difference in profits between National-National and Local-Local in order to highlight the rationale behind the enhanced profit under the national pricing policy. Moving from national to local pricing, both Chains A and B garner higher profits in their own stronghold markets in which they do not compete. Yet the chains lose profits due to the intensified competition in other markets in which they do compete. Because the portion of the competitive markets is sufficiently large relative to the markets in which the two chains do not compete, for both chains, the loss from the intensified competition is excessive and cannot be offset by the gains from the markets in which they have more market power. Overall, both chains become worse off by employing a local pricing policy.

Table 9 shows the average difference between the optimal price under the National-National scenario and each of the alternative pricing-policy scenarios in markets in which Chains A and B compete, and in markets in which they do not compete. Compared to national pricing, the prices under the local pricing policy are generally higher in the stronghold
Table 9: Average Price Difference from the National Pricing Policy across Market Types and Scenarios

<table>
<thead>
<tr>
<th>Chain</th>
<th>Type I</th>
<th>Type II</th>
<th>Type I</th>
<th>Type II</th>
<th>Type I</th>
<th>Type II</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>5.81%</td>
<td>-9.77%</td>
<td>5.81%</td>
<td>-7.17%</td>
<td>-2.54%</td>
<td>-2.63%</td>
</tr>
<tr>
<td>B</td>
<td>8.31%</td>
<td>-9.03%</td>
<td>-3.30%</td>
<td>-3.56%</td>
<td>8.31%</td>
<td>-6.23%</td>
</tr>
</tbody>
</table>

Note: Type I are markets in which A and B do not compete; Type II are markets in which A and B compete.

markets and lower in the contested markets. Switching to a local policy, regardless of the other chain’s policy, leads to an increase in the average price in the less competitive markets and a decrease in the competitive markets. Another interesting observation is the free-rider effect evidenced in the last four columns of Table 9 (see also in Table 7). If one chain chooses national pricing and the other chain chooses local pricing, the latter free rides on the former. The chain with the national prices would lower its prices relative to the National-National scenario, whereas the chain with the local pricing policy could raise the price in its own less competitive markets. The profit of the chain with national prices would be close to the level in the Local-Local scenario. Whether a chain would unilaterally deviate to local pricing depends on the incremental profit gain in its stronghold market, relative to the profit loss in the contested market as the other chain also cuts its uniform price. Under the current market structure, the losses are again excessive for both chains; therefore, neither chain would unilaterally deviate to local pricing, as is evident in Table 7.

We also simulate counterfactual profits for Chain D under alternative policy scenarios, as reported in Table 10. Switching to national pricing results in profit loss for Chain D. This is because, first, in more than half of its markets, D does not coexist with A or B; second, D mainly sells low-end products, which only leads to weak competition with A and/or B stores. From a managerial point of view, fixing D’s policy to local seems reasonable given that this large discount chain is not oriented towards consumer electronics, selling many categories beyond those sold by Chains A and B. Thus, digital camera sales would be unlikely to change D’s general product pricing strategy.
Table 10: Counterfactual Profits of Chain D ($ millions) under Alternative Pricing Policies

<table>
<thead>
<tr>
<th></th>
<th>A National</th>
<th>A Local</th>
<th>A National</th>
<th>A Local</th>
</tr>
</thead>
<tbody>
<tr>
<td>B National</td>
<td>47.21</td>
<td>45.29</td>
<td>46.57</td>
<td>44.65</td>
</tr>
<tr>
<td>B Local</td>
<td>44.75</td>
<td>40.08</td>
<td>42.84</td>
<td>40.19</td>
</tr>
</tbody>
</table>

5.2 Boundary Conditions for Local Pricing

Given the main counterfactual results in Table 7, we want to understand the conditions under which a chain would prefer a local pricing policy. Because market structure plays a critical role in our results, we implement another counterfactual experiment that varies the competitive landscape. Specifically, we gradually remove stores from the markets in which Chains A and B compete, leading to fewer competitive markets. After removing every few stores, we solve the counterfactual profits under national and under local pricing. To mimic the business reality in which struggling chains first close poorly performing stores, we remove stores in the increasing order of profit.

The results, plotted in Figure 4, show that as the number of competitive markets decreases, the profit gain from national pricing relative to local pricing due to softened competition declines. In particular, once Chain A retreats from 29% of its competitive markets, it would benefit from employing local pricing. Similarly, Chain B would benefit from local pricing once it closes 40% of its stores in the competitive markets. The difference between Chains A and B is primarily due to the fact that Chain B originally had fewer stores operating in markets in which Chain A is not present. At the extreme, when a chain has no major competition in all markets, local pricing strictly dominates national pricing, which is consistent with previous findings (e.g., Chintagunta et al. 2003) where competition is absent or not explicitly modeled.

A second boundary condition concerns the distribution of competitive intensities across markets. The exit of Chain B eased the competitive landscape of the industry. The absence of such a large rival could create incentives for Chain A to localize prices as it became the single dominant chain. To investigate this possibility, we use the demand and cost estimates
from the data period after B exits, and simulate the optimal national and local prices and profits for firm A. We find that, compared to local pricing, A’s profit is about 1.3% higher under national pricing. The result implies setting prices uniformly across markets is still optimal for Chain A. The rationale behind this result is that Chain A still faces substantial competition from Chain D. As is evident from Table 2, Chain A coexists with Chain D in 839 (84%) of the 1,004 markets in which it operates. Thus the extent of competition between A and D is sufficient to justify national pricing even after Chain B’s exit, although the advantage of national pricing over local pricing has largely disappeared because of the eased competitive landscape. Similar to the situation prior to B’s exit, maintaining local pricing is better for D.

5.3 Hybrid Pricing Policy

Purely local and national pricing policies lie at the extremes; instead, a chain may set prices locally in some markets and maintain uniform prices in the rest. Such a hybrid policy permits the chain to exploit some geographic variation in preferences without sacrificing its
Table 11: Profit and Price Changes Relative to the Observed Policies If Chains A and B Adopt Local Pricing in the Five Metro Areas

<table>
<thead>
<tr>
<th>Chain</th>
<th>% changes in local pricing zone</th>
<th>% changes in uniform pricing zone</th>
<th>overall profit change</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>profit</td>
<td>price</td>
<td>profit</td>
</tr>
<tr>
<td>A</td>
<td>-12.29%</td>
<td>-10.36%</td>
<td>0.57%</td>
</tr>
<tr>
<td>B</td>
<td>-15.33%</td>
<td>-12.57%</td>
<td>0.72%</td>
</tr>
</tbody>
</table>

Evaluating all possible hybrid policies is largely infeasible. Thus, our goal is not to thoroughly explore this strategy space, but to assess the implications of managerially relevant hybrid policies. We consider two candidate strategies that are intuitive and motivated by the business reality.

The first candidate policy is motivated by the notion that firms sometimes play different strategies in large and influential markets as opposed to other markets. To examine this possibility, we allow for local pricing by Chains A and B in the top five metropolitan areas, which are New York City, Los Angeles, Chicago, Houston, and Philadelphia. These cities account for about 6% of the U.S. population and 8.6% of national retail sales of digital cameras. Using the data prior to B’s exit, we simulate the profits as if both A and B adopted local pricing in these metropolitan areas and national pricing elsewhere.

Table 11 presents the relative changes in profit and price if Chains A and B replace the observed policy with the proposed hybrid pricing scheme. Consistent with the mechanism discussed earlier, switching to local pricing intensifies price competition between the two rivals in the five largest cities. Both firms would lower prices in response to the policy change. Setting local prices in the metropolitan areas would lead to a relative profit loss of 12.29% for Chain A and 15.33% for Chain B in the local pricing zone. This is due to the intense competition between the two firms in these cities. (Chains A and B compete in about 68% of these markets.) On the other hand, excluding the five biggest competitive markets slightly improves the profitability of both firms in the uniform pricing zone, thanks to the reduced “downward” force on the uniform prices. Aggregating across the two pricing zones, however, the proposed hybrid policy results in overall profit declines for both firms A
Table 12: Profit and Price Changes Relative to the Observed Policies If Chains A and B Adopt Local Pricing in Top Stronghold Markets

<table>
<thead>
<tr>
<th>Chain</th>
<th>% changes in local pricing zone</th>
<th>% changes in uniform pricing zone</th>
<th>overall profit change</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>profit</td>
<td>price</td>
<td>profit</td>
</tr>
<tr>
<td>Top 10% Stronghold Markets</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A</td>
<td>7.12%</td>
<td>6.61%</td>
<td>-0.23%</td>
</tr>
<tr>
<td>B</td>
<td>9.75%</td>
<td>9.52%</td>
<td>-0.99%</td>
</tr>
<tr>
<td>Top 20% Stronghold Markets</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A</td>
<td>5.86%</td>
<td>5.93%</td>
<td>-0.40%</td>
</tr>
<tr>
<td>B</td>
<td>7.94%</td>
<td>8.62%</td>
<td>-1.35%</td>
</tr>
</tbody>
</table>

and B, because of the excessive loss in the areas in which local pricing is applied.

Although the above proposal does not increase profits, many other alternative policies remain. Instead of localizing prices in large competitive markets, a chain could localize them in its stronghold markets where it faces little competition from major rivals, thereby leading to profit gains in these markets. Hence, we simulate the outcome as if A and B set price locally in some of their own stronghold markets while maintaining uniform pricing elsewhere. We start by ranking the SSAs in which A and B do not compete with each other, according to the total sales volume in 2007-2008 of local A and B stores, respectively. Then we let the top 10% or 20% of these markets be local pricing zones for A and for B. The relative profit and price changes are reported in Table 12.

After switching to local pricing in its top 10% stronghold markets, firm A generates 7.12% more profit in these SSAs relative to the observed policy. In the rest of A’s markets in which uniform pricing is maintained, prices drop because of the reduced market power A could leverage from the excluded stronghold markets. The decrease in price intensifies competition slightly and leads to a profit decline that can be offset by the gain in the local pricing zone. Overall, chain profitability improves for Chain A, although the improvement is rather small (0.06%). On the other hand, Chain B obtains incremental profit in its local pricing zone, similar to Chain A. However, the profit loss in B’s uniform pricing zone is large, and the chain profitability deteriorates slightly under the proposed hybrid policy. The
difference in profit change between the two chains is due to the fact that Chain A has many more stronghold markets with larger total sales relative to Chain B (see Table 2). Similar results are obtained when the two firms employ local pricing in 20% of their stronghold markets (see the bottom portion of Table 12).

The current model and analyses do not account for organizational costs associated with local or hybrid pricing policies. Therefore, the identification of an "optimal" hybrid pricing strategy and whether hybrid pricing is a managerially and institutionally viable policy remains an open question for future research.

5.4 Robustness Check on Market Definition

Properly defined local markets are important for the analysis of multimarket competition. In this paper we use store selling areas (SSAs), provided by NPD in its data set, as the definition of market boundaries. Alternative market boundary definitions, such as county and zipcode, can alter the estimates of the demand model and the results of the counterfactual experiments. Without consumer level shopping data (i.e., which set of stores does a group of consumers visit), however, it is hard to delineate local markets via aggregate store sales.

Before applying any formal test to assess the validity of the SSAs as local markets, we measure physical distances between stores to partially evaluate the SSA definition. Using store addresses from AggData, we compute the distance between all pairs of stores. The median distance between competing stores within an SSA is 0.58 miles, whereas the median and the bottom 5th-percentile distance to stores in neighboring SSAs are 10.20 and 3.45 miles, respectively. These statistics show that retail stores are indeed located near each other within a market and relatively farther from stores outside their SSAs. Although these distance statistics are suggestive, they are insufficient to determine the validity of the SSAs as being independent local markets.

To further verify the SSA definition is appropriate, we use store sales to gain a better understanding of cross-store substitution patterns. To this end, we use the Hypothetical Monopolist (HM) test, which is employed in the antitrust literature to assess market definitions
Table 13: Percent of Hypothetical Monopolists with Profitable Price Increase

<table>
<thead>
<tr>
<th>SSA Type</th>
<th>2007</th>
<th></th>
<th></th>
<th>2009</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>one-store</td>
<td>two-store</td>
<td>three-store</td>
<td>one-store</td>
<td>two-store</td>
<td></td>
</tr>
<tr>
<td>D-A</td>
<td>5.7%</td>
<td>92.3%</td>
<td>—</td>
<td></td>
<td>8.1%</td>
<td>90.2%</td>
</tr>
<tr>
<td>D-B</td>
<td>7.4%</td>
<td>90.8%</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>D-A-B</td>
<td>5.1%</td>
<td>4.9%</td>
<td>94.1%</td>
<td>—</td>
<td>—</td>
<td>—</td>
</tr>
</tbody>
</table>

in the context of horizontal mergers (Katz and Shapiro 2003; Davis 2006; DOJ-FTC 2010). The main idea of the test is straightforward. If an HM could profitably impose at least a “small but significant and nontransitory increase in price” (SSNIP), while holding constant the terms of sale for all products elsewhere, then the market definition is sufficiently broad. Otherwise, a good substitute must currently be excluded from the choice set. Therefore the market boundary must be expanded to include the best available substitute until the newly formed HM can profitably apply a SSNIP.

Following Davis (2006), we use the HM test for each SSA to evaluate the current SSA definition. Since the two major chains, A and B, primarily used national pricing policies, their prices are not intended to be locally optimal and so these chains cannot be used in the market definition test. Instead we rely on markets in which chain D operates because this firm uses local pricing.\textsuperscript{15}

Specifically, for the competitive SSAs involving D stores, we re-estimate the demand model separately with the alternative one-store (D-only), two-store (D-A or D-B) and three-store (D-A-B) HM market definitions. Then, assuming 30% average margins (Euromonitor 2010), we increase prices by 5% for one year. The percentage of HMs that achieve profitable 5% price increases over the one-year horizon, i.e., well-bounded markets immune to outside competition, are reported in Table 13. First, the majority of the SSAs require no further expansion. For example, 92.3% of the D-A SSAs are self-contained markets in which the

\textsuperscript{15}One additional complicating factor is the presence of small stores other than A, B, or D. In the preceding analysis, we grouped all small stores into a single chain, L, for simplicity. When delineating local markets, small stores located at various parts of a market blur the competition boundary of major stores, whereas their existence is unlikely to impact the substitution pattern between major stores. Therefore, we focus the test on the three major chain stores and combine small stores as the outside option.
Table 14: Percent of D-only SSAs with Profitable Price Increase

<table>
<thead>
<tr>
<th>Starting Point for Price Increase</th>
<th>Before B Exits</th>
<th>After B Exits</th>
</tr>
</thead>
<tbody>
<tr>
<td>0% below</td>
<td>10.6%</td>
<td>8.9%</td>
</tr>
<tr>
<td>5% below</td>
<td>96.3%</td>
<td>97.1%</td>
</tr>
<tr>
<td>10% below</td>
<td>98.9%</td>
<td>98.6%</td>
</tr>
<tr>
<td>15% below</td>
<td>99.4%</td>
<td>99.2%</td>
</tr>
</tbody>
</table>

HMs (i.e., a merger of D and A stores) are able to profit by imposing SSNIP. Second, very few D stores in the three types of SSAs are free from competition. For instance, only 5.1% of the 402 D-A-B SSAs (from Table 2) are overly broad in which the D stores must be separated out as independent local markets.

The HM test is not appropriate to monopolist markets due to the so-called Cellophane fallacy (Pitofsky 1990). Thus, an SSNIP cannot be applied to SSAs in which D stores do not compete with A or B stores. If a firm is truly a monopolist, then raising its prices should decrease profits. Given this issue, we treat the D-only SSAs differently from the other markets, and start the SSNIP from levels that are below the observed prices, as in (Davis 2006). Table 14 reports the percentage of D-only SSAs that experience profitable 5% price increases from various starting points. The vast majority of D-only SSAs would have profit gains, following an SSNIP to prices that are 5% or more below the observed prices, therefore no expansion is needed for these SSAs.

The HM test reveals that the vast majority of the SSAs indeed appropriately capture close competitive market. To further test the robustness of our main results, we remove the SSAs that failed the test and redo the main counterfactual with only the SSAs that passed the test. The direction of the results remains the same and national pricing is still the dominant strategy for both Chain A and B. Based on this finding and the results in Tables 13 and 14, using SSAs as our market definition appears reasonable.
6 Conclusion

In this paper, we empirically examine a firm’s choice of national versus local pricing policy in a multimarket competitive setting. To do so, we estimate an aggregate model of demand with random coefficients separately in each of the more than 1,500 markets. The separate estimation strategy leads to a significant increase in estimated heterogeneity across markets, reflecting the rich geographic variation in the data. We include a set of micro moments to improve model estimates, and incorporate these moments into the recently proposed MPEC framework. We further control for product congestion to remove the confounds caused by varying number of products across markets and over time. The counterfactual policy simulation demonstrates that relative to locally targeted pricing, national pricing results in substantially higher profit for the major retailers under the existing multimarket structure. The optimality of national pricing would hold as long as the ratio of competitive markets to non-competitive markets is high. These results have direct implications for the electronics retail industry. Furthermore, the insights from this investigation could generalize to other industries evaluating their chain-level pricing policies.

A few issues are left for future research. First, throughout the current analysis, we assume marginal costs associated with the sales of digital cameras, and ignore any potential costs related to the implementation of national or local pricing. For example, by switching from national to local, a chain may incur additional costs in customizing advertising to match locally varying prices. Also, consumers may dislike inconsistent prices offline and online, and across different stores. Therefore, moving to local pricing could incur certain psychological costs for which the current model does not account.

Second, several recent papers have documented that durable goods buyers may strategically delay their purchases in anticipation of technology improvement and price decline (e.g., Song and Chintagunta 2003; Gordon 2009; Carranza 2010). Similarly, sellers may trade off between current and future profit by setting optimal price sequences (Zhao 2006). In this paper, we ignore forward-looking dynamics on both the consumer and the retailer side. Given the nature of the research question, allowing for flexible consumer preferences at the market...
level is critical. Doing so in the context of a dynamic structural demand model is generally intractable in computation, especially because the model involves hundreds of local markets and hundreds of distinct products. Furthermore, the focus of the current study is geographic pricing policy and the differences between markets primarily drive the conclusion. The effect of forward-looking dynamics, if relatively similar across markets, would be canceled out when examining cross-market variations and would therefore not influence the main result qualitatively. Lastly, forward-looking behavior may also be less of a concern in this paper, given that the quality-adjusted prices in the period studied declined more slowly compared to the decline in earlier periods studied in previous research (e.g., Song and Chintagunta 2003).

Third, a more general model could endogenize the retailers’ product-assortment decisions. A retailer may have different incentives to stock a particular product under different pricing policies, and could also change the timing of a product’s clearance period. This option would require an explicit model of multi-product retail assortment under competition. We plan to pursue this specific avenue in future research.
References


Web Appendix

A An Analytical Model of Multimarket Competition

We present an analytical model of multimarket price competition between retail chains. We start by deriving demand function with consistent underlying utility specifications across markets. Then we construct the duopoly chain competition model to investigate the conditions under which national pricing generates more profit than local pricing. Building on Dobson and Waterson (2005), we expand their model to allow for more flexibility and asymmetry cross markets.

We derive the duopoly demand function based on the quadratic utility specification introduced by Shubik and Levitan (1980), which has been widely used in the marketing literature to study duopoly competition (e.g., McGuire and Staelin 1983; Desai et al. 2010; Subramanian et al. 2010). In the original specification, both utility and demand are symmetric between the two competing goods. To accommodate asymmetry, we follow Subramanian et al. (2010) to derive the demand function. Assume that by consuming two goods $a$ and $b$, a representative customer obtains the following quadratic utility of consumption, less the disutility of monetary expenditure:

$$U = \frac{1}{2} [\alpha' \Theta \alpha - (\alpha - q)' \Theta (\alpha - q)] - \beta p' q,$$

(A.1)

where $q = (q_a, q_b)'$ indicates consumption quantities, $p = (p_a, p_b)'$ is the vector of prices, and $\alpha = (\alpha_a, \alpha_b)'$ denotes the amount of consumption that yields maximum utility. According to Subramanian et al. (2010), $\Theta$ is a positive definite matrix and is normalized to be

$$\begin{pmatrix}
\frac{1}{1 + \theta} & \frac{\theta}{1 + \theta} \\
\frac{\theta}{1 + \theta} & \frac{1}{1 + \theta}
\end{pmatrix},$$

(A.2)

where $\theta \in [0, 1)$ denotes the degree of substitution between the two goods. When $\theta = 0$, they
are completely independent of each other. When \( \theta > 0 \), the two goods are substitutable and the substitutability increases with \( \theta \). As \( \theta \to 1 \), the two goods approach perfect substitutes. In Desai et al. (2010) and Subramanian et al. (2010), the coefficient \( \beta \) on expenditure is set to one because these studies primarily focus on the difference between the two competing goods, for which \( \beta \) is a common multiplier. The current analysis, however, examines differences not only within a market but also across markets (with different \( \beta \)'s), so we keep this parameter in the demand model.

This representative customer maximizes her utility by setting the optimal amount of consumption, which results in the following duopoly demand function:

\[
q_a = \alpha_a - \beta p_a + \frac{\beta \theta}{1 - \theta} (p_b - p_a) \\
q_b = \alpha_b - \beta p_b + \frac{\beta \theta}{1 - \theta} (p_a - p_b) .
\] (A.3)

In a market in which only one good is available, \( \theta = 0 \) and the utility function (A.1) reduces to

\[
U = \frac{1}{2} [\alpha^2 - (\alpha - q)^2] - \beta pq .
\] (A.4)

Accordingly, the monopoly demand is

\[
q = \alpha - \beta p .
\] (A.5)

Similar to Dobson and Waterson (2005), we hypothesize an industry with two chains, \( a \) and \( b \), and three independent and isolated markets, 1, 2, and 3. The first two markets are monopolized by \( a \) and \( b \), respectively, whereas the third market is a duopoly market in which \( a \) and \( b \) compete. Assuming both chains are single-product firms, demand in the three markets follows (A.3) and (A.5).

Under local pricing, a chain makes price decisions independently across markets. For instance, chain \( a \) solves two unrelated pricing problems given chain \( b \)'s price in market 3:

\[
\text{Max}_{p_{a1}} \pi_{a1}(p_{a1}) \quad \text{and} \quad \text{Max}_{p_{a3}} \pi_{a3}(p_{a3}|p_{b3}) ,
\]

42
<table>
<thead>
<tr>
<th>Chain a</th>
<th>National</th>
<th>Local</th>
</tr>
</thead>
<tbody>
<tr>
<td>π_{aN}, π_{bN}</td>
<td>π'<em>{aN}, π'</em>{bL}</td>
<td></td>
</tr>
<tr>
<td>π'<em>{aN}, π'</em>{bN}</td>
<td>π'<em>{aL}, π'</em>{bL}</td>
<td></td>
</tr>
</tbody>
</table>

where profit \( \pi_a(p_a) = q_a p_a \) and \( \pi_a(p_a)p_b = q_a p_a p_b \). On the other hand, under national pricing, a chain pools demand across markets and sets a single optimal price to maximize chain profit. For example, chain \( a \) solves

\[
\max_{p_a} \pi_a(p_a) + \pi_a(p_a)p_b
\]

subject to

\[
p_a = p_a = p_a
\]

The game of multimarket chain competition proceeds in two stages. In the first stage, chains choose between national and local pricing policies; in the second stage, chains set optimal prices according to the policy they chose in the first stage. Table A.1 summarizes all possible payoffs of the game, where individual payoffs are given by\(^1\)

\[
\pi_{1N} = \frac{(\theta - 1)[\beta_a(\theta - 1) - 1][2(\alpha_a + \alpha_a)(1 + \beta_a) + \theta(\alpha_a + \alpha_a - 2\beta_a(\alpha_a + \alpha_a))]^2}{[4(1 + \beta_a)(1 + \beta_a) - 4\theta(\beta_a + \beta_a + \beta_a\beta_a) + \theta^2(4\beta_a\beta_a - 1)]^2}
\]

\[
\pi_{2N} = \frac{(\theta - 1)[\beta_a(\theta - 1) - 1][\theta(\alpha_a + \alpha_a)(1 + \beta_a) + \theta(\alpha_a + \alpha_a - 2\beta_a(\alpha_a + \alpha_a))]^2}{[4(1 + \beta_a)(1 + \beta_a) - 4\theta(\beta_a + \beta_a + \beta_a\beta_a) + \theta^2(4\beta_a\beta_a - 1)]^2}
\]

\[
\pi'_{1L} = \frac{\alpha_a^2}{4\beta_a} - \frac{(\theta - 1)[\theta(\alpha_a + \alpha_a)(1 + \beta_a) + \theta(\alpha_a + \alpha_a - 2\beta_a(\alpha_a + \alpha_a))]^2}{[\theta^2 + 4\beta_a(\theta - 1) - 4]^2}
\]

\[
\pi'_{2L} = \frac{(\theta - 1)[\beta_a(\theta - 1) - 1][\theta(\alpha_a + \alpha_a)(1 + \beta_a) + \theta(\alpha_a + \alpha_a - 2\beta_a(\alpha_a + \alpha_a))]^2}{[\theta^2 + 4\beta_a(\theta - 1) - 4]^2}
\]

\[
\pi'_{1N} = \frac{(\theta - 1)[\beta_a(\theta - 1) - 1][\theta(\alpha_a + \alpha_a)(1 + \beta_a) + \theta(\alpha_a + \alpha_a - 2\beta_a(\alpha_a + \alpha_a))]^2}{[\theta^2 + 4\beta_a(\theta - 1) - 4]^2}
\]

\(^{1}\)For cross-market comparison, we set all variable costs to zero, and normalize the \( \beta \) of the duopoly market to one.
Because these profit functions contain seven parameters, drawing a closed-form conclusion regarding the conditions under which one policy is better than the other is impossible. Therefore, in the remainder of this section, we numerically analyze the results (A.6).

To show the profit-enhancing effect of national pricing and how such an effect changes with market structure, we first examine the profit change when a chain switches from national to local pricing, given the other chain does the same. Figure A.1 plots the profit difference for chain $a$ ($\Delta \pi = \pi_{aN} - \pi'_{aL}$) against both chains’ strength in the duopoly market. The colored region I represents the ranges of $\alpha_{a3}$ and $\alpha_{b3}$ under which $\Delta \pi > 0$. The shape of the region presents several interesting implications. First, if national pricing is better than local pricing, the presence of chain $a$ in the duopoly market can neither be too large nor too small compared to its monopoly market. When the chain is very small in the contested market, the local profit gain through national pricing cannot cover the profit loss in its monopoly market. On the other hand, when the chain is very large in the competitive market, the demand in its monopoly market is not sufficient to drive up the duopoly price, thereby barely softening competition and generating incremental profit. Further, if chain $b$ is strong in the duopoly market, chain $a$ would have difficulty raising the price in this market. Hence, a chain prefers national pricing over local pricing only if this chain has a medium presence in the duopoly market, and the other chain is also not too large.

Next, we examine the conditions under which national pricing is an equilibrium of this game. When $\Delta \pi_a = \pi_{aN} - \pi'_{aL} > 0$ and $\Delta \pi_b = \pi_{bN} - \pi'_{bL} > 0$ both hold, national pricing is the dominant strategy for both chains. The colored region II in Figure A.1 depicts the
range of the parameters under which the equilibrium exists. This range is narrower than the previous case due to a free-rider issue. Suppose a chain deviates from national to local pricing whereas the other chain still plays national. The deviating chain will raise price in its monopoly market to reap the maximal profit, and it will cut price in the duopoly market. The rival chain will respond by lowering its national price. Now, the deviating chain is benefiting from the other chain’s national price as it still softens competition in the contested market. But at the same time the local duopoly competition has intensified as both prices are lower. It is possible that, due to the strengthened competition, the profit loss for the deviating chain from the contested market exceeds the gain the chain reaps from its monopoly market. Then, the unilateral deviation is unprofitable, leading to the existence of a Nash equilibrium in this multimarket duopoly game (the colored region II).
The analytical model highlights the mechanism on how geographic pricing policy affects chain profitability. However, because the current model represents a simplified and abstract setting, it does not reflect the complexity of multimarket chain competition in the real world. For example, real industries usually contain many local markets and multiple competing chains, so the conditions supporting national pricing are not just about three markets and two firms, but about the distribution of market structures and the distribution of competitive intensities across many markets and firms. Also, chain stores sell multiple differentiated products, and these products are substitutes for each other as well. Moreover, consumer demand is usually not in the linear fashion. For these reasons, in this paper we rely on real data and use empirical models to investigate the choice of pricing policies.

### B MPEC Estimation Details

Denoting the set of constraints as $G(\phi)$, the constrained optimization problem (17) results in the following Lagrangian function:

$$L(\phi; \lambda) = F(\phi) - \langle \lambda, G(\phi) \rangle,$$

where $\lambda \in \mathbb{R}$ is a vector of Lagrange multipliers. Then the solution to (17) satisfies the Karush-Kuhn-Tacker condition on $L$:

$$\frac{\partial L}{\partial \phi} = 0, \quad G(\phi) = 0.$$  \hfill (B.2)

The model estimation proceeds in two stages. In the first stage, the identity matrix is used for the weighting matrix $W$ in (17). In the second stage, equal weighting is replaced by the inverse of the second moments $\Phi$, which is a function of the first-stage estimates. The micro moments (13) over $i$ and $r$ are sampled independently from demand moments (12) over $j$ and $t$; therefore, $\Phi$ has a block diagonal structure (Petrin 2002). Accordingly, the asymptotic variance matrix for parameter estimates is given as

$$\Gamma = \frac{1}{N_d + I}(J'WJ)^{-1} J'W\Phi W J (J'WJ)^{-1},$$  \hfill (B.3)
where $J$ is the Jacobian matrix of (16) and (13) with respect to $\theta_1$ and $\theta_2$.

C Analytic Derivatives for the MPEC Estimation

In this section, we derive the analytic derivatives for the optimization problem specified in (17). Our derivation follows matrix calculus and employs tensor operators such as Kronecker product. Thanks to the sparsity pattern of this optimization problem (i.e., shares being independent across markets), all Kronecker products that appear in the middle of the derivation drop out in the final results, thereby substantially saving computational time. All derivatives are formulated compactly in matrix notation to assist coding in computer programs.

The gradient and Hessian of the GMM objective function $F(\phi)$ are respectively

$$\frac{\partial F(\phi)}{\partial \phi} = (W + W')\eta$$  \hspace{1cm} (C.1)

$$\frac{\partial^2 F(\phi)}{\partial \phi \partial \phi'} = W + W'.$$  \hspace{1cm} (C.2)

The Jacobian matrices of the constraints imposed by the share equations are

$$\frac{\partial s_t(\delta_t, \theta_2)}{\partial \theta_2} = \int_{\forall i} \text{diag}(s_{it})[X_{\text{re}}^{it} - 1_{J_t} s_{it}' X_{\text{re}}^{it}] \text{diag}(v_i)$$  \hspace{1cm} (C.3)

$$\frac{\partial s_t(\delta_t, \theta_2)}{\partial \delta_t} = \int_{\forall i} \text{diag}(s_{it}) - s_{it}s_{it}'$$  \hspace{1cm} (C.4)

where $1_{J_t}$ is a $J_t$-element column vector of ones.

The Jacobian matrices of the constraints imposed by the demand side orthogonal conditions are
\begin{align}
\frac{\partial [\eta_1 - g(\delta, \theta_1)]}{\partial \theta_1} &= \frac{1}{N_d} Z' X 
\tag{C.5}
\end{align}

\begin{align}
\frac{\partial [\eta_1 - g(\delta, \theta_1)]}{\partial \delta} &= -\frac{1}{N_d} Z'
\tag{C.6}
\end{align}

\begin{align}
\frac{\partial [\eta_1 - g(\delta, \theta_1)]}{\partial \eta_1} &= I_{nz}.
\tag{C.7}
\end{align}

The Jacobian matrices of the constraints imposed by the micro moments are

\begin{align}
\frac{\partial [\eta_2 - \tilde{s}_{rt}(\delta_t, \theta_2)]}{\partial \theta_2} &= -\int_{i \in r} s_{\delta t} s'_t X_{it}' \mathbf{diag}(v_i) \tag{C.8}
\end{align}

\begin{align}
\frac{\partial [\eta_2 - \tilde{s}_{rt}(\delta_t, \theta_2)]}{\partial \delta_t} &= -\int_{i \in r} s_{\delta t} s'_t \tag{C.9}
\end{align}

The Hessian vector of the constraints in the \(\theta_2\) by \(\theta_2\) block is\(^2\)

\begin{align}
\sum_{\forall j, t} \lambda_{jt} \frac{\partial^2 s_{jt}(\delta_t, \theta_2)}{\partial \theta_2 \partial \theta_2} &= \sum_{t=1}^T \int_{\forall i} \mathbf{diag}(v_i)[(X'_{it} - X'_{it}' \mathbf{s}_{it}' \mathbf{1}''_{it}) \mathbf{diag}(\lambda) - \lambda'_t \mathbf{s}_{it} X'_{it}' \mathbf{diag}(v_i)] \frac{\partial \mathbf{s}_{it}}{\partial \theta_2} \tag{C.10}
\end{align}

\begin{align}
\sum_{\forall r, t} \lambda_{rt} \frac{\partial^2 [\eta_2 - \tilde{s}_{rt}]}{\partial \theta_2 \partial \theta_2} &= \sum_{\forall r, t} \lambda_{rt} \int_{i \in r} s_{\delta t} \mathbf{diag}(v_i) X'_{it} [\mathbf{s}_{it} \mathbf{s}'_{it} X'_{it}' \mathbf{diag}(v_i) - \frac{\partial \mathbf{s}_{it}}{\partial \theta_2}], \tag{C.11}
\end{align}

\(^2\)The following linear transformation is particularly useful in deriving the Hessian from the Jacobian given the necessity of taking derivatives over the diagonal matrix of share vectors. For example, an \(n\)-by-\(n\) diagonal matrix \(\mathbf{diag}(\mathbf{s})\) with a vector \(\mathbf{s}\) on its diagonal can be transformed linearly by

\begin{align}
\mathbf{diag}(\mathbf{s}) = \sum_{i=1}^n \mathbf{E}_i \mathbf{s}_i, \nonumber
\end{align}

where \(\mathbf{E}_i\) is an \(n\)-by-\(n\) matrix of all zeros except the \(i\)-th diagonal entry equal to one, and \(\mathbf{e}_i\) is a vector of all zeros except the \(i\)-th element equal to one. Because the transformation is linear, the derivative of the diagonal matrix with respect to \(\mathbf{s}\) can be compactly written as

\begin{align}
\frac{\partial \mathbf{diag}(\mathbf{s})}{\partial \delta} = \sum_{i=1}^n (\mathbf{e}_i \otimes \mathbf{E}_i) \frac{\partial \mathbf{s}}{\partial \delta}, \nonumber
\end{align}

where \(\otimes\) denotes Kronecker product.
where $\frac{\partial s_{it}}{\partial \theta_2}$ is calculated as in (C.3) without the integral. $\lambda_t$ is a vector of the Lagrange multipliers associated with the share equations at $t$.

The Hessian vector of the constraints in the $\delta_t$ by $\theta_2$ block is

$$\sum_{\forall j,t} \lambda_{jt} \frac{\partial^2 s_{jt}(\delta_t, \theta_2)}{\partial \delta_t \partial \theta_2} = \sum_{t=1}^{T} \int_{\forall i} [\text{diag}(\lambda_i) - \lambda_i^t s_{it} J_t - s_{it} \lambda_i^t] \frac{\partial s_{it}}{\partial \theta_2} \tag{C.12}$$

$$\sum_{\forall r,t} \lambda_{rt} \frac{\partial^2 [\eta_2 - \tilde{s}_{rt}]}{\partial \delta_t \partial \theta_2} = \sum_{\forall r,t} \lambda_{rt} \int_{i \in r} s_{it} [s_{it}^t X_{it}^c \text{diag}(v_i) - \frac{\partial s_{it}}{\partial \theta_2}] \tag{C.13}$$

The Hessian vector of the constraints in the $\delta_t$ by $\delta_t$ block is

$$\sum_{\forall j,t} \lambda_{jt} \frac{\partial^2 s_{jt}(\delta_t, \theta_2)}{\partial \delta_t \partial \delta_t} = \sum_{t=1}^{T} \int_{\forall i} [\text{diag}(v_i) - \lambda_i s_{it}^t J_t - s_{it} \lambda_i] \frac{\partial s_{it}}{\partial \delta_t} \tag{C.14}$$

$$\sum_{\forall r,t} \lambda_{rt} \frac{\partial^2 [\eta_2 - \tilde{s}_{rt}]}{\partial \delta_t \partial \delta_t} = \sum_{\forall r,t} \lambda_{rt} \int_{i \in r} s_{it} [2s_{it}^t X_{it}^c - \text{diag}(s_{it})], \tag{C.15}$$

where $\frac{\partial s_{it}}{\partial \delta_t}$ is calculated as in (C.4) without the integral.

After the optimization converges, standard errors of the parameter estimates are obtained through (B.3). The Jacobian matrix of the two sets of moments with respect to $\theta_1$ and $\theta_2$ is

$$J = \begin{pmatrix} \frac{\partial g}{\partial \theta_1} & \frac{\partial g}{\partial \theta_2} \\ \frac{\partial \tilde{s}}{\partial \theta_1} & \frac{\partial \tilde{s}}{\partial \theta_2} \end{pmatrix} \tag{C.16}$$

where

$$\frac{\partial g}{\partial \theta_1} = -\frac{1}{N_d} Z' X \tag{C.17}$$
\[
\frac{\partial g}{\partial \theta_2} = \frac{1}{N_d} Z' (\frac{\partial s_t}{\partial \delta_t})^{-1} \frac{\partial s_t}{\partial \theta_2} \tag{C.18}
\]

\[
\frac{\partial \tilde{s}_{rt}}{\partial \theta_1} = \left( \int_{i \in r} s_{i0t} s_{it}' \right) X_t \tag{C.19}
\]

\[
\frac{\partial \tilde{s}_{rt}}{\partial \theta_2} = \int_{i \in r} s_{i0t} s_{it}' X_{it}^{rc} \text{diag}(v_i) \tag{C.20}
\]

The second moments \( \Phi \) is

\[
\begin{pmatrix}
\Phi_1 & 0 \\
0 & \Phi_1
\end{pmatrix}, \tag{C.21}
\]

where

\[
\Phi_1 = \frac{1}{N_d} \sum_{j,t} \zeta_{jt}^2 Z_{jt} Z_{jt}' \tag{C.22}
\]

\[
\Phi_2 = \frac{1}{I} \text{diag} \left( \sum_{i} (\tilde{s} - \tilde{S})^2 \right). \tag{C.23}
\]

D Scaling for the Micro Moments

Because the PMA survey information is available at the national level, scaling is needed to match the survey statistics to the geographic variation in local demographics and market sizes. Assume a survey gives average purchase probabilities for four income segments, \( A, B, C, \) and \( D \), at the national level. Then we must obtain purchase probabilities \( a, b, c, \) and \( d \) for the corresponding four income segments in each local market. First, from the market-specific income distribution \( P(y_i) \), we obtain the weight of each segments in this market by

\[
w_r = \int_{i \in r} dP(y_i),
\]
where \( r = 1, 2, 3, 4 \). Denoting \( \tilde{S}_t = \sum_{j=1}^{J_t} s_{jt} \) as the sum of shares of all inside options observed in the sales data, we can solve the following equations to obtain \( a, b, c, \) and \( d \):

\[
\begin{align*}
\tilde{S}_t &= w_1 a + w_2 b + w_3 c + w_4 d \\
a/b &= A/B \\
b/c &= B/C \\
c/d &= C/D.
\end{align*}
\]

E Data Trimming

The raw data from NPD on store sales include nearly 10 million observations. We clean and trim the data before applying them to estimate the econometric model. First, we remove SSAs in which none of the three major chains had a presence. Then we delete cameras that are not compact point-and-shoot (e.g., digital SLRs, which account for less than 10% of the industry sales). Third, we retain only sales pertaining to the top seven brands. Fourth, we get rid of all observations in year 2010, due to the right truncation in calculating cumulative sales. Fifth, we remove observations with unreasonably high or low prices, as these are most likely data-collection errors. Lastly, in each chain, we sort camera models from largest to smallest market share and include models that yield a cumulative market share of at least 80%. We perform the last step year-by-year because of the frequent product entries and exits in this industry.