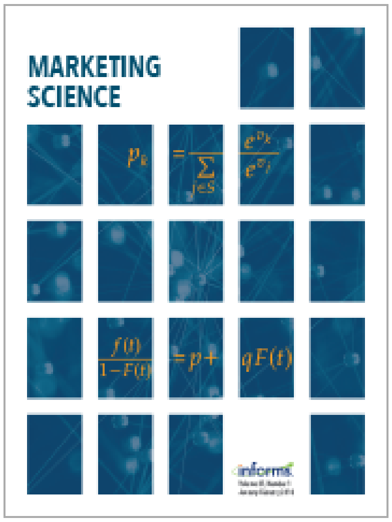

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An Empirical Study of National vs. Local Pricing by Chain Stores Under Competition

Yang Li,[a] Brett R. Gordon,[b] Oded Netzer[c]

[a] Cheung Kong Graduate School of Business, 100006 Beijing, China; [b] Northwestern University, Kellogg School of Management, Evanston, Illinois 60208; [c] Columbia Business School, Columbia University, New York, New York 10027

Contact: yangli@ckgsb.edu.cn, http://orcid.org/0000-0002-7380-1883 (YL); b-gordon@kellogg.northwestern.edu, http://orcid.org/0000-0001-9081-569X (BRG); onetzer@gsb.columbia.edu, http://orcid.org/0000-0002-0099-8128 (ON)

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Abstract. Geographic price discrimination is generally considered beneficial to firm profitability. However, theoretical results point to conditions under which firms might prefer to price across markets uniformly in oligopolistic settings. This paper provides an empirical analysis of competitive price discrimination and quantitatively assesses the profitability of national pricing relative to store-level pricing policies under different market conditions. Specifically, we construct and estimate a model of retail competition using extensive data from the digital camera market. A series of counterfactuals show that, under reasonable commitment mechanisms, two leading chains would benefit from employing national pricing policies, whereas a discount retailer should target prices in each local market. Additional results explore the boundary conditions of these findings and evaluate hybrid pricing policies.

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Keywords: pricing • retailing • competitive strategy • geographic price targeting • national pricing policy • local pricing policy • hybrid pricing policy

1. Introduction

Geographic price discrimination is generally considered beneficial to firm profitability. Varying prices across markets with different consumer preferences and socioeconomic characteristics enables a firm to extract more surplus by matching prices to local consumers' willingness to pay. Many large retail chains, such as Walmart, Starbucks, and McDonald's, implement region-based pricing policies that tailor prices to local market conditions.[1]

However, other retailers, such as Toys "R" Us and Best Buy, set uniform national prices across their stores.[2] Theoretical studies demonstrate that uniform pricing can help soften competition and improve firms' profits in competitive environments. But uniform pricing may not emerge in equilibrium because of the difficulty of ensuring commitment (Thisse and Vives 1988) or because of the requirements of particular demand and competitive conditions (Corts 1998). Thus, whether firms employ national or local pricing in a specific retail setting is an empirical question.

Our goal is to provide an empirical analysis of competitive price discrimination and to quantitatively assess the profitability of national pricing relative to store-level pricing policies under different market conditions. We explore the degree to which competitive forces—the intensity of competition and the distribution of market structures—can lead retailers to prefer national pricing over local pricing to ease competitive pressure. We investigate these issues using data from the U.S. digital camera industry, focusing on three major retailers that account for 70% of category sales. Two of the chains, chains A and B, are consumer electronics retailers that employ national pricing policies, whereas the other, chain D, is a general discount store that uses a local pricing policy.[3] We flexibly recover consumer preferences with a heterogeneous aggregate model of demand. We then compute retail chains' marginal costs, taking as given the observed pricing policies. Through a series of counterfactual simulations, we evaluate the relative benefits of national and local pricing policies. Our counterfactual analyses reveal that for the electronics chains, which face competition in most target markets, it is more profitable to employ a national pricing policy than a local policy. However, for the discount chain, which faces less intense spatial competition, a local pricing strategy is more profitable. We also explore how geographic variation in consumer preferences and market structures affects the profitability of national versus local pricing policies.

Our data contain approximately 11 million monthly store-level point-of-sales observations from the NPD

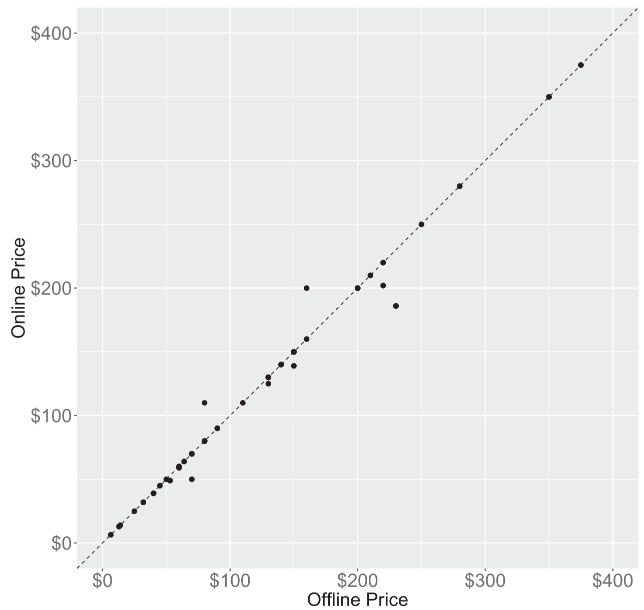
Group, which represents a near census of offline retail sales of digital cameras across 1,600 geographic markets.[4] First, we document the observed pricing policies for each retailer, demonstrating the adherence to uniform pricing by chains A and B and to local pricing by chain D. Next, we recover consumer preferences using an aggregate demand model with random coefficients. We estimate the model separately by market to achieve greater flexibility, which is necessary given the central role that local substitution patterns play in determining the benefits of local versus national pricing policies. To improve estimation, we augment the model in Berry et al. (1995) with micro moments from consumer survey data (Petrin 2002) and cast the estimation problem as a mathematical program with equilibrium constraints (MPEC) (Su and Judd 2012, Dubé et al. 2012).

On the supply side, we assume firms compete in a two-stage game, first selecting a pricing policy and then setting period prices for each product. Firms choose their pricing policy from among a small set of feasible strategies (e.g., national or local) and commit to their policy choice in the second stage. Similar to Corts (1998) and Adams and Williams (2017), we assume commitment to a national pricing policy is possible without explicitly modeling the commitment mechanism. In our setting, the increase in price awareness among consumers and the emergence of online competitors have contributed to the alignment of prices across channels. Firms have faced increasing pressure to maintain price parity between the offline and online channels. For instance, data obtained by Cavallo (2017) on a collection of products (not limited to digital cameras) show that the online and offline prices are largely the same for the electronics retailer Best Buy, as depicted in Figure 1.[5] The ease of price comparison makes store-level deviations less feasible and provides an opportunity for chains to compete using national pricing policies. Indeed, in our data, the two chains that used national pricing offered price match guarantees for their own online/offline price differences.

Given the observed pricing policies, we use the supply model to infer retailers' marginal costs and price margins. Based on the demand and supply estimates, we conduct several counterfactual analyses to assess the profitability of national versus local pricing policies for each retailer and to examine the conditions under which the national policy would yield higher profit for a chain relative to the local pricing policy.

First, a simulation that varies the policies of all three major retailers demonstrates that, given a choice between national and local pricing policies, two of the three major chains would benefit from employing national pricing policies, whereas the third firm should maintain its local pricing policy. For the first two chains, compared with a situation in which both chains use local pricing policies, national pricing results in profit increases of 5.3% to 8.4% across chains. For the third retailer, which localizes prices, switching to national pricing would yield an 8.7% profit loss on average. None of the chains would benefit from deviating unilaterally from the observed policy.

Figure 1. Online vs. Offline Prices in Best Buy



Note. Data taken from Cavallo (2017).

The difference in profits between national and local pricing is an empirical question that is determined by the strength of competition and the distribution of the markets in which competition is softened or intensified under each policy. To understand the counterfactual results, for the three major retailers, we decompose the changes in profits and prices in (1) contested markets, in which these chains compete head-to-head, and (2) uncontested markets, in which the chains do not overlap. Relative to a chain's prices under local pricing, a national pricing policy would set a price in between its (high) local prices in uncontested markets and its (low) local prices in contested market. Therefore, these retailers would lose profit in uncontested markets because of the suboptimal national price. But they gain profit in their contested local markets thanks to softened competition, because the competing chains raise prices together there. If the gain offsets the loss, national pricing is preferred; otherwise, local pricing wins. We show that the two national chains face heavy competition in most of their markets, and therefore benefit from national pricing. The third chain, on the other hand, operates in many uncontested markets, and thus prefers local pricing. In the presence of feasible commitment devices to enforce a uniform pricing policy, such as online prices and price match guarantee, these competitive forces may lead chains A and B to adopt national pricing to secure incremental profit.

In essence, uniform pricing across markets enables retailers to subsidize more competitive markets with profits from less competitive markets to ease otherwise intense local competition. Whether this yields a more profitable policy depends on the distributions of both "market structures" (i.e., number and sizes of contested versus uncontested markets) and "competitive intensity" across local markets. As such, in the second counterfactual, we investigate boundary conditions for the competitive advantage of national pricing. We find that as the number of contested markets gradually decreases, the firms that previously employed national pricing would begin to prefer local pricing to reap associated benefits in their uncontested markets. For instance, the leading retailer would earn more profit with local pricing if it had closed at least 29% of its stores in its contested markets.

Moreover, we leverage a unique feature of our data to examine the impact of competitive intensity on the profitability of pricing policies. At the beginning of the third year of the data period, the second largest retailer exited the industry, changing significantly the distribution of local competition. We find that although the leading retailer is still weakly better off by employing national pricing because of rivalry from the third chain, the profit-enhancing effect of national pricing is nearly gone compared with the situation when the major rival remained in operation.

Third, we investigate the performance of hybrid pricing policies. Local and national pricing represent extreme cases in the space of geographic pricing strategies. A national pricing policy can be sustained through the presence of the online channel. Alternative commitment mechanisms such as zoning represent other ways that a chain may set prices locally in some markets and maintain uniform pricing in others. For example, suppose the two leading chains customize prices in the five largest metropolitan areas in the United States and set uniform prices in the remaining national regions. The outcome is that profits of both chains decline because competition in these large markets is especially intense, and thus the counterfactual local prices would further intensify competition and reduce profits.

This paper broadly relates to the literature on retail pricing (Rao 1984, Eliashberg and Chatterjee 1985, Lal and Rao 1997, Besanko et al. 1998, Zettelmeyer 2000, Shankar and Bolton 2004, Bronnenberg 2008, Ellickson and Misra 2008) and, in particular, that on geographic price discrimination (Sheppard 1991, Hoch et al. 1995, Dobson and Waterson 2005, Duan and Mela 2009, Hitsch et al.2017, DellaVigna and Gentzkow 2017). The intuition behind our results is related to the theoretical findings in Thisse and Vives (1988) that were extended by Shaffer and Zhang (1995) and Chen et al. (2001). Thisse and Vives (1988) study spatially continuous demand with two competing firms that sequentially choose whether to set a uniform price or a location-specific price. They show price discrimination emerges as the unique equilibrium outcome, even though it produces a prisoner's dilemma that leaves the firms worse off relative to uniform pricing. Our study examines this intuition and provides a quantitative assessment of chain stores under competition. We obtain different profit results, as our empirical setup consists of spatially discrete demand with distinct local characteristics, and of multiple firms competing simultaneously with differentiated products. Another relevant theoretical study is Corts (1998), who uses a demand setup different from that of Thisse and Vives (1988) to show that even with unilateral commitment uniform pricing may become an equilibrium in the two-stage pricing game, if the demand conditions satisfy: (1) firms are constrained to employ only incentive-compatible price discrimination, and (2) best-response functions of competing firms are asymmetric. In our paper, we concentrate on the empirical context of chain store competition, and find a different set of demand and competitive conditions (i.e., the distribution of local competition intensity and the distribution of market structures) that may lead to the profit-enhancement effect of national pricing.

Two prior empirical studies are most relevant. Chintagunta et al. (2003) study a single chain's zone-pricing policy across different Chicago neighborhoods. The authors find that a chain, by further localizing prices, 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. More recently, Adams and Williams (2017) explicitly consider competition in the retail home improvement market using data on drywall. They show zone pricing enhances consumer surplus relative to more granular price discrimination policies.

The rest of the paper is organized as follows. Section 2 introduces the data, explores the variation in market structure, and describes the pricing policies observed. Section 3 presents the demand and supply models. Section 4 discusses model estimation and reports parameter estimates. Section 5 sets out several counterfactual experiments on pricing policies. Section 6 concludes with a discussion of limitations, and highlights areas of future research.

2. Data and Industry Facts

Here, we discuss the data sets. Although we are bound by a nondisclosure agreement with the data provider to protect chain and brand identities, we provide detailed

Table 1. Annual Market Share (%) of Top Seven Camera Brands

	Brand 1	Brand 2	Brand 3	Brand 4	Brand 5	Brand 6	Brand 7	Total
2007	21.4	17.0	7.3	16.4	6.4	5.5	3.8	77.8
2008	21.5	19.1	11.1	13.7	6.1	5.4	4.5	81.4
2009	21.6	20.6	12.8	12.2	5.6	5.2	5.2	83.2

summary statistics on product characteristics, retail environment, geographic markets, and pricing policies implemented by the major retail chains.

2.1. Data

Our data come from multiple sources: (1) point-of-sales records and product characteristics of digital cameras in the United States from the NPD Group, (2) two consumer-survey data sets from PMA, (3) shares of digital camera sales by distribution format from Euromonitor International, and (4) ZIP-code-level consumer demographics from the U.S. Census.

First, the NPD data contain 10,940,061 monthly store-level point-of-sales observations between January 2007 and April 2010, covering a significant portion of digital camera sales in the United States during this period.[6] Each observation is at the month-market-store-camera level, providing a granular picture of product sales across a large number of stores and periods.

Although the data contain nearly 60 camera brands, we focus our analysis on the largest seven brands, which represent approximately 80% of sales in our data. Table 1 reports the annual market shares of these brands. We further restrict the analysis to point-and-shoot cameras, which appeal to the market's largest consumer segment. We drop digital SLRs, which account for only 4.98% of overall unit sales, because they are much more expensive and target a narrower consumer segment.[7]

The NPD data also provide detailed product-attribute information. In the demand model, we include five attributes that most commonly appear on digital camera retail websites and in prior literature (Carranza 2010, Song and Chintagunta 2003, Zhao 2006). These attributes are price, resolution in megapixels, optical zoom, thickness, and display size. Table 2 summarizes the NPD data for these product characteristics. To calculate price, we divide monthly dollar sales by unit sales for each observation.

For our definition of market we use the 2,100 distinct store selling areas (SSAs) constructed by NPD. Each SSA consists of several ZIP codes and contains no more than one store per chain. We match the Census data to each SSA via ZIP codes and summarize the demographic variations across SSAs in Table 3. To examine the validity and robustness of this market definition, we conduct a hypothetical monopoly test (HM test; Davis 2006) using the store sales data. The test reveals that the vast majority of SSAs appropriately capture close competitive markets and our main results are robust after excluding the small number of SSAs that fail the test. Appendix A reports the details of the HM test.

Second, we incorporate consumer survey data from PMA, a market research firm. The survey reports digital camera purchases by household income bracket, based on annual surveys of 10,000 representative U.S. households over three years. Table 4 reports a summary of the PMA statistics. Later we use these microdata to construct demand-side micro moments. In addition, we obtain another set of survey results from PMA to characterize the outside option relative to digital camera purchase.

Third, we use channel sales data from Euromonitor International to construct an appropriate market size definition. A proper measure of market size is important to accurately recover firms' markups. Common measures are population size, number of households

Table 2. Summary of Camera Attributes

	No. camera models	Average price (dollar)	Average resolution (million pixel)	Average zoom (X)	Average thickness (cm)	Average display size (in)
2007	84	191.72	7.17	3.60	1.13	2.53
2008	77	173.17	8.25	4.05	1.06	2.65
2009	78	170.29	10.62	4.76	1.07	2.74

Table 3. Demographic Summary Across SSAs

	Mean	Median	Standard deviation	10th percentile	90th percentile
No. ZIP codes	14.9	5.0	29.9	1.0	40.5
No. households	50,147.0	29,785.0	55,577.3	9,294.5	116,233.5
Household income	\$47,955.0	\$44,333.5	\$14,996.4	\$32,142.8	\$69,580.1

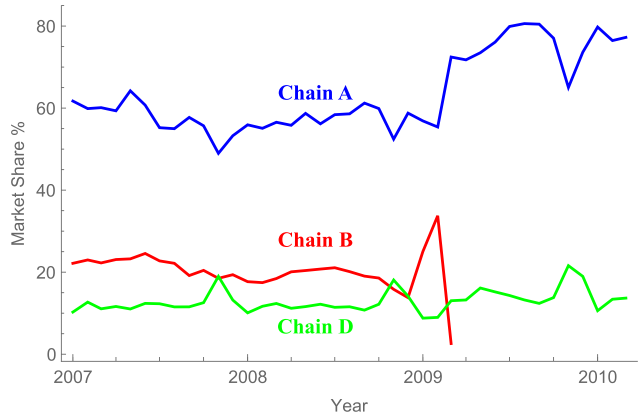
Table 4. Percentage of Households Purchasing Digital Cameras

Year	<$29,999	$30,000–$49,999	$50,000–$74,999	>$75,000
2007	8%	16%	20%	20%
2008	8%	12%	14%	18%
2009	7%	11%	14%	15%

Table 5. Shares of Digital Camera Sales by Distribution Format

	Store-based retailing	Home shopping	Internet retailing
2007	89.3%	2.0%	8.7%
2008	89.2%	2.0%	8.8%
2009	89.0%	1.8%	9.2%

Figure 2. (Color online) Market Shares of Major Retailers



(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 consumers considers purchasing cameras. To correctly specify market size, we attempt to quantify the set of potential buyers, 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 use data on digital camera sales by distribution channel from Euromonitor International (2010) to estimate the share of consumers who purchased cameras outside of the retail chains. Table 5 shows the NPD data cover the majority of digital camera sales, with 8.9% of cameras purchased online and 1.9% through other channels. We use these statistics to approximate the unit sales through non-store-based channels. The third group represents non-purchasers who were in the market but chose not to buy. To estimate the relative size of this group, we use another survey on camera purchase intentions from PMA (2006, 2007, 2008, 2009). This annual survey measures household purchase plans in the next 3, 6, or 12 months. The difference between the purchase plan and the actual purchase probability provided by the PMA report of the following year yields an approximate measure of the share of nonpurchasers. In the demand model, we combine the second and third groups to obtain the share of the composite outside good. Online Appendix A reports the calculated yearly market sizes during the data period.

2.2. Market Structure and Major Retailers

The primary profitability trade-off between national and local pricing relies on two key characteristics of market conditions: (1) the number and sizes of a chain's contested markets versus its uncontested markets and (2) the degree of local competition, in terms of the elasticity of substitution across products and between stores within a market. Next, we describe the variations in competitive market structure and product assortment, which help us estimate our model.

The retail digital camera market is moderately concentrated, with our three focal national chains A, B, and D accounting for 70% of total industry sales in our data. Other retailers had shares below 3% each, so we group these small sellers into a single chain L. We remove markets in which none of the three national chains exists, resulting in a 24% reduction to 1,600 SSAs and leaving the three major chains controlling a total of 90% market share in the remaining markets in our data.

Among the three major firms, chains A and B are consumer electronics retailers, whereas chain D is a general discount store. Figure 2 shows that before 2009, chains A and B had about 55% and 22% market shares, respectively. At the beginning of 2009, chain B terminated operations and liquidated all stores within three months. The market share chain B relinquished was quickly taken up by chain A, making it the dominant player, with a share of nearly 80%. Chain D's share was relatively steady, around 13% throughout this period. The exit of chain B, for reasons mostly independent of camera sales, provides a valuable source of variations in market structure and substitution patterns to examine the impact of chain competition on geographic pricing strategy.

All three chains operated in a mix of contested and uncontested markets. Table 6 presents the distribution of market structures across SSAs before and after chain B exits, as well as average annual total sales over SSAs of the same structure. The table sheds some light on why chains A and B could earn more profit with national pricing, whereas chain D may prefer a local policy. Chains A and B competed with each other and/or with chain D in the vast majority of the SSAs in which they operated. The fact that chains A and B

Table 6. SSA Structure, Number of SSAs, and Average Annual Total Sales over SSAs

SSA structure	SSA competitiveness	Before B exits		After B exits	
		No. SSAs	Sales	No. SSAs	Sales
A-only	Uncontested	101	0.47	165	0.97
A-D	Contested	315	1.88	839	5.79
B-only	Uncontested	79	0.25	—	—
B-D	Contested	118	0.53	—	—
A-B	Contested	59	0.57	—	—
A-B-D	Contested	402	4.20	—	—
D-only	Uncontested	525	0.64	600	0.84

Note. Sales are in million units.

located in so many contested markets with large sales creates opportunities for them to use national pricing to ease competition. After chain B's exit, although chain A gained many uncontested markets, it still faced rivalry from chain D in most of its SSAs. By contrast, chain D operated in a number of markets without competition from chains A or B, affording it more flexibility to implement a local pricing policy.

Another measure of competition can be inferred from product assortment overlap across chains. Table 7 reports cameras' retail chain affiliation, the number of distinct models carried by different sets of stores before and after chain B exits, as well as average annual total sales over cameras of the same chain affiliation. The table shows the bestselling cameras are the ones available at all the retailers. Cameras carried by just one or two chains often have lower sales. The table also shows that the overlapped assortment between chains A and B is wider and generates more sales than the overlapped assortments between chains A and D and between chains B and D, indicating the relatively lower competition that chain D faces from the other two major retailers. Again, the difference in assortment overlap alludes to the profit benefits to chains A and B when they adopt competition-dampening pricing policies. In the demand specification, we model camera choice at the store-product level, thus accounting directly for the assortment overlap between chains in every local market.

In summary, the three major retailers competed in a large number of markets, with significant overlap in product assortment. Meanwhile, variation exists across chains and over time along these two dimensions. The profit advantage for national or local pricing ultimately depends on the relative size of the contested versus uncontested markets and the intensity of competition in these markets. How these factors play out for the three chains is an empirical question, which we investigate using a structural model of chain competition and a set of counterfactual analyses.

2.3. Pricing Policies

As described earlier, chains A and B implement national pricing policies, whereas chain D uses local pricing. Next, we provide descriptive evidence for the employment of such policies, highlighting the contrast in price variation observed for chains A and B relative to chain D.

First, for the three bestselling cameras in the data, we present the distribution of prices across stores by chain. Figure 3 displays this distribution in the third, sixth, and ninth months of each camera's product lifetime. The plots show that the interquartile range is wider at chain D than at the other chains for each camera and across time. Even though chains A and B have some price variation, it is consistently small relative to the price variation at chain D.[8] Figures B.1 and B.2 in Appendix B show similar patterns for the next six top selling cameras.

Second, consider the top 20% of products by total sales from each chain. In Figure 4, we report the fraction of stores in a month with the same price for a given product against the cumulative sales share of that product.[9] Each point 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. By contrast, for chain D, the share of stores with uniform prices is much lower over a product's life cycle. We further report the coefficients of variation of prices across stores for all products against their life cycle in Figure B.3 of Appendix B and find similar price variation patterns from this figure to those reported in Figure 4. These results jointly indicate that chains A and B employ national pricing policies for the majority of their products' time in the store, only resorting to clearance pricing for the last 20% of a product's sales, whereas chain D uses local pricing throughout its products' life cycle.

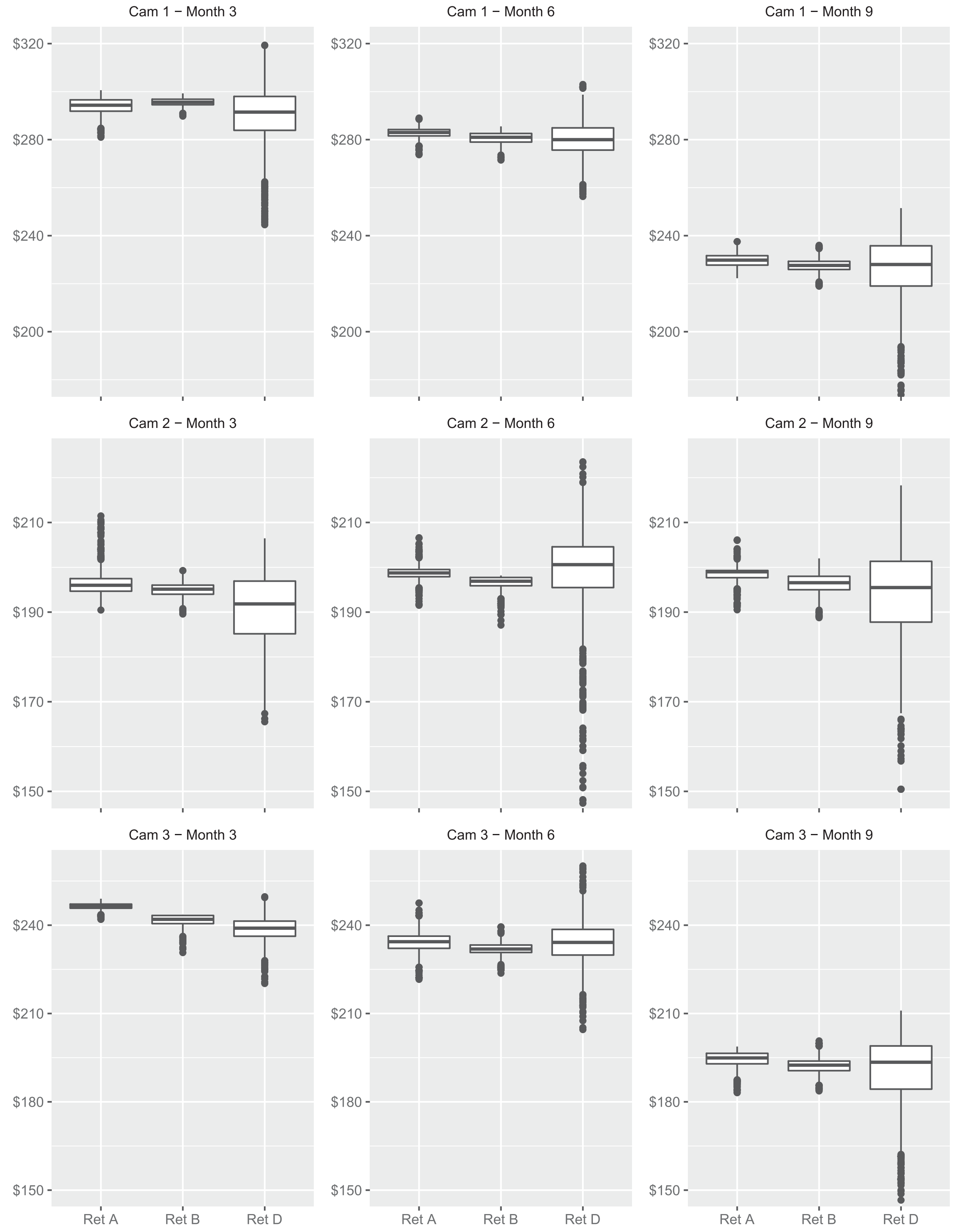
Discussions with a senior pricing manager at one of the chains further support this descriptive evidence for the firms' pricing policies. The manager confirmed that chains A and B both follow national pricing policies across categories for most of a product's life cycle.[10] The chains shift to local pricing when the firm predicts

Table 7. Chain Affiliation, Number of Camera Models, and Average Annual Total Sales over Cameras

Chain affiliation	Before B exits		After B exits	
	No. models	Sales	No. models	Sales
A-only	26	0.32	71	2.37
A-D	3	0.13	37	4.58
B-only	31	0.27	—	—
B-D	10	0.29	—	—
A-B	21	2.11	—	—
A-B-D	34	5.20	—	—
D-only	9	0.22	21	0.64

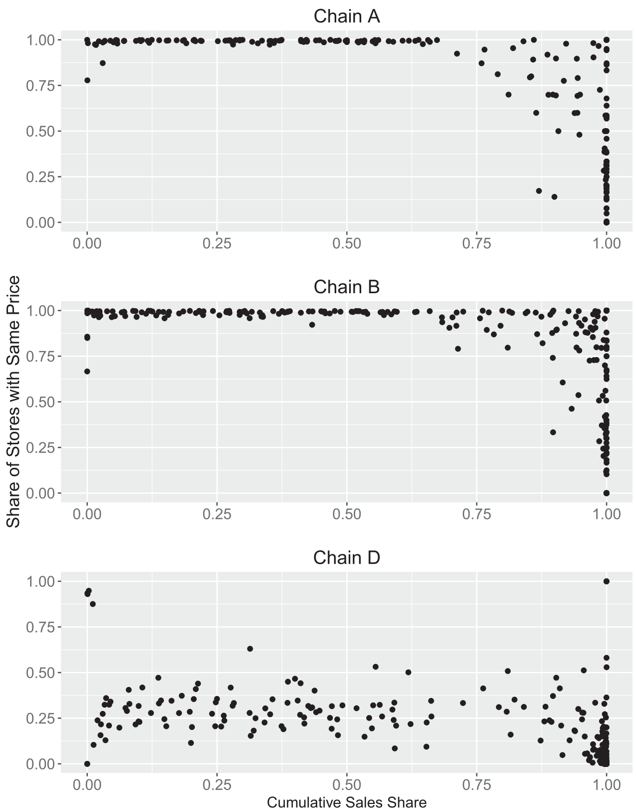
Note. Sales are in million units.

Figure 3. Price Distribution Across SSAs for Cameras 1–3



sales have reached around 80% of cumulative lifetime sales, after which they transition to clearance pricing and allow stores to manage the pricing process. The manager also confirmed chain D does not use national pricing. As this chain is a general discount store carrying many products that are not sold online, such as groceries, it does not feel the same pressure imposed by the online channel as the two electronics retailers and is relatively comfortable with store-level targeted prices.

Figure 4. Share of Stores with Same Price for Top 20% Bestselling Cameras



3. Model

We specify a model of aggregate demand to estimate consumer preferences, and a model of retail competition to recover marginal costs and to conduct counterfactuals. To facilitate demand estimation, we incorporate micro moments that relate consumer demographics to digital camera purchasing patterns. Given the large number of products, markets, and time periods, and that quality-adjusted prices in the data declined more slowly than in earlier periods studied in previous research (e.g., Song and Chintagunta 2003, Gowrisankaran and Rysman 2012), we sidestep consumer forward-looking behavior in order to leverage the abundant spatial variation. To this end, we estimate the demand model separately in each of the 1,600 SSAs in which the chains operated, obtaining a flexible semiparametric representation of heterogeneous consumer preferences across markets.

On the supply side, retailers compete in a two-stage game. In the first stage, each retail chain selects a pricing policy, such as national pricing, local pricing, or a hybrid. In the second stage, conditional on a particular pricing policy, the chains set period prices in a static Nash fashion. Through the price-setting process, we recover marginal costs for subsequent counterfactuals. With the exception of local pricing, the other policies in the first stage constrain the pricing flexibility of the firm. If national pricing is chosen, we assume the firm can fully and credibly commit to this policy because of the pressure to maintain pricing parity across online and offline channels, although we do not formally include online prices in the model.

3.1. Aggregate Demand

We model consumer demand in each market using a static aggregate discrete choice model (Berry 1994, Berry et al. 1995). We omit market subscripts for clarity of exposition. A product j represents a particular camera model sold in a specific store of an SSA. The same camera available at another retailer in the same SSA is considered a different product because product characteristics such as price may vary across stores. Thus, each choice alternative is defined at the store-camera level, and all store-camera pairs within an SSA of a month constitute the choice set.[11] We consider Cobb-Douglas for specifying consumer utility, such that a household i that purchases product j in month t obtains

$$U_{ijt} = (y_i - p_{jt})^{\alpha} G(x_{jt}, \xi_{jt}, \beta_i) e^{\epsilon_{ijt}}, \tag{1}$$

where $t = 1, \ldots, T$ is the month and $j = 1, \ldots, J_t$ is the set of store-camera pairs available in this market at month t. x_{jt} is observed product characteristics with coefficients β_i. ξ_{jt} represents unobservable shocks common to all households of this SSA. These shocks may include missing product attributes, unquantifiable factors such as camera design and style, and measurement errors due to aggregation or sampling.[12] y_i is the income of household i, p_{jt} is the price of product j at month t, and α is the price coefficient indicating the marginal utility of expenditures. We incorporate geographic variation in inflation-adjusted income by estimating the distribution of y_i using the Census data matched by ZIP code.

Assuming $G(\cdot)$ is linear in logs, the transformed utilities are given by

$$\begin{aligned} u_{ijt} &= x'_{jt}\beta_i + \alpha \log(y_i - p_{jt}) + \xi_{jt} + \rho \log(J_t) + \epsilon_{ijt} \\ u_{i0t} &= \alpha \log(y_i) + \epsilon_{i0t}. \end{aligned} \tag{2}$$

The additional "congestion" term $\log(J_t)$ helps correct bias in the estimated price elasticity due to variation in the size of choice set over time and across SSAs (Ackerberg and Rysman 2005). Later, we will show this term helps produce more realistic price margins.

When ϵ's are distributed as type I extreme value, the market share of option j at month t is a logit choice probability aggregated over all households in the local market:

$$s_{jt} = \int_{\forall i} s_{ijt} = \int_{\forall i} \frac{\exp\left[x'_{jt}\beta_i + \alpha\log(1-p_{jt}/y_i) + \xi_{jt} + \rho\log(J_t)\right]}{1+\sum_{k=1}^{J_t}\exp[x'_{kt}\beta_i + \alpha\log(1-p_{kt}/y_i) + \xi_{kt} + \rho\log(J_t)]} \times d\mathrm{P}(\beta_i)d\mathrm{P}(y_i), \tag{3}$$

where $\mathrm{P}(\beta_i)$ and $\mathrm{P}(y_i)$ are probability density functions of heterogeneous tastes and household income, respectively. We use the Census data to recover the distribution of y_i under the assumption of lognormality. We assume β_i follows a multivariate normal distribution, and estimate its mean and variance as part of the structural estimation.[13]

The observed camera attributes include price and six other attributes: store affiliation, camera brand, resolution in megapixels, optical zoom, thickness, and display size. To simplify the estimation, we do not estimate a full set of random coefficients on each attribute. Instead, we divide x_{jt} into x_{jt}^{fc} and x_{jt}^{rc}, and assign random coefficients only to the latter, which includes resolution, store affiliation, and camera brand. The other three nonprice attributes are included in x_{jt}^{fc}. We also include dummies for "November-December" and "June" in x_{jt}^{fc} because the industry exhibits strong seasonality.

3.2. Micro Moments

Leveraging information that links consumer demographics to consumer purchase behavior can improve estimates of aggregate demand models (Petrin 2002). The PMA survey provides average purchase probabilities of households for each of the four income brackets, as Table 4 shows. To supplement this additional information as moments for estimation, we first divide each market into R distinct income tiers, with varying price coefficients assigned to each:

$$\alpha_r = \begin{cases} \alpha_1, & \text{if } y_i < \bar{y}_1 \\ \alpha_2, & \text{if } \bar{y}_1 \le y_i < \bar{y}_2 \\ \vdots & \\ \alpha_R, & \text{if } y_i \ge \bar{y}_{R-1}, \end{cases} \tag{4}$$

where $\{\bar{y}_1, \bar{y}_2, \ldots, \bar{y}_{R-1}\}$ are income cutoffs. Then we construct moments according to

E[{household i bought a new camera at t}| {i belongs to income tier r at t}],

and match them to the PMA survey statistics. The micro moments serve a different role than hierarchically linking demographics with parameter heterogeneity. The latter approach only provides extra flexibility to the model, whereas the micro moments restrict the generalized method of moments (GMM) to match additional statistics, making the estimated substitution patterns directly reflect demographic-driven differences in choice probabilities. Also, such variation in purchase probabilities by income facilitates the identification of demand parameters.[14]

3.3. Chain-Level Pricing Model

In each month, conditional on their first-stage pricing policies, the chains set period prices in a static Nash fashion. This approach is reasonable because the chains change products' prices frequently, whereas the choice of a chain-level pricing policy represents a long-term strategic decision. In the first stage we consider only the national and local pricing policies, for several reasons. First, among the three chains, these two policies are the only observed policies in the data. Second, the emergence of the online channel places pressure on retailers to commit to the same price offline and online. Third, both chains A and B employ price match guarantee to further discipline stores to national prices. Next, we describe the firm's objective function under either a national or local pricing policy.

3.3.1. National Pricing Policy.

Under a national pricing policy, a chain sets the same price for a product across all markets in a given period. Because the model is static, we suppress the time subscript in the following discussion. Denote J_f as the set of products chain f offers (although we have dropped time subscripts, we should note J_f varies over time), and m as the index of an SSA. The profit of chain f is the sum of local profits across markets for every product that has a national price:

$$\Pi_f = \sum_{j=1}^{J_f}(p_j - c_j)\sum_{\forall m: j\in m} s_{jm}M_m, \tag{5}$$

where c_j is the marginal cost of camera j, M_m is the size of market m, and s_{jm} is the share of product j in market m. Because prices are nationally determined, the marginal costs are also estimated at the national level. The first-order condition with respect to camera j's price is

$$\sum_{\forall m: j\in m} s_{jm}M_m + \sum_{r=1}^{J_f}(p_r - c_r)\sum_{\forall m: j\in m}\frac{\partial s_{rm}}{\partial p_j}M_m = 0, \quad \text{for } j = 1, \ldots, J_f. \tag{6}$$

Stacking prices, costs, and shares, the pricing Equation (6) can be written succinctly in matrix notation for all competing products under national pricing across the relevant chains:

$$c = p - \mathbf{\Delta}^{-1} q, \tag{7}$$

where $q = \sum_{\forall m} M_m \int_{i \in m} s_i$ is a vector of total unit sales of each product after integrating out the demographic distribution of SSA m. $\mathbf{\Delta}$ is a block diagonal matrix in which each block $\mathbf{\Delta}_f$ pertains to a chain using a national pricing policy. With $\mu_i(p) = \alpha_r \log(1 - p/y_i)$, we can succinctly write $\mathbf{\Delta}_f$ as

$$\mathbf{\Delta}_f = -\sum_{\forall m} M_m \int_{i \in m} \left[\frac{\partial \mu_i(p)}{\partial p} (\mathrm{diag}(s_i) - s_i s_i') \right]. \tag{8}$$

3.3.2. Local Pricing Policy. Under a local pricing policy, a chain sets period prices for each product separately across markets because profit in one market is independent of profits in other markets. As a result, we drop the summation over m in (8) and let market size M_m cancel each other out in (7). The pricing equation for all competing products under local pricing policy between retailers in market m is then given by

$$c = p - \mathbf{\Delta}^{-1} s, \tag{9}$$

where $s = \int_{i \in m} s_i$ is a vector of product shares in that local market, and

$$\mathbf{\Delta}_f = -\int_{i \in m} \left[\frac{\partial \mu_i(p)}{\partial p} (\mathrm{diag}(s_i) - s_i s_i') \right]. \tag{10}$$

4. Estimation

In this section, we discuss our identification strategy and the estimates of demand parameters, elasticities, and margins under alternative model specifications. First, rich variation exists in consumer income across geographic markets, as Table 3 indicates. Second, the propensities to purchase reflected in the microdata vary over time and across SSAs because of the different sizes of income tiers in different markets. Third, choice sets substantially vary across SSAs and over time. Although popular models are available in all stores, niche cameras may be found in only one or two stores of a local market. The average size of a choice set is 51.7, and the standard deviation is 29.6. Fourth, for a given product, prices differ across retailers in the same month, and across time at the same retailer. Fifth, market structure varies across SSAs, with different chains operating in different sets of markets and with varying product assortments, as reported in Tables 6 and 7. Together, these features of our data produce significant variation to recover consumer preferences.

To best capture local variation in preferences and market conditions, we estimate the demand model separately in each of the 1,600 SSAs. On average, a local market contains about 1,200 observations, allowing us to model taste heterogeneity within each market. From the separate estimation, we can draw a semiparametric representation of the consumer preference distribution at the national level. For comparison purposes, we also estimate a single-demand model that pools data across all SSAs.

4.1. Moments

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

$$s_{jt} = \int_{\forall i} \frac{\exp(V_{ijt})}{1 + \sum_{k=1}^{J_t} \exp(V_{ikt})} dP(\beta_i) dP(y_i), \tag{11}$$

$$\tilde{s}_{rt} = \int_{i \in r} \sum_{j=1}^{J_t} s_{ijt}, \tag{12}$$

where (11) is a market share equation with systematic utility

$$V_{ijt} = x_{jt}^{fc\prime} \beta_{fc} + x_{jt}^{rc\prime} \beta_i + \alpha_r \log(1 - p_{jt}/y_i) + \rho \log(J_t) + \xi_{jt},$$

and (12) represents the micro moments, with $\tilde{s}_{rt}$ denoting the percentage of households at income tier r that purchased new cameras in month t. The integrals in these equations are numerically approximated with $I = 2000$ random draws from Sobol sequence (Train 2003).

We append four identical terms, $\log(1 - p_{jt}/y_i)$ to x_{jt}^{rc}, to obtain x_{ijt}^{rc} that accounts for the $R = 4$ income tiers in the micro moments. Stacking these observations by j and t in matrices gives

$$V_i = X\theta_1 + X_i^{rc} \theta_2 v_i + \xi, \tag{13}$$

where X is a stack of x_{jt}^{fc}, x_{jt}^{rc}, and $\log(J_t)$, and X_i^{rc} is a stack of x_{ijt}^{rc}. θ_1 is a vector combining the fixed coefficients β_{fc}, the means of the random coefficients, $\bar{\beta} = \mathrm{E}[\beta_i]$, and the coefficient of the congestion term ρ. θ_2 is a diagonal matrix in which the diagonal includes the standard deviations of the random coefficients and the four α_r's. v_i is a vector consisting of random draws from a standard multivariate normal distribution, and of four binary indicators of household i's income tier. With (13), the mean utility that facilitates estimation can be written as

$$\delta = X\theta_1 + \xi. \tag{14}$$

We use GMM to estimate the demand system with two sets of moments. Assuming ξ is mean independent of some exogenous instruments Z, we obtain the demand-side moments:

$$g(\delta, \theta_1) = \frac{1}{N_d} Z'\xi = \frac{1}{N_d} Z'(\delta - X\theta_1) = 0, \tag{15}$$

where N_d denotes the number of sale observations. The second set of moments includes the micro moments derived from the PMA survey statistics in (12).

We follow the approximation to optimal instruments in Berry et al. (1995) to construct a set of instruments orthogonal to the demand shocks. Our instruments include own-firm 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 average R^2 in the regression of price on the instruments is 0.72 across SSAs. The F-statistic, 47.17 on average, rejects the hypothesis that our instruments do not explain observed prices in all SSAs.

4.2. MPEC Approach

We formulate the GMM estimation of aggregate demand as an MPEC (Su and Judd 2012, Vitorino 2012, Dubé et al. 2012). In particular, the GMM estimator minimizes the ℓ^2-norm of $g(\delta, \theta_1)$ in (15), subject to the constraints imposed by the share in Equation (11) and by the micro moments in Equation (12). The constrained optimization can be written as

$$\begin{aligned} \min_{\phi} \quad & \mathrm{F}(\phi) = \eta' W \eta \\ \text{s.t.} \quad & s(\delta, \theta_2) = S \\ & \eta_1 - g(\delta, \theta_1) = 0 \\ & \eta_2 - \tilde{s}(\delta, \theta_2) = -\tilde{S}, \end{aligned} \tag{16}$$

where the vector $\phi = \{\theta_1, \theta_2, \delta, \eta_1, \eta_2\}$ contains the optimization parameters. W is a weighting matrix, S is a vector of actual shares, and $\tilde{S}$ is a vector of the microdata collected from the PMA survey. $\eta = \{\eta_1, \eta_2\}$ represents a set of auxiliary variables that yield extra sparsity to the Hessian of the Lagrangian.[15] To facilitate the optimization, we derive closed-form Jacobian and Hessian expressions for the objective function, the demand moments, and the micro moments. All details for the MPEC are provided in Appendix C.

4.3. Recovering Marginal Costs

Given estimates of the demand parameters (θ_1, θ_2), we recover marginal costs using the observed pricing policies for each chain. As discussed in Section 2.3, chains A and B employ national pricing for most of a product's life cycle, after which they switch to local pricing, whereas chain D always implements local pricing. To reflect this empirical reality, we assume that in every month chains A, B, and D simultaneously set (1) national prices with Equation (7) for the products at chains A and B during the products' regular sales period (i.e., prior to reaching 80% lifetime sales) and (2) local prices with Equation (9) for the products at chain D, as well as the products at A and B under clearance (i.e., after reaching 80% lifetime sales).

We assemble the national pricing (7) and local pricing (9) equations appropriately for the corresponding products based on their chain affiliation and sales status, and in each period solve the system of equations across products, markets, and chains. The cost of a camera in a chain is constrained to be the same across the SSAs of that chain (but not across time), because we expect that national retailers obtain units from the manufacturers at prices independent of store location or pricing policy. Differences in distribution costs are likely to be small for digital cameras.

In Section 5.4, we implement a robustness check to recover marginal costs under alternative pricing policies. We find the recovered marginal costs and the resultant counterfactual outcomes are not sensitive to the pricing policy choice.

4.4. Estimation Results

For every SSA, we estimate a separate demand model, including brand and chain fixed effects. For comparison, we estimate a single pooled-demand model across all SSAs. We also compare our full model with a 2-stage least squares (2SLS) model that does not account for unobserved heterogeneity. Because of the large number of model parameters, we mainly report price elasticity and price margin estimates, because they are mostly relevant to our study. Moreover, note that parameter estimates from different logit models are not directly comparable due to differences in utility scale (Swait and Louviere 1993). Therefore, we compare alternative model setups based on elasticity results. Additional estimation outputs can be found in Online Appendix C.

4.4.1. Demand Estimates. Table 8 reports elasticities on price, resolution, optical zoom, thickness, and display size. Figure 5 plots histograms of price and resolution elasticities under the pooled and separate estimations. Overall, preferences toward camera attributes are highly heterogeneous across households. Both Table 8 and Figure 5 suggest estimating demand separately for each local market yields lower and more dispersed elasticities than the pooled estimation. Whereas the pooled estimation requires coefficients across markets share a common heterogeneity distribution, estimation by market relaxes such an assumption and therefore generates more realistic price margins, as we will show below.

The elasticity estimates indicate that, as expected, consumers favor cameras with higher resolution, better optical zoom, and larger displays, and dislike cameras that are thick in size.[16] The inclusion of congestion term $\log(J_t)$ yields an extra 9.68% decrease in average price elasticities. To make sense of these numbers, we translate the full model estimates into dollar terms

Table 8. Elasticity Estimates

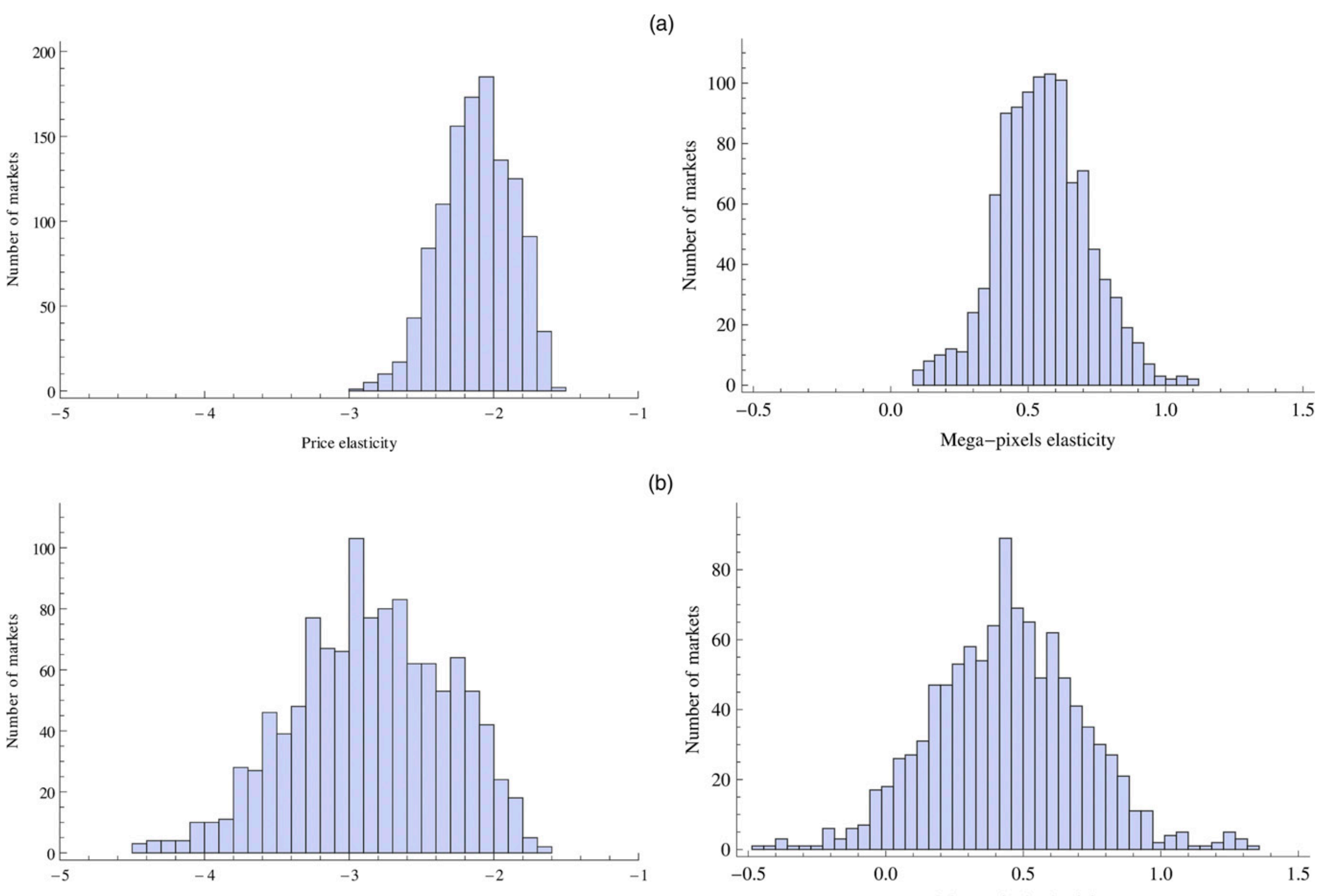
	Separate estimation		Pooled estimation	
Elasticity	2SLS	Random coefficients and microdata	2SLS	Random coefficients and microdata
Price	−1.496	−2.903	−1.245	−2.184
	[0.248]	[0.773]	[0.152]	[0.373]
Resolution	0.390	0.434	0.460	0.576
	[0.179]	[0.260]	[0.099]	[0.181]
Optical zoom	0.080	0.067	0.051	0.064
	[0.169]	[0.181]	[0.059]	[0.043]
Thickness	−0.206	−0.305	−0.228	−0.367
	[0.270]	[0.264]	[0.126]	[0.132]
Display size	0.212	0.179	0.118	0.253
	[0.559]	[0.532]	[0.012]	[0.094]

Note. Standard deviations, in squared brackets, are computed across SSAs.

based on a one-unit improvement in each camera attribute. This approach shows an average consumer would value an additional megapixel at $15.25, a 1× increase in optical zoom at $8.74, a 1-mm reduction in thickness at $4.48, and a one-inch larger display at $21.93.

4.4.2. Price-Margin Estimates. Using observed prices, we compute margins given the marginal costs recovered from the supply model. Table 9 compares the average margins inferred across alternative demand specifications. Relative to the full model with random coefficients and micro moments, 2SLS produces

Figure 5. (Color online) Histograms of Market-Specific Elasticities of Price and Resolution



Notes. (a) Pooled estimation (top two graphs). (b) Separate estimation (bottom two graphs).

Table 9. Inferred Price Margins Across Demand Specications

	Separate estimation		Pooled estimation	
Margin	2SLS	Random coefficient and microdata	2SLS	Random coefficient and microdata
Mean	69.62%	34.53%	82.05%	45.13%
Median	63.19%	28.59%	78.36%	41.08%
10th percentile	45.46%	21.24%	74.42%	33.87%
90th percentile	93.82%	42.89%	87.63%	58.40%

Note. The margin is defined as $(p - c)/p$.

higher margins. The 35% average margin obtained in the full model is the lowest and the closest to estimates in industry reports. For example, Euromonitor International (2010) documents that retail margins for point-and-shoot cameras range from 25% to 35%. By contrast, pooled estimation produces unrealistically high margins.

Table 10 breaks down the margins by chain under the full model. From the breakdown we see that, on average, chain A enjoyed slightly higher margins than chain B, whereas chain D has relatively lower margins than the two specialty retailers. These differences reflect the contrasts in market share, product mix, store locations, and prices among the three retailers.

5. Counterfactual Simulations

Having recovered consumer preferences and marginal costs, our goal is to conduct a series of counterfactual simulations to evaluate the extent to which a national pricing policy can lead to higher profits than a fully customized (local) pricing policy. First, we consider how the three firms' prices and profits would change if the chains switched between national and local pricing policies. Second, we examine the boundary conditions under which national pricing achieves higher profits than local pricing. Third, given that national and local pricing policies represent opposite extremes, we explore outcomes if the chains were to implement one of two possible hybrid policies that allow limited geographic pricing flexibility. Finally, we provide sensitivity analysis to show the counterfactual results are robust to our approach to recovering marginal costs.

Each counterfactual analysis involves "switching" one or more chains from their observed policies to an alternative policy. If a chain moves from national to local pricing, we use the local pricing Equation (9) for this chain, and similarly use the national pricing Equation (7) if the chain switches in the opposite direction. To implement these counterfactuals, we substitute the marginal costs c into Equations (7) and (9), and solve the system of equations to generate the counterfactual prices p for each chain.

5.1. National vs. Local Pricing

5.1.1. Pricing Policies for Chains A and B. First, we evaluate the profitability of chains A and B under different pricing policies in the first stage. Given either national or local pricing policies, we use the demand and costs estimates obtained before B exits to compute prices and profits. We assume chain D sticks with local pricing and address a deviation of its policy in the subsequent analyses. The smallest Chain L, consisting of small sellers, is passive and does not respond to any market changes.

Table 11 reports the two-year profits of chains A and B under four alternative pricing scenarios in the first stage of the game: local-local, local-national, national-local, and national-national.[17] The results show that employing national pricing is more profitable for both chains A and B. Switching from local to national increases profits for chain A by 5.3% and for chain B by 8.4%.[18] More importantly, neither chain A nor B would find it profitable to deviate unilaterally from national to local pricing. To understand why national-national is the preferred pricing policy for both chains, in Table 12, we decompose the differences in profits and prices across policies relative to national-national, for both contested and uncontested SSAs.

First, suppose both firms switch to local-local. In their respective uncontested markets, moving from national to local pricing raises profits by \$4.09 million and \$2.91 million. Such gains result from the 5.81% and 8.31% price increase by A and B, respectively, because neither chain is constrained to match the (lower) national price in these SSAs and each can now charge locally optimal prices. On the contrary, in the contested markets, switching from national to local pricing reduces profits by

Table 10. Inferred Price Margins by Chains

Margin	Chain A	Chain B	Chain D	Overall
Mean	35.41%	34.09%	32.76%	34.53%
Median	30.27%	28.05%	25.37%	28.59%
10th percentile	22.06%	21.06%	18.46%	21.24%
90th percentile	43.93%	41.86%	40.50%	42.89%

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

Table 11. Counterfactual Profits (π_A, π_B) Before B Exits ($ millions)

	Chain B	
	Local	National
Chain A		
Local	(307.60, 104.06)	(320.58, 105.17)
National	(310.03, 110.47)	(323.91, 112.78)

$20.40 million for A and $11.63 million for B. Freed of the national pricing constraint, local competition in these SSAs pushes down prices by 9.77% and 9.03%, respectively. For both chains, the profit loss in the contested markets outweighs the gain in the uncontested markets, because the contested markets outnumber and are on average larger than the uncontested markets, as reported in Table 6. Therefore, a simultaneous shift from national pricing to local pricing is unprofitable for both firms.

Next, we use Table 12 to explain why a unilateral deviation to local pricing is unprofitable for either firm. Suppose chain A were to deviate from national to local pricing, whereas chain B maintains its national policy. Chain A would raise prices by 5.81% on average in its uncontested markets, and the new locally optimal prices would increase A's profit in these markets by $4.09 million. Also, chain A would lower prices by 7.17% in its contested markets, because of the irrelevance of demand from the uncontested markets. Although chain B's policy is fixed, the chain would simultaneously adjust its nationally uniform prices in response to chain A's move. We find that chain A's unilateral action would result in chain B reducing prices by 3.30% and 3.56%, in its uncontested and contested markets, respectively.[19] Now, in the contested SSAs, both chains have effectively lowered prices; therefore local profits decline due to heightened price competition. In particular, chain A would lose $7.42 million, and chain B would lose $5.09 million. As before, collectively, chain A's contested markets are larger and more plentiful relative to its uncontested markets, such that its profit loss in the contested markets slightly outweighs the gains in its uncontested markets. Thus, the unilateral deviation to local pricing is unprofitable for chain A. Similar logic can be applied to a unilateral deviation by chain B, with the same conclusion.

We have shown the use of national pricing enhances profitability for the two largest retailers relative to local pricing. Next, we consider the large discount chain D, and evaluate its counterfactual adoption of a pricing policy.

5.1.2. Pricing Policies for Chain D. We perform a similar simulation of alternative pricing policies for chain D, prior to B's exit. Table 13 reports the counterfactual profits ($ millions) when this retailer uses either national or local pricing across the four possible policy configurations of chains A and B. A comparison between the top and bottom rows shows that a national policy reduces chain D's profit regardless of the other chains' strategies. To understand these results, we again decompose the profits across markets in which chain D does or does not compete with the other chains in Table 14.

Similar to the other two firms, chain D could use national pricing to soften price competition in its contested markets with A and/or B, but the benefit is not sufficient to cover the profit loss in its own uncontested markets. The reason behind this contrasting finding is straightforward: unlike chains A or B, chain D operated in many more uncontested markets. Table 6 shows that, before B exits, chain D has 525 SSAs with no presence of the other two retailers, whereas A and B have only 101 and 79 uncontested SSAs, respectively. Similarly, the uncontested markets account for more than half of chain D's total sales. Also, according to Table 7, chain D's camera assortment overlaps less with chains A and B relative to the overlap between the latter two chains. These points of differentiation weaken the price competition between D and the other chains. Without sufficiently intense competition to begin with, chain D does not profit from adopting national pricing as much as the other two retailers do. In addition, chain D does not feel the same pressure imposed by online prices as the two large electronics retailers because it is a general discount store selling many products not available online. During the data period, chain D offered a price match guarantee that did not cover the online/offline difference. Therefore,

Table 12. Profit and Price Decomposition between Contested and Uncontested Markets (Chain A, Chain B)

	Uncontested markets Chain B		Contested markets Chain B	
	Local	National	Local	National
Profit difference ($ millions)				
Chain A				
Local	(4.09, 2.91)	(4.09, −2.52)	(−20.40, −11.63)	(−7.42, −5.09)
National	(−5.86, 2.91)	(—, —)	(−8.02, −5.22)	(—, —)
Price difference (%)				
Chain A				
Local	(5.81%, 8.31%)	(5.81%, -3.30%)	(−9.77%, −9.03%)	(−7.17%, −3.56%)
National	(−2.54%, 8.31%)	(—, —)	(−2.63%, −6.23%)	(—, —)

Table 13. Profits of Chain D ($ millions) Under Alternative Policy Scenarios

	A national B national	A local B national	A national B local	A local B local
D local	47.21	45.29	46.57	44.65
D national	44.75	40.08	42.84	40.19

chain D could comfortably choose to customize local prices rather than commit to national pricing to obtain higher profit.

5.2. Boundary Conditions for National Pricing

Thus far, we have demonstrated that under the current competitive landscape, employing national pricing is more profitable for chains A and B than use of local pricing, while the reverse is true for chain D. Now we explore the boundary conditions for the profit trade-off between these two pricing strategies.

5.2.1. Variation in Market Structure. The decomposition in Table 12 demonstrates the critical role of market structure in our results. To explore this dimension further, we conduct a counterfactual simulation that varies market structure by gradually removing stores from the contested markets of either chains A or B. We shut down stores in a chain by starting from the least profitable location and continuing in ascending order of profit, so as to mimic the real world, in which the weakest stores are likely to close first. This process decreases the relative proportion of contested markets of the focal chain and therefore reduces the competition this chain faces. After removing each store, we recompute the counterfactual profits under both national and local pricing.

Figure 6 reports the simulation results. As the number of contested markets decreases, the profit gain from national pricing relative to local pricing declines. In particular, once chain A retreats from 29.3% of its contested markets, it would benefit from employing local pricing. Similarly, chain B would prefer local pricing once it closes 40.1% of its stores in contested markets. The difference in the transition point between A and B is primarily because chain B originally had fewer uncontested SSAs. At the extreme, when either chain exits from all its contested markets and hence faces no competition from the other chain in remaining 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.

The counterfactual analysis above implies that changes in competitive market structures can significantly affect the potential profit benefit of a national pricing policy versus a fully localized pricing policy. Next, we examine variation in local competitive intensity without artificially closing stores.

5.2.2. Variation in Competitive Intensity. The second boundary condition concerns the distribution of competitive intensities across markets due to the exit of one major chain. The departure of chain B in early 2009 eased the industry's competitive landscape. The absence of such a large rival could create incentives for chain A to localize prices as it became the single dominant electronics specialty retailer. To investigate this possibility, we use the demand and cost estimates from the data period after B exits and simulate national and local prices and profits for chain A.[20] We find that, compared with local pricing, A's profit ($176.83 million) is approximately 1.3% higher under national pricing. This result highlights that, although the benefit becomes much smaller, employing national pricing after chain B's exit is still marginally favorable over local pricing for chain A. The rationale behind this is that chain A still faces some competition from chain D. As Table 6 shows, chain A overlaps with chain D in 839 (84%) of the 1,004 SSAs in which A operates. Thus, the extent of competition between chains A and D is sufficient to justify national pricing in the absence of B, even though the profit enhancement from national pricing over local pricing largely disappears, due to the eased competitive landscape. Similar to the situation prior to B's exit, maintaining local pricing is always more profitable for chain D, especially because the share of its uncontested markets increases.

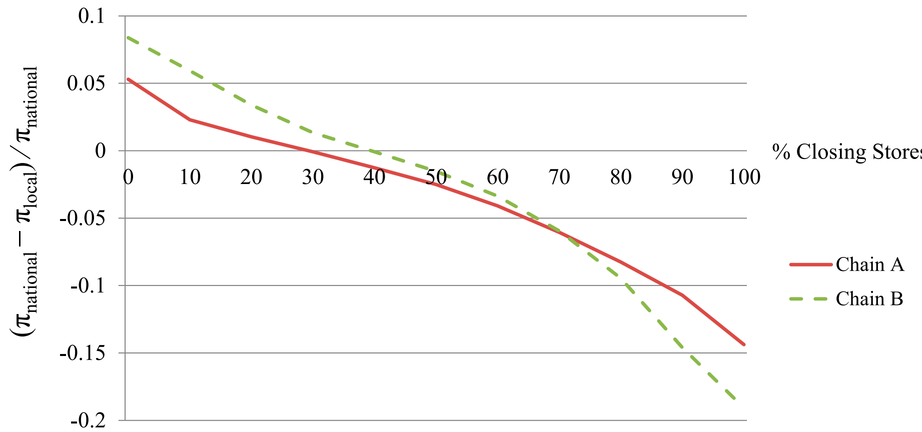
5.3. Hybrid Pricing Policies

Local and national pricing represent extreme cases in the space of geographic pricing strategies. Instead, a chain may set prices locally in some markets and maintain uniform pricing in others. Such a hybrid policy permits the chain to exploit some geographic variation

Table 14. Profits of Chain D ($ millions) Between Uncontested and Contested Markets

	Uncontested markets without A or B				Contested markets with A and/or B			
	A national B national	A local B national	A national B local	A local B local	A national B national	A local B national	A national B local	A local B local
D local	28.87	28.87	28.87	28.87	18.34	16.42	17.70	15.78
D national	26.15	23.35	24.83	23.98	18.60	16.73	18.01	16.21
Difference	2.72	5.52	4.04	4.89	−0.26	−0.31	−0.31	−0.43

Figure 6. (Color online) Relative Profit Difference Between National and Local Pricing



in preferences without sacrificing its national policy. Evaluating all possible hybrid strategies is largely unfeasible due to the enormous number of combinatory cases. Furthermore, the organizational structure of the retailers does not provide obvious commitment mechanisms for such hybrid policies. Thus, our goal is not to explore this nearly infinite strategy space thoroughly, but to assess the implications of some managerially relevant hybrid policies. In particular, we consider two candidate strategies that are intuitive and motivated by business reality.

The first candidate policy is inspired by the notion that firms sometimes employ different pricing strategies in large, influential markets. To examine this possibility, we allow local pricing for chains A and B in the top five metropolitan areas: 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 had adopted local pricing in these metropolitan areas and national pricing elsewhere.

Table 15 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 metropolitan areas, and the chains 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, because of the intense competition between the two firms in these cities. 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 uniform prices. Aggregating across the two pricing zones, however, the proposed hybrid policy results in overall profit declines for both chains A and B.

Although the proposal above does not increase chain profits, many other alternative hybrid policies remain. Instead of localizing prices in large competitive markets, for example, a chain could localize prices in its largest uncontested markets, thereby driving profit gains in these markets. To simulate such a policy, we assume chains A and B set prices locally in some of their own uncontested markets while maintaining uniform pricing elsewhere. We start by ranking the SSAs in which A and B do not overlap with each other, according to the sales volume of the A and B stores in 2007–2008, respectively. Then we let the top 10% or 20% of these markets change to local pricing zones. The relative profit and price changes are reported in Table 16.

After switching to local pricing in its top 10% uncontested markets, chain A would gain 7.12% higher profit in these SSAs relative to the observed policy. In the rest of chain A's markets, in which uniform pricing is maintained, prices decline because of the reduced market power A could leverage from the excluded uncontested markets. The 0.57% decrease in price slightly intensifies competition and leads to a profit decline that can be offset by the gain in the local pricing zone. Collectively across SSAs, 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 chain B's uniform pricing zone is large, and the chain profitability deteriorates slightly under the proposed hybrid policy.

Table 15. Profit and Price Changes Relative to Observed Policies with Local Pricing in Five Largest Metro Areas

	Local pricing zone		Uniform pricing zone		
Chain	Profit	Price	Profit	Price	Chain profit
A	−12.29%	−10.36%	0.57%	1.03%	−0.76%
B	−15.33%	−12.57%	0.72%	1.31%	−1.23%

Table 16. Profit and Price Changes Relative to Observed Policies with Local Pricing in Top Uncontested Markets

Chain	Local pricing zone		Uniform pricing zone		Chain
	Profit	Price	Profit	Price	profit
Top 10% uncontested markets					
A	7.12%	6.61%	−0.23%	−0.57%	0.06%
B	9.75%	9.52%	−0.99%	−1.64%	−0.70%
Top 20% uncontested markets					
A	5.86%	5.93%	−0.40%	−0.87%	0.11%
B	7.94%	8.62%	−1.35%	−2.06%	−0.83%

The difference in profit change between the two chains is because chain A has many more uncontested markets with larger sales relative to chain B, as Table 6 shows. Similar results are obtained when the two firms employ local pricing in their top 20% uncontested markets (the bottom portion of Table 16).

The analysis above identifies a hybrid policy that is slightly more profitable than the national policy for chain A, but not for chain B. Of course, many other hybrid scenarios are possible. The current model and analyses do not account for implementation costs associated with local or hybrid pricing policies. In particular, with the rise of the internet channel, online pricing is visible to customers across the country, and so deviation from uniform prices in individual markets is likely to cause fairness problems for large electronics retailers like chains A and B. Therefore, what constitutes an "optimal" hybrid pricing strategy and whether such a hybrid policy is managerially and institutionally viable remain open questions for future research.

5.4. Robustness Analyses

So far, we have calculated marginal costs for each chain based on the observed pricing policy of that chain. For instance, we recover the marginal costs of chains A and B by assuming national pricing for the regular sales period and local pricing for the clearance period. Now we relax this assumption to examine the robustness of our main findings. In particular, we apply local pricing (9) instead of the observed policy to compute the marginal costs for chains A and B and perform the main counterfactual simulation with the new sets of costs.

We first compare the cost results under local pricing with those under the observed policy. Note the former are market specific and vary across SSAs, whereas the latter are at the national level. Therefore, to have a meaningful comparison, we aggregate the former set of costs across markets. We find the relative difference between the two sets of costs averaged over products and periods is only 0.81%, indicating strong similarity between the cost results under alternative policies. Figure 7 shows the histograms of these cost estimates for chains A and B, respectively. From the figure, we can see that the distributions of marginal costs under different policy assumptions are very similar.

Next, we recompute the counterfactual profits in Table 11 and report the new results in Table 17. From the table, we can see that although the profit values have changed slightly due to the minor cost differences, national pricing remains a more profitable policy than local pricing for both chains. Thus, our approach to backing out marginal costs does not affect the qualitative conclusion about national pricing.

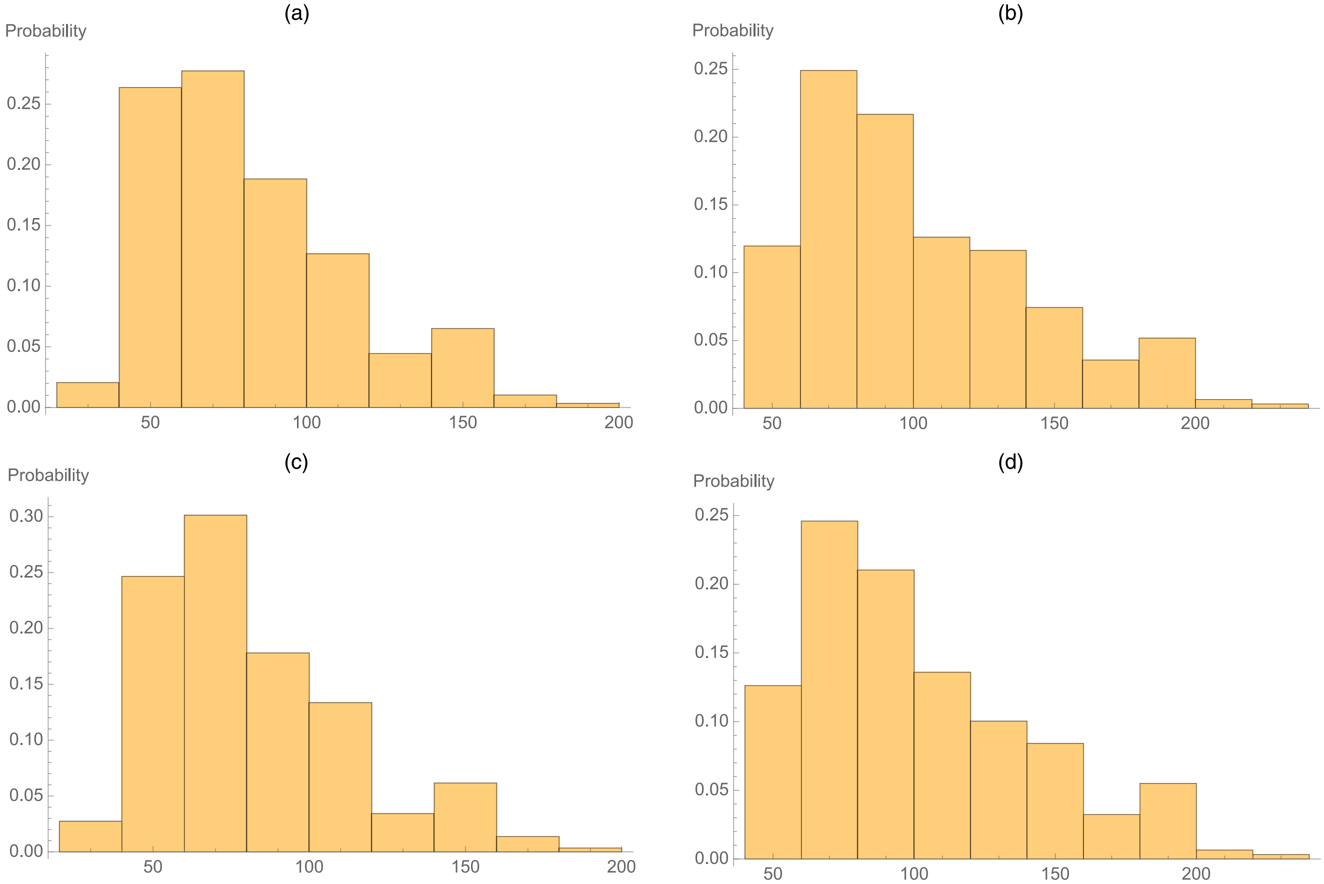
6. Conclusion

In this paper, we empirically evaluate the profitability of national versus local pricing policies in the context of chain store competition. To do so, we estimate an aggregate model of demand for digital cameras, with random coefficients and micro moments separately in each distinct local market to capture a high degree of preference heterogeneity across geographic areas. Using counterfactual policy simulations, we demonstrate that retail chains under certain competitive market conditions may obtain substantially higher profits by employing national pricing relative to local pricing, assuming commitment to national pricing is feasible.

We find these conditions hold for the two major national electronics retail chains in our study, and the profit enhancement of national pricing relative to local pricing is maintained as long as the ratio of contested markets to uncontested markets is high. For the national discount retailer, we find a local pricing strategy is more profitable because this chain operates in many uncontested markets. More generally, we demonstrate that the distribution of competitive market structures can affect the chains' profitability associated with employing national versus local pricing strategies. Chain retailers can use the econometric approach we suggest for flexibly estimating demand and examining competitive market structures, to evaluate the extent to which committing to a national pricing policy may be profitable.

This paper presents several limitations and directions 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, local, or hybrid pricing. For example, by switching from national to local pricing, a chain may incur additional costs in customizing advertising to match locally varying prices. In addition, consumers may perceive inconsistent prices offline and online and across different stores as unfair. Therefore, local pricing could incur certain economic and psychological costs for which our model does not account. Our results demonstrate that competitive forces play an important role in the profitability trade-off

Figure 7. (Color online) Histograms of Marginal Cost Estimates Under Alternative Pricing Policies



Notes. Under observed pricing policy: (a) chain A and (b) chain B. Under local pricing policy: (c) chain A and (d) chain B.

between national and local pricing strategies over and above the alternative accounts, but such competitive forces should be weighed relative to other organizational considerations. The inclusion of implementation costs is particularly important if one decides to do an all-out search for the "optimal" hybrid pricing policy, because such a policy may involve a high degree of price customization and complex commitment mechanism.

Second, several recent papers have documented that durable goods buyers may delay their purchases strategically in anticipation of technology improvement and price decline (e.g., Song and Chintagunta 2003, Gordon 2009, Carranza 2010, and Gowrisankaran and Rysman 2012). Similarly, sellers may make a trade-off between current and future profits by setting optimal price sequences (Zhao 2006). Here, we ignore forward-looking dynamics on both the consumer and the retailer sides. 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 thousands of choice options. Furthermore, the focus of the current study is geographic pricing policy, and the differences between markets primarily drive the conclusion. Forward-looking behavior may be less of a concern in this paper, given that the quality-adjusted prices in the data period declined more slowly compared with the decline in earlier periods studied in previous research (e.g., Song and Chintagunta 2003, Gowrisankaran and Rysman 2012).

Third, in this paper we use online prices as a commitment mechanism for the chains to implement national pricing. That being said, we have not explicitly characterized the effect of the online channel on offline prices, nor have we modeled the commitment mechanism(s) through a repeated game. Including the effect of online prices in our setting is difficult because (a) we

Table 17. Counterfactual Profits (π_A, π_B) ($ millions)

	Chain B	
	Local	National
Chain A		
Local	(302.79, 102.58)	(316.52, 103.38)
National	(305.67, 108.98)	(319.78, 110.94)

Table A.1. Percent of Hypothetical Monopolists with Profitable Price Increase

	2007			2009	
	One-store	Two-store	Three-store	One-store	Two-store
SSA type	HM	HM	HM	HM	HM
D-A	5.7%	92.3%	—	8.1%	90.2%
D-B	7.4%	90.8%	—	—	—
D-A-B	5.1%	4.9%	94.1%	—	—

do not observe online sales and prices directly and (b) working out a dynamic equilibrium with such a complex empirical setting is computationally prohibitive. Thus, we leave this interesting and demanding inquiry to future research.

Fourth, a more general model could endogenize 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 multiproduct retail assortment under competition. We plan to pursue this and other possible avenues in future research.

In summary, this study provides a first step in empirically investigating the role of competition in retail chains' decisions to forgo the flexibility of local pricing and to implement national pricing strategies. As the competitive landscape in many industries rapidly changes because of consolidation of major players or, conversely, because of lower barriers to entry, we encourage researchers and practitioners to examine the impact of such competitive forces on firms' geographic pricing decisions.

Acknowledgments

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Appendix A. 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), defined by NPD Group that provided the data, to determine market boundaries. Alternative market definitions, such as county and ZIP codes, 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 a group of consumers visits), however, delineating local markets via aggregate store sales is difficult.

Before applying any formal test to assess the validity of 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 any pairs of stores. The median distance between competing stores within an SSA is 0.58 miles, whereas the median and the bottom fifth percentile distance to stores in neighboring SSAs are 10.20 and 3.45 miles, respectively. These statistics show 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 indicate the independence of SSAs in terms of market demand.

To further verify the SSA definition, we use the store sales to gain a better understanding of cross-store substitution patterns. In particular, we apply the hypothetical monopolist (HM) test, which the antitrust literature has employed to assess market definitions in the context of horizontal mergers (Katz and Shapiro 2003, Davis 2006). The main idea behind 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, the market definition is sufficiently broad. Otherwise, a good substitute currently must 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 perform the HM test to evaluate the SSA definition. Because 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.[21]

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 International 2010), we increase prices by 5% for one year. Table A.1 reports the percentage of HMs for which the price increase results in higher profits over the one-year horizon, that is, well-bounded markets immune to outside competition. 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 HMs (i.e., a merger of D and A stores) are able to profit by imposing SSNIP. Second,

Table A.2. Percent of D-only SSAs with Profitable Price Increase

Starting point for price increase	Before B exits	After B exits
0% below	10.6%	8.9%
5% below	96.3%	97.1%
10% below	98.9%	98.6%
15% below	99.4%	99.2%

Figure B.1. Price Distribution Across SSAs for Cameras 4–6

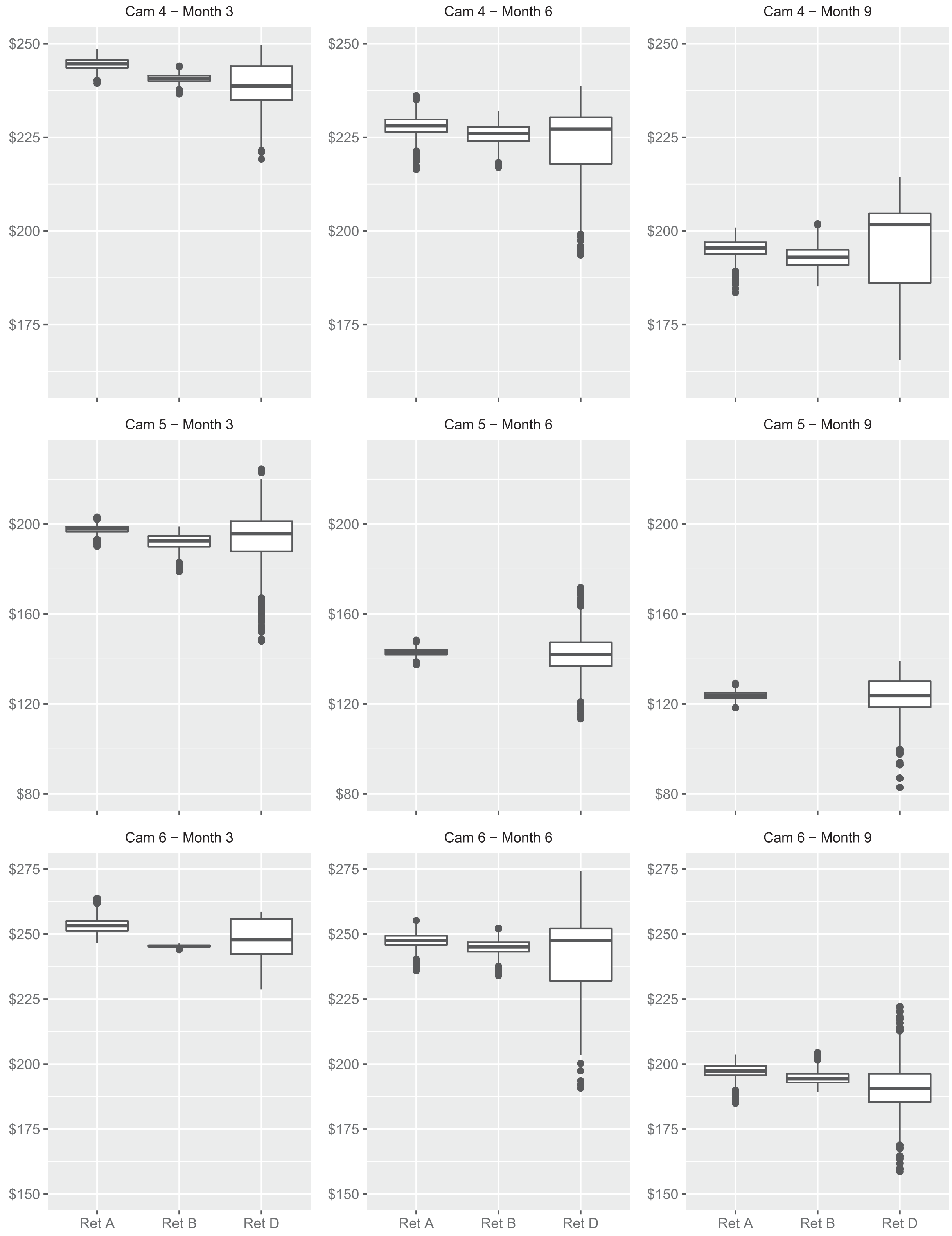


Figure B.2. Price Distribution Across SSAs for Cameras 7–9

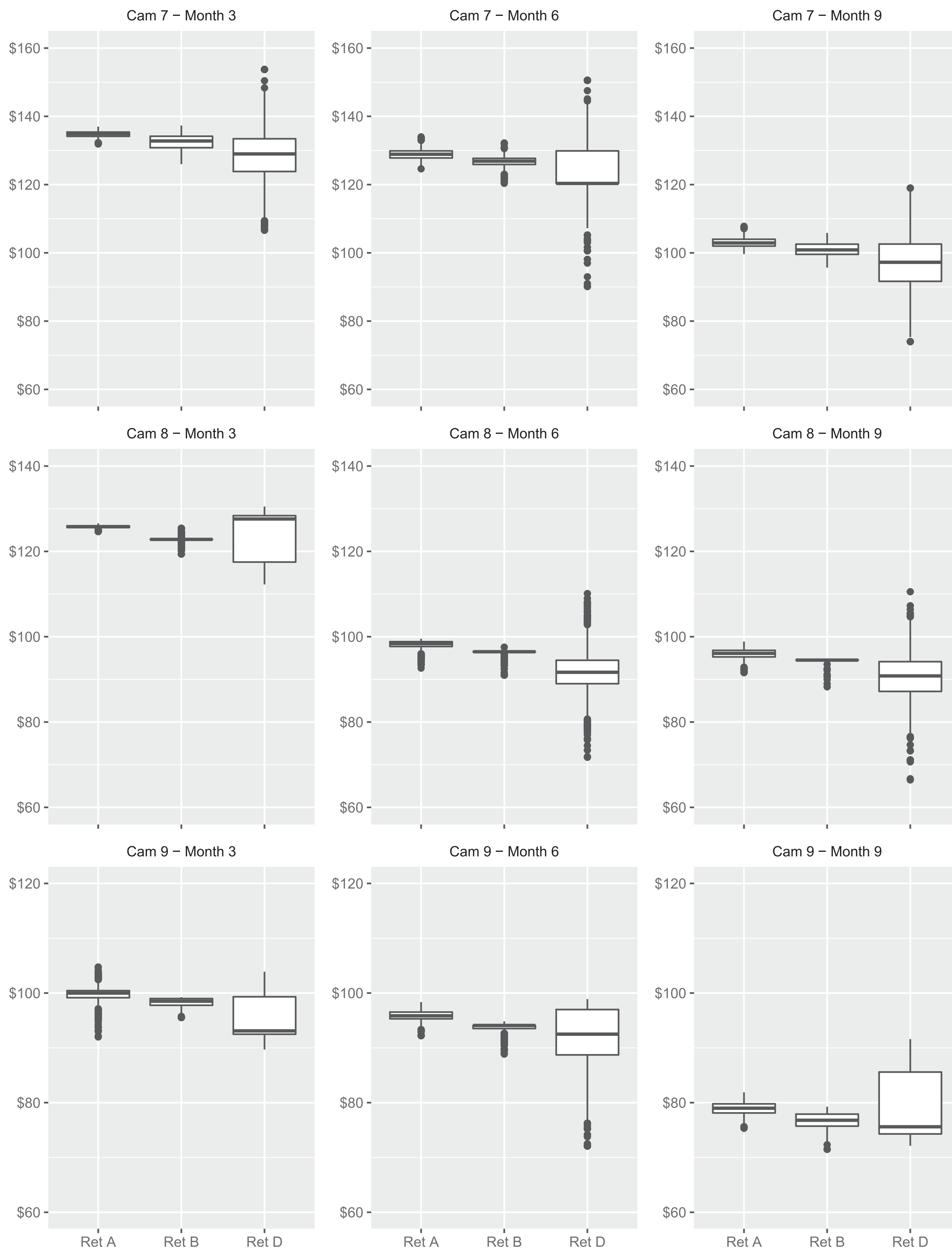
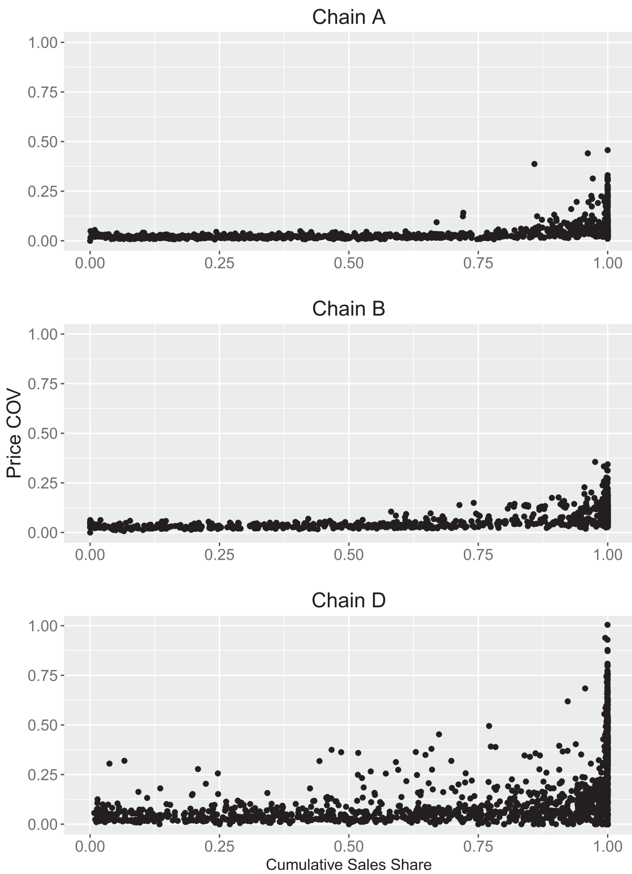


Figure B.3. Coeffcients of Variation in Price Across SSAs for Digital Cameras



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 6) 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, raising its prices should decrease profits. Given this issue, we treat the D-only SSAs differently from the other markets. Following Davis (2016), we start the SSNIP in these markets from levels that are below the observed prices. Table A.2 reports the percentage of D-only SSAs that enjoy 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 the vast majority of the SSAs indeed appropriately capture close competitive markets. 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 more profitable strategy for both chains A and B. Based on this finding and the results in Table A.1 and A.2, using SSAs as our market definition appears appropriate.

Appendix B. Additional Evidence for Geographic Price Variation in Digital Cameras and Digital TVs

Figures B.1 and B.2 show the price distribution across stores of the forth to ninth bestselling cameras in the three chains. Figure B.3 presents the sales-weighted coefficients of variation of prices across stores for every camera, against their life cycle, measured by the cumulative share of total 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, but transits to clearance pricing for the last 20% of sales. In chain D, by contrast, the prices exhibit substantial variation throughout a product's life cycle.

Next, we present data from an additional electronics category—digital TV—to assess whether the price variation observed for the digital camera category is representative of other categories at the same retailers. For digital TVs, there were four main retailers—A, B, D, and S—that collectively captured 80.4% of the digital TV sales during the data period between 2007 and 2009. Chains A, B, and D are the same retail chains in the digital camera category. Chain S is a big-box mass retailer similar to chain D.

Figure B.4 shows strong similarity in pricing patterns between the digital TV and digital camera categories. In this figure, the vertical axis is the coefficient of variation in price (weighted by sales) across markets for every product. The horizontal axis represents the cumulative share of sales in each product's life cycle. For chains A and B, a product's price exhibits little geographic differences for the majority of its lifetime sales, whereas in chains D and S, the price variation across locations is much higher and relatively constant over a product's life cycle.

This evidence suggests price variation patterns in the TV category are similar to those in the digital camera category. With the addition of chain S as a leading retailer, the competition landscape in this category may differ from the cameras. However, according to Table B.1, the two largest retailers—chains A and B—still competed in most of their local markets, whereas the smaller chains—D and S—both had many markets in which they did not compete with other leading chains. Therefore, the competitive account that we have discussed for digital cameras can explain the competitive advantages of national pricing for chains A and B and of local pricing for chains D and S in the digital TV category. These two categories represent two (very) important sets of products for the retailers. These findings jointly suggest the retailers apply pricing strategies consistently across product categories (Adams and Williams 2017), which is also consistent with the senior manager's claim that pricing policies are implemented broadly at the chain level rather than the category level.

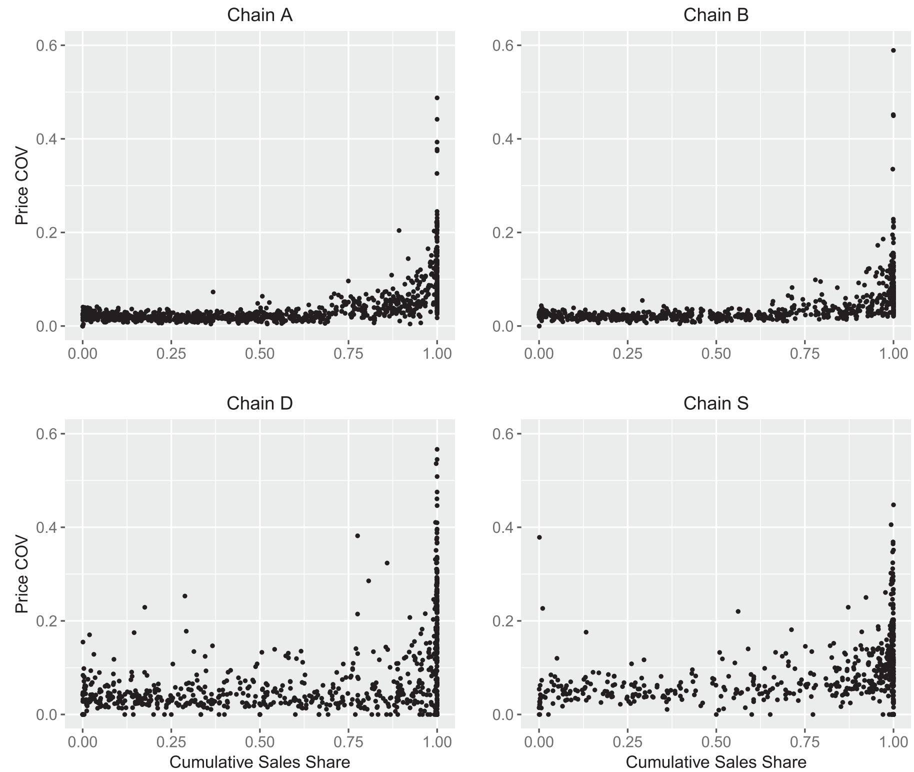
Appendix C. MPEC Estimation

C.1. Optimization Problem

Denoting the set of constraints as $\mathcal{G}(\phi)$, the constrained optimization problem (16) results in the following Lagrangian function:

$$\mathcal{L}(\phi;\lambda) = \mathrm{F}(\phi) - \langle \lambda, \mathcal{G}(\phi) \rangle, \tag{C.1}$$

Figure B.4. Coeffcients of Variation in Price Across SSAs for Digital TVs



where $\lambda \in \mathbb{R}$ is a vector of Lagrange multipliers. The solution to (16) satisfies the Karush-Kuhn-Tacker condition on $\mathscr{L}$:

$$\frac{\partial \mathscr{L}}{\partial \phi} = 0, \quad \mathscr{G}(\phi) = 0. \tag{C.2}$$

The model estimation proceeds in two stages. In the first stage, we use an identity matrix as the weighting matrix W in (16). In the second stage, equal weighting is replaced by the inverse of the second moments $\mathbf{\Phi}$, which is a function of the first-stage estimates. The micro moments (12) over i and r are sampled independently from demand moments (11) over j and t; therefore, $\mathbf{\Phi}$ has a block diagonal structure (Petrin 2002). Accordingly, the asymptotic variance matrix for parameter estimates is given as

$$\mathbf{\Gamma} = \frac{1}{N_d + I}(J'WJ)^{-1}J'W\mathbf{\Phi}WJ(J'WJ)^{-1}, \tag{C.3}$$

where J is the Jacobian matrix of (12) and (15) with respect to θ_1 and θ_2.

Table B.1. SSA Structure, Number of SSAs, and Average Annual Total Sales over SSAs in Digital TVs

SSA structure	SSA competitiveness	Before B exits		After B exits	
		No. SSAs	Sales	No. SSAs	Sales
A-only	Uncontested	61	0.17	91	0.61
B-only	Uncontested	45	0.09	—	—
D-only	Uncontested	433	0.22	462	0.34
S-only	Uncontested	176	0.13	186	0.26
A-B	Contested	32	0.19	—	—
A-D	Contested	189	0.62	390	1.75
A-S	Contested	56	0.21	92	0.07
B-S	Contested	49	0.15	—	—
B-D	Contested	73	0.18	—	—
D-S	Contested	152	0.17	172	0.27
A-B-D	Contested	120	0.77	—	—
A-B-S	Contested	35	0.24	—	—
A-D-S	Contested	145	0.60	456	2.90
B-D-S	Contested	61	0.19	—	—
A-B-D-S	Contested	283	2.15	—	—

Note. Sales are in million units.

C.2. Analytic Derivatives

Here, we derive the analytic derivatives for the optimization problem specified in (16). Our derivation uses matrix calculus and tensor operators such as Kronecker product. Thanks to the sparsity of this optimization problem (i.e., shares are 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 facilitate coding.

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

$$\frac{\partial F(\phi)}{\partial \phi} = (W + W')\eta, \tag{C.4}$$

$$\frac{\partial^2 F(\phi)}{\partial \phi \partial \phi'} = W + W'. \tag{C.5}$$

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

$$\frac{\partial s_t(\delta_t, \theta_2)}{\partial \theta_2} = \int_{\forall i} \mathrm{diag}(s_{it})[X_{it}^{rc} - 1_{J_t} s_{it}' X_{it}^{rc}]\,\mathrm{diag}(v_i), \tag{C.6}$$

$$\frac{\partial s_t(\delta_t, \theta_2)}{\partial \delta_t} = \int_{\forall i} \mathrm{diag}(s_{it}) - s_{it}s_{it}', \tag{C.7}$$

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

$$\frac{\partial[\eta_1 - g(\delta, \theta_1)]}{\partial \theta_1} = \frac{1}{N_d} Z'X, \tag{C.8}$$

$$\frac{\partial[\eta_1 - g(\delta, \theta_1)]}{\partial \delta} = -\frac{1}{N_d} Z', \tag{C.9}$$

$$\frac{\partial[\eta_1 - g(\delta, \theta_1)]}{\partial \eta_1} = I_{nz}. \tag{C.10}$$

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

$$\frac{\partial[\eta_2 - \tilde{s}_{rt}(\delta_t, \theta_2)]}{\partial \theta_2} = -\int_{i \in r} s_{i0t} s_{it}' X_{it}^{rc} \mathrm{diag}(v_i), \tag{C.11}$$

$$\frac{\partial[\eta_2 - \tilde{s}_{rt}(\delta_t, \theta_2)]}{\partial \delta_t} = -\int_{i \in r} s_{i0t} s_{it}'. \tag{C.12}$$

The Hessian of the constraints in the θ_2 by θ_2 block is[22]

$$\sum_{\forall j,t} \lambda_{jt} \frac{\partial^2 s_{jt}(\delta_t, \theta_2)}{\partial \theta_2 \theta_2'} = \sum_{t=1}^{T} \int_{\forall i} \mathrm{diag}(v_i)[(X_{it}^{rc'} - X_{it}^{rc'} s_{it} 1_{J_t}')\mathrm{diag}(\lambda_t) - \lambda_t' s_{it} X_{it}^{rc'}] \frac{\partial s_{it}}{\partial \theta_2} \tag{C.13}$$

$$\sum_{\forall r,t} \lambda_{rt} \frac{\partial^2[\eta_2 - \tilde{s}_{rt}]}{\partial \theta_2 \theta_2'} = \sum_{\forall r,t} \lambda_{rt} \int_{i \in r} s_{i0t} \mathrm{diag}(v_i) X_{it}^{rc'} \times \left[s_{it} s_{it}' X_{it}^{rc} \mathrm{diag}(v_i) - \frac{\partial s_{it}}{\partial \theta_2}\right], \tag{C.14}$$

where $\frac{\partial s_{it}}{\partial \theta_2}$ is calculated similar to (C.6) but without the integral. λ_t is a vector of the Lagrange multipliers associated with the share equations at t.

The Hessian of the constraints in the δ_t by θ_2 block is

$$\sum_{\forall j,t} \lambda_{jt} \frac{\partial^2 s_{jt}(\delta_t, \theta_2)}{\partial \delta_t \theta_2'} = \sum_{t=1}^{T} \int_{\forall i} [\mathrm{diag}(\lambda_t) - \lambda_t' s_{it} I_{J_t} - s_{it} \lambda_t'] \frac{\partial s_{it}}{\partial \theta_2}, \tag{C.15}$$

$$\sum_{\forall r,t} \lambda_{rt} \frac{\partial^2[\eta_2 - \tilde{s}_{rt}]}{\partial \delta_t \theta_2'} = \sum_{\forall r,t} \lambda_{rt} \int_{i \in r} s_{i0t} \left[s_{it} s_{it}' X_{it}^{rc} \mathrm{diag}(v_i) - \frac{\partial s_{it}}{\partial \theta_2}\right]. \tag{C.16}$$

The Hessian of the constraints in the δ_t by δ_t block is

$$\sum_{\forall j,t} \lambda_{jt} \frac{\partial^2 s_{jt}(\delta_t, \theta_2)}{\partial \delta_t \delta_t'} = \sum_{t=1}^{T} \int_{\forall i} [\mathrm{diag}(v_i) - \lambda_t s_{it}' I_{J_t} - s_{it} \lambda_t'] \frac{\partial s_{it}}{\partial \delta_t}, \tag{C.17}$$

$$\sum_{\forall r,t} \lambda_{rt} \frac{\partial^2[\eta_2 - \tilde{s}_{rt}]}{\partial \delta_t \delta_t'} = \sum_{\forall r,t} \lambda_{rt} \int_{i \in r} s_{i0t}[2 s_{it} s_{it}' - \mathrm{diag}(s_{it})], \tag{C.18}$$

where $\frac{\partial s_{it}}{\partial \delta_t}$ is calculated similar to (C.7) but without the integral.

Upon convergence of the optimization, we use (C.3) to obtain standard errors of the parameter estimates. The Jacobian matrix of the two sets of moments with respect to θ_1 and θ_2 is

$$J = \begin{pmatrix} \frac{\partial g}{\partial \theta_1} & \frac{\partial g}{\partial \theta_2} \\ \frac{\partial \tilde{s}}{\partial \theta_1} & \frac{\partial \tilde{s}}{\partial \theta_2} \end{pmatrix}, \tag{C.19}$$

where

$$\frac{\partial g}{\partial \theta_1} = -\frac{1}{N_d} Z'X, \tag{C.20}$$

$$\frac{\partial g}{\partial \theta_2} = \frac{1}{N_d} Z' \left(\frac{\partial s_t}{\partial \delta_t}\right)^{-1} \frac{\partial s_t}{\partial \theta_2}, \tag{C.21}$$

$$\frac{\partial \tilde{s}_{rt}}{\partial \theta_1} = \left(\int_{i \in r} s_{i0t} s_{it}'\right) X_t, \tag{C.22}$$

$$\frac{\partial \tilde{s}_{rt}}{\partial \theta_2} = \int_{i \in r} s_{i0t} s_{it}' X_{it}^{rc} \mathrm{diag}(v_i). \tag{C.23}$$

The second moments $\mathbf{\Phi}$ is

$$\begin{pmatrix} \mathbf{\Phi}_1 & 0 \\ 0 & \mathbf{\Phi}_1 \end{pmatrix}, \tag{C.24}$$

where

$$\mathbf{\Phi}_1 = \frac{1}{N_d} \sum_{j,t} \xi_{jt}^2 Z_{jt} Z_{jt}', \tag{C.25}$$

$$\mathbf{\Phi}_2 = \frac{1}{I} \mathrm{diag}\left(\sum_{i}^{I} (\tilde{s} - \tilde{S})^2\right). \tag{C.26}$$

Appendix D. Market Shares in Counterfactual Simulation

Table D.1 shows the counterfactual market shares behind the profit simulation in Table 11. Note that under national-national, chains A and B have the lowest market shares but the highest profits compared with other scenarios.

Table D.2 presents the counterfactual market shares of chains A and D following B's exit.

Table D.3 reports the market shares of chains A and B under the observed national pricing policy and the two sets of hybrid pricing policies.

As can be seen across these tables, when chains A and B switch to national pricing, their market shares decrease because of increased prices, but their overall profits also improve.

Table D.1. Counterfactual Market Shares Before B Exits

	Chain B	
	Local	National
Chain A		
Local	(64.97%, 22.61%)	(59.87%, 22.74%)
National	(62.93%, 21.15%)	(57.47%, 20.17%)

Table D.2. Counterfactual Market Shares after B Exits

	Chain A	
	Local	National
Chain D		
Local	(81.43%, 12.62%)	(78.61%, 10.74%)

Table D.3. Counterfactual Market Shares Between Observed and Hybrid Pricing Policies

	Observed national pricing policies	Local pricing in five largest areas	Local pricing in top 10% uncontested SSAs	Local pricing in top 20% uncontested SSAs
Chain A	57.82%	58.41%	58.77%	59.34%
Chain B	20.33%	20.79%	20.56%	20.71%

Endnotes

[1] Evidence can be found at, for example, https://walmartstores.com/317.aspx and in Jargon (2011).

[2] In the remainder of the paper, we use the terms "national pricing" and "uniform pricing" interchangeably to refer to the policy of fixing prices across geographic regions. The same goes for "geographic price discrimination," "local pricing," and "store-level pricing."

[3] Because of 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.

[4] Our data exclude internet sales. During the data period, the online channel accounts for 8.9% of total digital camera sales (Euromonitor International 2010).

[5] Figure 1 is generated using data in "offline.dta" in the replication archive of Cavallo (2017).

[6] To examine the NPD data coverage, we use data from Statista (2017), which provides an estimate of the total dollar sales of digital cameras nationwide. Adjusting the Statista estimate for the offline sales and point-and-shoot cameras, we find the NPD data cover over 70% of the sales in the relevant market.

[7] We have also removed (1) observations with unreasonably high or low prices, because these are most likely data-collection errors, and (2) niche camera models with very small sales. This step results in a less than 1% reduction in the total observations.

[8] Despite the national pricing policies, there are several explanations for the variation in price across stores for chains A and B. First, we derive unit prices by dividing monthly unit sales into monthly revenues for every product in each store. 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 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. An unobservable demand shock term in the demand model captures all these errors.

[9] To 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.

[10] For further evidence that the pricing policies are implemented consistently across categories, we obtain a second data set on digital TV sales from NPD and show in Appendix B that the price variation patterns in TVs are very similar to those for digital cameras at the same three retailers.

[11] The current decision context may suggest a nested choice model if we assume consumers in a market first choose a store and then select a camera or some similar sequential choices. However, our data lack store characteristics that would help us inform such a model. Instead, we employ random coefficient demand specification with chain intercept in the utility.

[12] Because of the aggregation into monthly sales by NPD, we are unable to separate actual posted prices from promotional activities. This unobservable is captured by the demand shock in the utility specification. This shock motivates the need for appropriate instruments.

[13] The normality assumption on consumer heterogeneity may cause estimation bias if the actual distribution is heavily tailed or multimode (Li and Ansari 2014). Estimating the model separately by market should reduce such bias.

[14] Incorporating the PMA data requires scaling the survey statistics to match the NPD data appropriately. Online Appendix B reports the scaling details.

[15] We enter the micro moments into the objective function because the (two-stage) GMM can adaptively determine the optimal weighting of these moments.

[16] In Online Appendix C, we include camera age in the demand model and find little impact on the demand estimates.

[17] Appendix D reports chain market shares associated with the profit results.

[18] Figure 4 shows chains A and B used a nearly national pricing (80/20) policy in the data. Under this policy, the estimated profits are $320.95 million and $111.27 million for chains A and B, respectively, during the period before B exits. These profits are very similar to those under the 100% national policy.

[19] The small gap between the two percentages results from variations in product assortment across chain B's SSAs.

[20] In Online Appendix C, we report the model estimates after chain B's exit.

[21] 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 affect the substitution pattern between major stores. Therefore, we focus the HM test on the three major chain stores and combine small stores as the outside option.

[22] 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 diag(s) with a vector s on its diagonal can be transformed linearly by

$$\mathrm{diag}(s) = \sum_{i=1}^{n} E_i s e_i',$$

where E_i is an n-by-n matrix of all zeros, except the ith diagonal entry equal to 1, and e_i is a vector of all zeros, except the ith element equal to 1. Because the transformation is linear, the derivative of the diagonal matrix with respect to s can be compactly written as

$$\frac{\partial \mathrm{diag}(s)}{\partial \delta} = \sum_{i=1}^{n} (e_i \otimes E_i) \frac{\partial s}{\partial \delta},$$

where $\otimes$ denotes Kronecker product.

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