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

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Abstract

Geographic price discrimination is generally considered beneficial to firm profitability. Firms can extract higher rents by varying prices across markets to match consumers’ preferences. This paper empirically demonstrates, however, that a firm may prefer to forego the flexibility to customize prices and instead employ a national pricing policy that fixes prices across markets. For retailers that operate in multiple geographic markets with varying degrees of competitive intensity, a national pricing policy helps avoid intense local competition due to targeted prices. We examine how competitive forces shape a firm’s choice of national versus local pricing in a model of multimarket retail competition. Using extensive data from the digital camera market, a series of counterfactual analyses show that two leading chains should employ a national pricing policy to maximize profits, whereas the discount retailer should target prices in each local market. Additional results explore the boundary conditions of these findings and evaluate hybrid pricing policies, which could assist retail managers’ choice of geographic pricing policies.

Keywords: Pricing, Retailing, Competitive Strategy, Geographic Price Targeting, National Pricing Policy, Local Pricing Policy.

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1 Introduction

Geographic price discrimination is generally considered beneficial to firm profitability. Varying prices across markets with different consumer preferences and socio-economic characteristics allows a firm to extract more surplus by matching prices to local consumers’ willingness to pay. Prior empirical work on geographic price discrimination documents such profit-enhancing effects (e.g., Chintagunta, Dubé, and Singh 2003). 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, ALDI Australia, and Best Buy, employ national pricing policies in which a product’s price is uniform across markets.\(^2\) What factors lead a retail chain to adopt a national versus local pricing policy?

One important, and perhaps overlooked, reason to employ national pricing is that it may soften price competition. To understand the intuition, suppose a chain that sets prices locally switches to national pricing—how would prices and profits adjust? In markets where the chain previously operated as a local monopolist, the uniform price would fall below the original price due to the new relevance of demand from competitive markets. Assuming local prices maximized local profits, profits in these non-competitive markets would decline under the new national price. Conversely, in previously competitive markets, the uniform price would lie above the original price because of the relevance of non-competitive markets. Such a price increase would likely spur competitors to increase their prices, and hence local profits for all firms could increase. The chain will prefer national pricing if the gains in competitive markets offset the losses in non-competitive markets. Whether this occurs is an empirical question that depends on (i) consumer substitution patterns within each market and (ii) the distribution of market sizes across market structures.

We examine how these competitive forces shape retailers’ choice of pricing policies. To

\(^1\)Evidence can be found at, for example, http://walmartstores.com/317.aspx, and “Coffee talk: Starbucks chief on prices, McDonald’s rivalry,” Wall Street Journal, March 7, 2011.

\(^2\)In the remainder of the paper, we use the terms national, uniform, and fixed interchangeably to refer to the policy of fixing prices across geographic regions.
this end, we construct and estimate empirical models of multimarket retail competition using extensive data from the US digital camera industry. We flexibly recover consumer preferences and retailers’ marginal costs without imposing assumptions on a retailer’s pricing policy choice. Through a series of counterfactual simulations, we evaluate the impact of competitive intensity on a retailer’s pricing policy choice. Although firms might opt for a national pricing policy to simplify the price-setting process or to help equate online/offline prices, our results highlight that, over and beyond such factors, competitive forces may give rise to a national pricing policy that softens price competition and raises profits.

Our data contain about 10 million monthly store-level point-of-sales observations from the NPD Group that provides a near census of retail sales of digital cameras across 1,600 geographic markets. We focus on the behavior of three major retailers that account for 70% of digital camera sales. Because variation in consumer preferences across markets plays a central role in determining the benefits of local versus national pricing policies, we separately estimate in each market an aggregate demand model with random coefficients. Relative to a pooled-demand model, our flexible semiparametric estimation by market produces more dispersion in elasticities and price margins. These estimates are also more consistent with industry data. To improve estimation, we augment the model in Berry, Levinsohn, and Pakes (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). Our modeling approach allows us to explore how the geographic variation in consumer preferences and market structure shapes firms’ pricing policy choices.

After estimating the demand model without equilibrium assumptions, we assume retail chains choose period prices for each product in a Bertrand-Nash fashion. Whereas national pricing constrains a product’s price to be identical across markets, a local policy provides a chain with complete flexibility. Under alternative pricing policies, we infer retailers’ marginal

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3Our data exclude internet sales. However, during the data period, the online channel only accounts for 8.9% of the total digital camera sales.

4Due to a data-confidentiality requirement, we are prohibited from disclosing the names of retailers and camera brands. Throughout the paper, we denote chains and brands by generic letters and numbers.
costs and price margins, which are largely consistent with industry reports. Using the demand and supply estimates, we conduct several counterfactual analyses to assess the profitability of national versus local pricing policies and to examine the conditions under which the chains would prefer a particular policy.

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

The assertion that imposing a price constraint on firms’ objective functions could produce higher profits compared to an unconstrained game might appear counterintuitive. Regardless of the pricing policy, retailers choose prices to maximize national profits. Under local pricing, the equilibrium of the full game is the union of equilibria across markets—firms effectively play separate pricing games in each geographic market. However, imposing a national pricing constraint links prices across markets and firms, strengthening competition in some markets while weakening it in others. Therefore, the equilibrium of the game under national pricing is not necessarily nested within the equilibria of the union of games under local pricing. The tradeoff between national and local pricing 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 profit and prices in (i) contested markets, in which these chains compete head to head, and (ii) uncontested markets, in which the chains do not overlap. National pricing makes demand relevant across both types of markets of a chain in terms of pricing. 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 local profit in their contested markets thanks to softened local competition, because, in equilibrium, the competing chains raise prices together. If the gain offsets the loss, national pricing is preferred; otherwise, local pricing wins. We show the two national chains face heavy competition in most of their markets, and therefore benefit from national pricing. The third chain operates in many uncontested markets, and thus prefers local pricing. These competitive forces rationalize the pricing strategies chosen by the three major retailers in our data. Alternative supply-side justifications for these policies, such as menu costs, are unlikely to vary across chains and hence cannot explain the observed variation in policy choices.

In essence, uniform pricing across markets allows retailers to subsidize more competitive markets with profits from less competitive markets to ease the otherwise intense local competition. Whether this yields an optimal policy depends on the distributions of both market structure (i.e., number and sizes of contested vs. uncontested markets) and competitive intensity across local markets. As such, in the second counterfactual, we investigate the boundary conditions under which a firm would switch its optimal pricing policy. 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 recap the benefits in their uncontested markets. For instance, the leading retailer would switch to local pricing if it had closed at least 29% of its stores in this chain’s contested markets.

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

Third, we investigate the performance of hybrid pricing policies. Specifically, suppose
the two leading chains customize prices in the five largest metropolitan areas in the United States and set uniform prices in the rest of the country. 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. We also consider a related hybrid policy in which the leading chains convert a portion (e.g., the top 10% or 20%) of their largest uncontested markets into local pricing zones, while maintaining uniform pricing elsewhere. The results indicate such a hybrid strategy outperforms national pricing for the largest chain, but underperforms for the second largest chain.

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

The rest of the paper is organized as follows. Section 2 introduces the data, explores the variation in market structure, and describes the pricing policies observed in the data.
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

In this section, we discuss the data sets. Although we are bound by an NDA with the data provider to protect chain and brand identities, we provide detailed summary statistics on product characteristics, retail environment, geographic markets, and pricing policies implemented by the major retail chains.

### 2.1 Data

The data in this paper 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, 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. The data cover most stores in the United States that sell digital cameras, therefore representing a near census of this industry. 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.

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

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

Although the data contain nearly 60 camera brands, we focus our analysis on the largest
seven brands that comprise 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 largest consumer segment in the market. We drop digital SRLs, which account for only 4.98% of overall unit sales, because they are much more expensive and target a narrower consumer segment.\textsuperscript{5}

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 mega-pixels, 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 camera observation.

Table 2: Summary of Camera Attributes

<table>
<thead>
<tr>
<th>Year</th>
<th># Camera Models</th>
<th>Avg Price (dollar)</th>
<th>Avg Resolution (million pixel)</th>
<th>Avg Zoom (X)</th>
<th>Avg Thickness (cm)</th>
<th>Avg Display Size (in)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2007</td>
<td>84</td>
<td>191.72</td>
<td>7.17</td>
<td>3.60</td>
<td>1.13</td>
<td>2.53</td>
</tr>
<tr>
<td>2008</td>
<td>77</td>
<td>173.17</td>
<td>8.25</td>
<td>4.05</td>
<td>1.06</td>
<td>2.65</td>
</tr>
<tr>
<td>2009</td>
<td>78</td>
<td>170.29</td>
<td>10.62</td>
<td>4.76</td>
<td>1.07</td>
<td>2.74</td>
</tr>
</tbody>
</table>

We use as our market definition 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 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 sur-

\textsuperscript{5}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.
surveys of 10,000 representative U.S. households over three years. Table 4 reports a summary of the PMA statistics. Later we use these micro data to construct demand side micro moments. In addition, we also 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 to construct an appropriate market size definition. A proper measure of market size is important to accurately recover firms’ mark-ups. Common measures are population size, number of households (e.g., Berry et al. 1995), or total category demand (e.g., Song 2007). The use of population size as a proxy for potential demand can be problematic because in any given month, only a fraction of consumers consider purchasing cameras. To correctly specify market size, we attempt to quantify the set of potential buyers, including (i) those who bought cameras in the stores under investigation, (ii) those who bought cameras through other channels (e.g., online), and (iii) those who considered buying but chose not to.

The first group of consumers corresponds directly 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 only 8.9% of cameras purchased online and
1.9% through other channels. We use these statistics to approximate the unit sales through the non-store-based channels. The third group represents non-purchasers who were in the market but later chose not to buy. To estimate the relative size of this group, we use another survey on camera purchase intentions from PMA (2008; 2009; 2010). This annual survey measures household purchase plans in the next 3, 6, or 12 month periods. The difference between the purchase plan and the actual purchase probability provided by PMA report of the following year yields an approximate measure of the share of non-purchasers. In the demand model, we combine the second and third groups to obtain the share of the composite outside good. Web Appendix E reports the calculated yearly market sizes during the data period.

<table>
<thead>
<tr>
<th></th>
<th>Store-based Retailing</th>
<th>Homeshopping</th>
<th>Internet Retailing</th>
</tr>
</thead>
<tbody>
<tr>
<td>2007</td>
<td>89.3%</td>
<td>2.0%</td>
<td>8.7%</td>
</tr>
<tr>
<td>2008</td>
<td>89.2%</td>
<td>2.0%</td>
<td>8.8%</td>
</tr>
<tr>
<td>2009</td>
<td>89.0%</td>
<td>1.8%</td>
<td>9.2%</td>
</tr>
</tbody>
</table>

**2.2 Market Structure and Major Retailers**

The primary tradeoff between national and local pricing relies on two key characteristics of market conditions: (i) the number and sizes of a chain’s contested markets versus its uncontested markets and (ii) 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 the three national chains, A, B, and D, accounting for 70% of the total industry sales in our data. In this study, we focus on the three major chains. Other retailers each had shares below 3%, so we group these small sellers into a single chain L. We remove markets in which none of the three national chains exist, resulting in 1,600 SSAs (a 24% reduction), and leaving the three
Figure 1: Market Shares of Major Retailers

Among the three major firms, Chains A and B are consumer electronics retailers, whereas Chain D is a general discount store. Figure 1 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 left 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 mixture of contested and uncontested markets. Table 6 presents the distribution of market structures across SSAs before and after Chain B exits, as well as the average annual total sales over SSAs of the same structure. The table sheds some light on why Chains A and B employ national pricing whereas Chain D uses 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 located in so many contested markets with large sales creates incentives for them to use national pricing to ease
Table 6: SSA Structure, Number of SSAs, and Average Annual Total Sales over SSAs

<table>
<thead>
<tr>
<th>SSA Structure</th>
<th>SSA Competitiveness</th>
<th>Before B Exits</th>
<th>After B Exits</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td># SSAs</td>
<td>Sales</td>
<td># SSAs</td>
</tr>
<tr>
<td>A-only uncontested</td>
<td>101</td>
<td>0.47</td>
<td>165</td>
</tr>
<tr>
<td>A-D contested</td>
<td>315</td>
<td>1.88</td>
<td>839</td>
</tr>
<tr>
<td>B-only uncontested</td>
<td>79</td>
<td>0.25</td>
<td>—</td>
</tr>
<tr>
<td>B-D contested</td>
<td>118</td>
<td>0.53</td>
<td>—</td>
</tr>
<tr>
<td>A-B contested</td>
<td>59</td>
<td>0.57</td>
<td>—</td>
</tr>
<tr>
<td>A-B-D contested</td>
<td>402</td>
<td>4.20</td>
<td>—</td>
</tr>
<tr>
<td>D-only uncontested</td>
<td>525</td>
<td>0.64</td>
<td>600</td>
</tr>
</tbody>
</table>

Note: Sales are in million units.

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, giving 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 the average annual total sales over cameras of the same chain-affiliation. The table shows the best-selling 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 the overlapped assortment between Chains A and B is wider and generates more sales than the overlapped assortments between A and D and between B and D, indicating the relatively less competition that Chain D faces against the other two major retailers. Again, the difference in assortment overlap alludes to the incentives of Chains A and B to adopt competition-dampening pricing policies. In the demand specification, we model camera choice at the store-product level, thus directly accounting for the assortment overlap between chains in every local market.

In summary, the three major retailers competed in a large number of markets and with significant overlap in their product assortment. Meanwhile, variation exists across chains and over time along these two dimensions. A firm’s preference for national or local pricing
Table 7: Chain Affiliation, Number of Camera Models, and Average Annual Total Sales over Cameras

<table>
<thead>
<tr>
<th>Chain Affiliation</th>
<th># Models</th>
<th>Sales</th>
<th># Models</th>
<th>Sales</th>
</tr>
</thead>
<tbody>
<tr>
<td>A-only</td>
<td>26</td>
<td>0.32</td>
<td>71</td>
<td>2.37</td>
</tr>
<tr>
<td>A-D</td>
<td>3</td>
<td>0.13</td>
<td>37</td>
<td>4.58</td>
</tr>
<tr>
<td>B-only</td>
<td>31</td>
<td>0.27</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>B-D</td>
<td>10</td>
<td>0.29</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>A-B</td>
<td>21</td>
<td>2.11</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>A-B-D</td>
<td>34</td>
<td>5.20</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>D-only</td>
<td>9</td>
<td>0.22</td>
<td>21</td>
<td>0.64</td>
</tr>
</tbody>
</table>

Note: Sales are in million units.

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

To describe the pricing policies implemented by the three retailers, Figure 2 presents the sales-weighted coefficients of variation of prices across stores for every product, against their life cycle, measured by the cumulative share of total lifetime sales.\(^6\) 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.\(^7\) This finding indicates 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

\(^6\)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.

\(^7\)Even though Chains A and B employ national pricing, the small variation observed in price across stores for these chains has several explanations. First, we must derive unit prices through dividing monthly revenue by monthly sales for every product in each store. This aggregation leads to small differences in monthly average product price across stores. Second, some sales are made using store-level coupons, open-box sales, or other local 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.
Figure 2: Price Dispersion across SSAs in Chains A (top), B (middle), and D (bottom)
product’s sales. By contrast, for Chain D, the price variation across stores is much higher and relatively constant over a product’s life cycle, consistent with our understanding that 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 on the firms’ pricing policies. The manager confirmed Chains A and B both follow national pricing policies across categories for most of a product’s life cycle.\(^8\) The chains shift to local pricing when the firm predicts 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.

For further evidence that the pricing policies are implemented consistently across categories, we obtain a second data set on digital TV sales from NPD covering the same retailers. The pattern of price variations in TVs from the three retailers is very similar to digital cameras, as Figure B.1 of Appendix B shows. (We also show in Table B.1 that the distribution of market structures for digital TVs is close to the distribution for digital cameras, i.e., Chains A and B competed in most of their markets, whereas other smaller chains did not.) These results jointly suggest the retailers apply the same pricing policy across product categories, which is also consistent with the senior manager’s claim that pricing policies are implemented broadly at the chain level rather than category level.

3 Model

In this section, we specify a model of aggregate demand to estimate consumer preferences and a model of retail competition to recover marginal costs. 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, we

\(^8\)Chains A and B credibly commit to national pricing through two mechanisms. First, both chains state on their websites that they follow national pricing policies. Second, both chains offer price-match guarantees to compensate consumers for any price differences on their own sales across store locations. By contrast, Chain D has no such policy, explicitly excluding its own stores from the company’s price-matching guarantee.
sidestep consumer forward-looking behavior in order to focus on leveraging the abundant spatial variations to address the question of geographic pricing policies while achieving model tractability. To do so, we estimate the demand model separately in each of the 1,600 SSAs in which Chains A, B, and/or D operated, thereby obtaining a flexible semi-parametric representation of heterogeneous consumer preferences across markets.

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 being 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 the product characteristics, such as price, may vary across stores. Thus, each choice alternative is defined at the store-camera level, and all the store-camera pairs within an SSA of a month constitute the choice set. \(^9\) We consider Cobb-Douglas for specifying consumer utility, such that a household \( i \) that purchases product \( j \) in month \( t \) obtains

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

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 \( \beta_i \). \( \xi_{jt} \) 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. \(^10\) \( y_i \) is the income of household \( i \), \( p_{jt} \) is the price of product \( j \) at month \( t \), and \( \alpha \) is the price coefficient indicating the marginal utility of expenditures. We incorporate geographic variation in inflation-adjusted income by

---

\(^9\) 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.

\(^10\) Because of the aggregation to 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, which motivates the need for appropriate instruments.
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

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

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

(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 $\epsilon$’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 market,

$$s_{jt} = \int \sum_{i} s_{ijt} = \int \sum_{i} \frac{\exp[\mathbf{x}'_{jt}\beta_i + \alpha \log(1 - p_{jt}/y_i) + \xi_{jt} + \rho \log(J_t)]}{1 + \sum_{k=1} \exp[\mathbf{x}'_{kt}\beta_i + \alpha \log(1 - p_{kt}/y_i) + \xi_{kt} + \rho \log(J_t)]} dP(\beta_i)dP(y_i),$$

(3)

where $P(\beta_i)$ and $P(y_i)$ 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 log-normality. For $\beta_i$, we assume it follows a multivariate normal distribution, and estimate its mean and variance as part of the structural estimation.\textsuperscript{11}

The observed camera attributes include price and six other attributes: store affiliation, camera brand, resolution in mega pixels, 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 $\mathbf{x}_{jt}$ into $\mathbf{x}^{fc}_{jt}$ and $\mathbf{x}^{rc}_{jt}$, and assign random coefficients only to the latter, which includes resolution, store affiliation, and camera brand. The other three non-price attributes are included in $\mathbf{x}^{fc}_{jt}$. We also include dummies for “November-December” and “June” in $\mathbf{x}^{fc}_{jt}$ because the industry exhibits strong seasonality.

\textsuperscript{11}The normality assumption on consumer heterogeneity may cause estimation bias if the actual distribution is heavily tailed or multi-mode (Li and Ansari 2014). Estimating the model separately by market should reduce such bias.
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 tier:

$$
\alpha_r = \begin{cases} 
\alpha_1, & \text{if } y_i < \bar{y}_1 \\
\alpha_2, & \text{if } \bar{y}_1 \leq y_i < \bar{y}_2 \\
\vdots & \\
\alpha_R, & \text{if } y_i \geq \bar{y}_{R-1}, 
\end{cases}
\quad (4)
$$

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

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

and match them to the PMA survey statistics. The role of the micro moments is different from hierarchically linking demographics with parameter heterogeneity. The latter approach only provides extra flexibility to the model, whereas the micro moments restrict the 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.$^{12}$

3.3 Chain-level Pricing Model

In each month, a chain sets camera prices in a static Bertrand-Nash fashion, conditional on the chain’s pricing policy. Through the price-setting process, we recover marginal costs for the subsequent counterfactuals. Note the Nash assumption only applies to the period price-setting game, and not to the game of pricing policy choices (i.e., national vs. local). This approach is reasonable because the chains typically change prices on a monthly basis.

$^{12}$Incorporating the PMA data requires scaling the survey statistics to appropriately match the NPD data. Web Appendix F reports the scaling details.
whereas the choice of a chain-level geographic pricing policy represents a long-term strategic decision.

### 3.3.1 National Pricing Policy

Under a national pricing policy, a chain sets an optimal uniform 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:

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

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

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

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:

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

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 $m$. $\Delta$ is a block diagonal matrix in which each block $\Delta_f$ pertains to a chain using a national pricing policy. With $\mu_i(p) = \alpha_r \log(1 - p/y_i)$,
we can succinctly write $\Delta_f$ as,

$$\Delta_f = - \sum_{m} M_m \int_{i \in m} \left[ \frac{\partial \mu_i(p)}{\partial p} (\text{diag}(s_i) - s_i s'_i) \right]. \quad (8)$$

### 3.3.2 Local Pricing Policy

Under a local pricing policy, a chain sets optimal 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

$$c = p - \Delta^{-1} s, \quad (9)$$

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

$$\Delta_f = - \int_{i \in m} \left[ \frac{\partial \mu_i(p)}{\partial p} (\text{diag}(s_i) - s_i s'_i) \right]. \quad (10)$$

### 3.3.3 Recovery of Marginal Costs

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 (i) optimal 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 (ii) optimal 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 solve a system of equations across products, markets, chains, and periods. The cost of a camera is constrained to be the same across SSAs (but not across time), because we expect that
national retailers obtain units from the manufacturers at prices that are independent of store location or pricing policy. Differences in distribution costs are likely small for digital cameras. We later test the robustness of our results to some of these assumptions.

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 micro data vary over time and across SSAs because of the different sizes of income tiers in different markets. Third, choice sets vary substantially across SSAs and over time. Although popular models are available in all stores, niche cameras may only be found in 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 semi-parametric 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:

\[ s_{jt} = \int \frac{\exp(V_{ijt})}{1 + \sum_{k=1}^{d_i} \exp(V_{ikt})} dP(\beta_i) dP(y_i) \]  

(11)
\[
\tilde{s}_{rt} = \int_{i \in r} \sum_{j=1}^{J'} s_{ijt},
\]

(12)

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

\[
V_{ijt} = x_{jt}^{fe} \beta_{fc} + x_{jt}^{rc} \beta_i + \alpha_r \log(1 - p_{jt}/y_i) + \rho \log(R_{jt}) + \xi_{jt},
\]

and (12) represents the micro moments, with \( \tilde{s}_{rt} \) denoting the percentage of households at income tier \( r \) who 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

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

(13)

where \( X \) is a stack of \( x_{jt}^{fe} \), \( x_{jt}^{rc} \), and \( \log(R_{jt}) \), and \( X_{ir}^{rc} \) is a stack of \( x_{ijt}^{rc} \). \( \theta_1 \) is a vector combining the fixed coefficients \( \beta_{fc} \), the means of the random coefficients, \( \bar{\beta} = E[\beta_i] \), and the coefficient of the congestion term \( \rho \). \( \theta_2 \) is a diagonal matrix in which the diagonal includes the standard deviations of the random coefficients and the four \( \alpha_r \)'s. \( v_i \) is a vector consisting of random draws from a standard multivariate normal, and of four binary indicators of household \( i \)'s income tier. With (13), the mean utility that facilitates estimation can be written as

\[
\delta = X \theta_1 + \xi.
\]

(14)

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

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

(15)

where \( N_d \) denotes the number of sale observations. The second set of moments include 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 that are orthogonal to the demand shocks. Our instruments include own product characteristics, the sum of the characteristics across other own-firm products, and the sum of the characteristics across competing firms. These instruments explain a relatively large portion of price variation. In the separate estimation by market, 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 in all SSAs that our instruments do not explain observed prices.

### 4.2 MPEC Approach

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

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

s.t. \begin{align*}
    s(\delta, \theta_2) &= S \\
    \eta_1 - g(\delta, \theta_1) &= 0 \\
    \eta_2 - \tilde{s}(\delta, \theta_2) &= -\tilde{S},
\end{align*}

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 micro data 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.\textsuperscript{13} To facilitate the optimization, we derive closed-form Jacobian and Hessian expressions for the objective function, the demand moments, and the micro moments. All the details of the MPEC are set out in Appendix C.

\textsuperscript{13}We enter the micro moments into the objective function because the (two-stage) GMM can adaptively determine the optimal weighting of these moments.
4.3 Estimation Results

For every SSA, we estimate a separate demand model, including year, brand, and chain fixed effects. For comparison, we also estimate a single pooled-demand model across all SSAs. Due to 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 Web Appendix G.

4.3.1 Demand Estimates

Table 8 reports elasticities on price, resolution, optical zoom, thickness, and display size. Figure 3 plots histograms of price and resolution elasticities under the pooled and the separate estimation. Overall, preferences toward camera attributes are highly heterogeneous across households. Both Table 8 and Figure 3 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.\textsuperscript{14} 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 based on a one-unit improvement in each camera attribute. This approach shows an average consumer would value an additional mega pixel at $15.25, a 1X increase in optical zoom at $8.74, a 1mm reduction in thickness at $4.48, and a one-inch larger display

\footnote{\textsuperscript{14}In Web Appendix G.2, we include camera age in the demand model and find little impact on the demand estimates.}
Table 8: Elasticity Estimates

<table>
<thead>
<tr>
<th>Elasticity</th>
<th>Separate Estimation</th>
<th>Pooled Estimation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2SLS</td>
<td>Random Coefficients &amp; Microdata</td>
</tr>
<tr>
<td>Price</td>
<td>-1.496</td>
<td>-2.903</td>
</tr>
<tr>
<td>[0.248]</td>
<td>[0.773]</td>
<td>[0.152]</td>
</tr>
<tr>
<td>Resolution</td>
<td>0.390</td>
<td>0.434</td>
</tr>
<tr>
<td>[0.179]</td>
<td>[0.260]</td>
<td>[0.099]</td>
</tr>
<tr>
<td>Optical Zoom</td>
<td>0.080</td>
<td>0.067</td>
</tr>
<tr>
<td>[0.169]</td>
<td>[0.181]</td>
<td>[0.059]</td>
</tr>
<tr>
<td>Thickness</td>
<td>-0.206</td>
<td>-0.305</td>
</tr>
<tr>
<td>[0.270]</td>
<td>[0.264]</td>
<td>[0.126]</td>
</tr>
<tr>
<td>Display Size</td>
<td>0.212</td>
<td>0.179</td>
</tr>
<tr>
<td>[0.559]</td>
<td>[0.532]</td>
<td>[0.012]</td>
</tr>
</tbody>
</table>

Note: Standard deviations in the brackets are computed across SSAs.

at $21.93.

4.3.2 Price-margin Estimates

Table 9: Inferred Price Margins across Demand Specifications

<table>
<thead>
<tr>
<th>Margin</th>
<th>Separate Estimation</th>
<th>Pooled Estimation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2SLS</td>
<td>Random Coefficient &amp; Microdata</td>
</tr>
<tr>
<td>Mean</td>
<td>69.62%</td>
<td>34.53%</td>
</tr>
<tr>
<td>Median</td>
<td>63.19%</td>
<td>28.59%</td>
</tr>
<tr>
<td>10%-percentile</td>
<td>45.46%</td>
<td>21.24%</td>
</tr>
<tr>
<td>90%-percentile</td>
<td>93.82%</td>
<td>42.89%</td>
</tr>
</tbody>
</table>

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

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. Two-stage least squares (2SLS) produces higher margins relative to the full model with random coefficients and micro moments. The 35% average margin obtained in the full model is the lowest and the closest to estimates in industry reports. For example,

15 Under the full model, the camera with the highest margin is priced at $198.96 and has an estimated
Euromonitor (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 between the three retailers.
Table 10: Inferred Price Margins by Chains

<table>
<thead>
<tr>
<th>Margin</th>
<th>Chain A</th>
<th>Chain B</th>
<th>Chain D</th>
<th>Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>35.41%</td>
<td>34.09%</td>
<td>32.76%</td>
<td>34.53%</td>
</tr>
<tr>
<td>Median</td>
<td>30.27%</td>
<td>28.05%</td>
<td>25.37%</td>
<td>28.59%</td>
</tr>
<tr>
<td>10%-percentile</td>
<td>22.06%</td>
<td>21.06%</td>
<td>18.46%</td>
<td>21.24%</td>
</tr>
<tr>
<td>90%-percentile</td>
<td>43.93%</td>
<td>41.86%</td>
<td>40.50%</td>
<td>42.89%</td>
</tr>
</tbody>
</table>

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

5 Counterfactual Simulations

Having recovered consumer preferences and marginal costs, our goal is to conduct a series of counterfactual simulations to disentangle retailers’ incentives to choose a particular geographic 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 a chain would prefer national versus local pricing policies. Third, because these policies represent two extremes, we consider a pair of alternative hybrid policies, in which the firms employ national pricing except in selected geographic markets. Finally, we provide sensitivity analysis to show the counterfactual results are robust to our approach to recovering marginal costs.

Each counterfactual 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. Specifically, using the demand and cost estimates obtained before B exits, we simulate equi-
librium prices and profits when A and B choose between national and local pricing. In this simulation, we assume Chain D sticks with local pricing and address a deviation of its policy in the subsequent discussion. The smallest Chain L, consisting of small sellers, is assumed to be passive and does not respond to any market changes.

Table 11: Counterfactual Profits \((\pi_A, \pi_B)\) before B Exits ($m)

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

Table 11 reports the two-year profits of Chains A and B prior to B’s exit under four alternative pricing-policy scenarios: Local-Local, Local-National, National-Local, and National-National.\(^\text{16}\) The results show that under the existing market conditions, employing national pricing is optimal for both Chains A and B. When switching from local to national, profits increase by 5.3% for Chain A and by 8.4% for Chain B.\(^\text{17}\) More importantly, neither A nor B would find it profitable to unilaterally deviate from national pricing. To understand why National-National is an equilibrium of the policy game, in Table 12, we decompose the differences in profits and prices across policies relative to National-National, for both contested and uncontested SSAs.

Table 12: Profit and Price Decomposition between Contested and Uncontested Markets

<table>
<thead>
<tr>
<th></th>
<th>Uncontested Markets</th>
<th></th>
<th>Contested Markets</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Chain B</td>
<td></td>
<td>Chain B</td>
</tr>
<tr>
<td></td>
<td>Local</td>
<td>National</td>
<td>Local</td>
</tr>
<tr>
<td>Chain A Local</td>
<td>(4.09, 2.91)</td>
<td>(4.09, -2.52)</td>
<td>(-20.40, -11.63)</td>
</tr>
<tr>
<td>Chain A National</td>
<td>(-5.86, 2.91)</td>
<td>(—, —)</td>
<td>(-8.02, -5.22)</td>
</tr>
<tr>
<td>Chain A Local</td>
<td>(5.81%, 8.31%)</td>
<td>(5.81%, -3.30%)</td>
<td>(-9.77%, -9.03%)</td>
</tr>
<tr>
<td>Chain A National</td>
<td>(-2.54%, 8.31%)</td>
<td>(—, —)</td>
<td>(-2.63%, -6.23%)</td>
</tr>
</tbody>
</table>

\(^{16}\)Appendix D reports chain market shares associated with the profit results.

\(^{17}\)Figure 2 shows both Chains A and B used a nearly national pricing (80/20) policy in the data. Under such policy, the estimated profits are $320.95m and $111.27m for Chains A and B, respectively, during the period before B exits, which are very similar to the profits under the 100% national policy.
First, suppose both firms switch to Local-Local. In their respective uncontested markets, moving from national to local pricing raises profits by $4.09m and $2.91m. Such profit 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 they can now charge locally optimal prices. On the contrary, in the contested markets, switching from national to local pricing reduces profits by $20.40m for A and $11.63m 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 to local pricing is unprofitable for both firms.

Next, we use Table 12 to explain why a unilateral deviation to local pricing is sub-optimal 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 $4.09m. 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%, respectively, in B’s uncontested and contested markets.\(^{18}\) 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 $7.42m and Chain B would lose $5.09m. 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 outweighs the gains in its uncontested markets. Thus, the unilateral deviation to local pricing is not optimal for Chain A. Similar logic can be applied to a unilateral deviation by Chain B with the same conclusion.

\(^{18}\)The small gap between the two percentages results from the variations in product assortment across B’s SSAs.
We have shown the two largest retailers would not simultaneously or unilaterally move to local pricing from national policies. Therefore, National-National is sustained as an equilibrium policy between Chains A and B. Next, we consider the large discount chain D and evaluate its counterfactual deviation from local pricing.

5.1.2 Pricing Policies for Chain D

We perform a similar simulation of alternative pricing policies on 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 row and the bottom row shows that moving to 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.

Table 13: Profits of Chain D ($m) under Alternative Policy Scenarios

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

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 without the presence of the other two retailers, whereas A and B only have 101 and 79 uncontested SSAs, respectively. Also, the uncontested markets account for more than half of Chain D’s total sales. In addition, according to Table 7, Chain D’s camera assortment overlaps less with Chains A and B relative to the latter two chains’ overlap with each other. These points of differentiation help soften 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.

Table 14: Profits of Chain D ($m) between Contested and Uncontested Markets

<table>
<thead>
<tr>
<th>Markets without A or B</th>
<th>Markets with A and/or B</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>A National</td>
</tr>
<tr>
<td>A National</td>
<td>28.87</td>
</tr>
<tr>
<td>B National</td>
<td></td>
</tr>
<tr>
<td>D Local</td>
<td>26.15</td>
</tr>
<tr>
<td>D National</td>
<td>28.87</td>
</tr>
<tr>
<td>Difference</td>
<td>2.72</td>
</tr>
</tbody>
</table>

5.2 Boundary Conditions for National Pricing

Thus far, we have demonstrated that under the current competitive landscape, employing national pricing is profitable for Chains A and B, and implementing a local strategy is profitable for Chain D. Now we explore the conditions under which a chain would start switching from national to local pricing.

5.2.1 Variation in Market Structure

The decomposition in Table 12 demonstrates the critical role of market structure in our results. To further explore this dimension, 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 an increasing 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 4 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 due to the fact that 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 the 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 above counterfactual analysis implies that, over and beyond non-competitive forces such as menu cost and internet posted prices that may entice a retail chain to employ national pricing, changes in the competitive market structures can significantly affect the multimarket firm’s pricing decisions. 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 competitive landscape of the industry. The absence of such a large rival could create incentives for Chain A to localize prices as it became the single dominant electronics specialty retailer. To investigate this possibility, we use the demand and cost estimates from the data
period after B exits,\footnote{We report model estimates after B’s exit in Web Appendix G.3.} and simulate optimal national and local prices as well as profits for Chain A. We find that, compared to local pricing, A’s profit ($176.83m) 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 optimal 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 A and D is sufficient to justify national pricing in the absence of B, even though the advantage of national pricing over local pricing is largely gone because of the eased competitive landscape. Similar to the situation prior to B’s exit, maintaining local pricing is always optimal for Chain D, especially because the share of its uncontested markets increases.

5.3 Hybrid Pricing Policies

Local and national pricing represent extreme cases of a continuum of geographic pricing strategies. Instead, a chain may set prices locally in some markets and maintain uniform pricing in other markets. Such a hybrid policy permits the chain to exploit some geographic variation in preferences without sacrificing its national policy. Evaluating all possible hybrid strategies is largely infeasible due to the enormous number of combinatory cases. Thus, our goal is not to thoroughly explore this strategy space, 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 and influential markets. To examine this possibility, we allow local pricing at 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
Table 15: Profit and Price Changes Relative to Observed Policies with Local Pricing in Five Largest Metro Areas

<table>
<thead>
<tr>
<th>Chain</th>
<th>Local Pricing Zone</th>
<th>Uniform Pricing Zone</th>
<th>Chain Profit</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Profit</td>
<td>Price</td>
<td>Profit</td>
</tr>
<tr>
<td>A</td>
<td>-12.29%</td>
<td>-10.36%</td>
<td>-0.76%</td>
</tr>
<tr>
<td>B</td>
<td>-15.33%</td>
<td>-12.57%</td>
<td>-1.23%</td>
</tr>
<tr>
<td></td>
<td>0.57%</td>
<td>1.03%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.72%</td>
<td>1.31%</td>
<td></td>
</tr>
</tbody>
</table>

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 the 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 above proposal does not increase chain profits, many other alternative hybrid policies remain. Instead of localizing prices in large competitive markets, a chain could localize prices in its largest uncontested markets where it faces little competition from major rivals, thereby leading to 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 zone. 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 metropolitan areas and national pricing elsewhere.
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. The difference in profit change between the two chains is due to the fact that 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 above analysis identifies a hybrid policy that is slightly more profitable for Chain A, but not for Chain B. Of course, many other hybrid scenarios are possible. In addition, the current model and analyses do not account for organizational costs associated with local or hybrid pricing policies. Therefore, the search of an “optimal” hybrid pricing strategy and whether such a hybrid policy is managerially and institutionally viable remains an open question 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, for Chains A and B, we recover their marginal costs 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 both 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 significant similarity between the cost results under alternative policies. Figure 5 shows the histograms of these cost estimates for Chains A and B, respectively. From the figure, we can see the distributions of the marginal costs under different policy assumptions are of little difference with respect to each other.

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 slightly changed due to the minor cost differences, national pricing remains the policy equilibrium for both chains. Thus, our approach to backing out marginal costs does not affect the qualitative conclusion about national pricing.

<table>
<thead>
<tr>
<th>Chain A</th>
<th>Chain B</th>
</tr>
</thead>
<tbody>
<tr>
<td>Local</td>
<td>National</td>
</tr>
<tr>
<td>(302.79,102.58)</td>
<td>(305.67,108.98)</td>
</tr>
<tr>
<td>(316.52,103.38)</td>
<td>(319.78,110.94)</td>
</tr>
</tbody>
</table>

Table 17: Counterfactual Profits \((\pi_A, \pi_B)\) ($millions)
6 Conclusion

In this paper, we empirically examine a firm’s choice of national versus local pricing policy in a multimarket competitive setting. To do so, we estimate an aggregate model of demand with random coefficients and micro moments separately in each market. The separate estimation strategy recovers a significant increase in preference heterogeneity across markets. Using counterfactual policy simulations, we demonstrate that under certain competitive market conditions, retail chains may enjoy substantially higher profits by employing national pricing, letting go of the flexibility local pricing offers. We find these conditions hold for the two major national electronics retail chains, and the optimality of national 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 optimal because this chain
operates in many uncontested markets. More generally, we demonstrate the distribution of competitive market structures affects the chains’ decision to employ national versus local pricing strategies. These results have direct implications for the retail electronics industry. Furthermore, the insights from this investigation could generalize to other industries evaluating their chain-level pricing policies.

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 or local pricing. For example, by switching from national to local pricing, a chain may incur additional costs in customizing advertising to match locally varying prices. Also, consumers may dislike inconsistent prices offline and online, and across different stores. Therefore, moving to local pricing could incur certain economic and psychological costs for which our model does not account. Our results demonstrate competitive forces play an important role in the tradeoff between national and local pricing strategies over and beyond the alternative accounts, but such competitive forces should be weighed relative to other organizational considerations.

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

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

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

References


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 code, 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 hard.

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 5th-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; DOJ-FTC 2010). 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 must currently be excluded from the choice set. Therefore, the market boundary must be expanded to include the best available substitute until the newly formed HM can profitably apply a SSNIP.

Following Davis (2006), we 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.\(^1\)

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-

\(^1\)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 test on the three major chain stores and combine small stores as the outside option.
Table A.1: Percent of Hypothetical Monopolists with Profitable Price Increase

<table>
<thead>
<tr>
<th>SSA Type</th>
<th>2007</th>
<th>2009</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>One-store</td>
<td>Two-store</td>
</tr>
<tr>
<td></td>
<td>HM</td>
<td>HM</td>
</tr>
<tr>
<td>D-A</td>
<td>5.7%</td>
<td>92.3%</td>
</tr>
<tr>
<td>D-B</td>
<td>7.4%</td>
<td>90.8%</td>
</tr>
<tr>
<td>D-A-B</td>
<td>5.1%</td>
<td>4.9%</td>
</tr>
</tbody>
</table>

store (D-A-B) HM market definitions. Then, assuming 30% average margins (Euromonitor 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, 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, and start the SSNIP from levels that are below the observed prices, as in (Davis 2006). 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 dominant strategy for both Chain A and B. Based on this finding and the results in Tables A.1 and A.2, using SSAs as our market definition appears appropriate.

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

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

Now we present data on 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 2007-2009. Chains A, B, and D are the same chains in the digital camera category. Chain S is a big-box mass retailer similar to Chain D.

![Graphs showing geographic price dispersion for digital TVs](image)

Figure B.1: Geographic Price Dispersion of Digital TVs

Figure B.1 shows strong similarity in pricing patterns between 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 choice of national pricing by Chains A and B and the choice of local pricing by Chains D and S for digital TVs. These two categories represent two (very) important sets of products for the retailers. Discussions with the executives of Chain A confirmed the national pricing pattern observed in these two categories is consistent across other categories as well.

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

<table>
<thead>
<tr>
<th>SSA Structure</th>
<th>SSA Competitiveness</th>
<th>Before B Exits</th>
<th>After B Exits</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td># SSAs</td>
<td>Sales</td>
</tr>
<tr>
<td>A-only</td>
<td>uncontested</td>
<td>61</td>
<td>0.17</td>
</tr>
<tr>
<td>B-only</td>
<td>uncontested</td>
<td>45</td>
<td>0.09</td>
</tr>
<tr>
<td>D-only</td>
<td>uncontested</td>
<td>433</td>
<td>0.22</td>
</tr>
<tr>
<td>S-only</td>
<td>uncontested</td>
<td>176</td>
<td>0.13</td>
</tr>
<tr>
<td>A-B</td>
<td>contested</td>
<td>32</td>
<td>0.19</td>
</tr>
<tr>
<td>A-D</td>
<td>contested</td>
<td>189</td>
<td>0.62</td>
</tr>
<tr>
<td>A-S</td>
<td>contested</td>
<td>56</td>
<td>0.21</td>
</tr>
<tr>
<td>B-S</td>
<td>contested</td>
<td>49</td>
<td>0.15</td>
</tr>
<tr>
<td>B-D</td>
<td>contested</td>
<td>73</td>
<td>0.18</td>
</tr>
<tr>
<td>D-S</td>
<td>contested</td>
<td>152</td>
<td>0.17</td>
</tr>
<tr>
<td>A-B-D</td>
<td>contested</td>
<td>120</td>
<td>0.77</td>
</tr>
<tr>
<td>A-B-S</td>
<td>contested</td>
<td>35</td>
<td>0.24</td>
</tr>
<tr>
<td>A-D-S</td>
<td>contested</td>
<td>145</td>
<td>0.60</td>
</tr>
<tr>
<td>B-D-S</td>
<td>contested</td>
<td>61</td>
<td>0.19</td>
</tr>
<tr>
<td>A-B-D-S</td>
<td>contested</td>
<td>283</td>
<td>2.15</td>
</tr>
</tbody>
</table>

Note: Sales are in million units.

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:

\[
\mathcal{L}(\phi; \lambda) = F(\phi) - \langle \lambda, \mathcal{G}(\phi) \rangle,
\]  

(C.1)
where $\lambda \in \mathbb{R}$ is a vector of Lagrange multipliers. The solution to (16) satisfies the Karush-Kuhn-Tacker condition on $\mathcal{L}$:

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

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 $\Phi$, 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, $\Phi$ has a block diagonal structure (Petrin 2002). Accordingly, the asymptotic variance matrix for parameter estimates is given as

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

where $J$ is the Jacobian matrix of (12) and (15) with respect to $\theta_1$ and $\theta_2$.

### C.2 Analytic Derivatives

In this section, we derive the analytic derivatives for the optimization problem specified in (16). Our derivation applies 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 assist coding processes.

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

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

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

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

$$
\frac{\partial s_i(\delta, \theta_2)}{\partial \theta_2} = \int_{\forall i} \text{diag}(s_{it})[X_{it}^{rc} - 1_{j_i} s_{it}' X_{it}^{rc}] \text{diag}(v_i), \quad \text{(C.6)}
$$
\[
\frac{\partial s_i(\delta_t, \theta_2)}{\partial \delta_t} = \int_{\forall i} \text{diag}(s_{it}) - s_{it} s_{it}', \quad (C.7)
\]

where \( \mathbf{1}_{J_t} \) is a \( J_t \)-element column vector of ones.

The Jacobian matrices of the constraints imposed by the demand side orthogonal conditions are

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

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

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

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

\[
\frac{\partial [\eta_2 - \tilde{s}_{rt}(\delta_t, \theta_2)]}{\partial \theta_2} = -\int_{i \in r} s_{\tilde{0}t} s_{it}' X_{rt} \text{diag}(v_i), \quad (C.11)
\]

\[
\frac{\partial [\eta_2 - \tilde{s}_{rt}(\delta_t, \theta_2)]}{\partial \delta_t} = -\int_{i \in r} s_{\tilde{0}t} s_{it}'. \quad (C.12)
\]

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

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

\[
\text{diag}(s) = \sum_{i=1}^{n} E_i s e_i',
\]

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

\[
\frac{\partial \text{diag}(s)}{\partial \delta} = \sum_{i=1}^{n} (e_i \otimes E_i) \frac{\partial s'}{\partial \delta},
\]

where \( \otimes \) denotes Kronecker product.
\[
\sum_{j,t} \lambda_{jt} \frac{\partial^2 s_{jt}(\delta_t, \theta_2)}{\partial \theta_2} = \sum_{t=1}^{T} \int_{vi} \text{diag}(v_i)[(X_{it}^{rc} - X_{it}^{rc} s_{it}1_{J_t})\text{diag}(\lambda_t) - \lambda'_t s_{it} X_{it}^{rc}] \frac{\partial s_{it}}{\partial \theta_2}, \tag{C.13}
\]

\[
\sum_{r,t} \lambda_{rt} \frac{\partial^2 [\eta_2 - \tilde{s}_{rt}]}{\partial \theta_2} = \sum_{r,t} \lambda_{rt} \int_{i \in r} s_{it} \text{diag}(v_i) X_{it}^{rc} [s_{it} s_{it} X_{it}^{rc} \text{diag}(v_i) - \frac{\partial s_{it}}{\partial \theta_2}], \tag{C.14}
\]

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

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

\[
\sum_{j,t} \lambda_{jt} \frac{\partial^2 s_{jt}(\delta_t, \theta_2)}{\partial \delta_t \theta_2} = \sum_{t=1}^{T} \int_{vi} \text{diag}(v_i)[(\lambda_t) - \lambda'_t s_{it} I_{J_t} - s_{it} \lambda'_t] \frac{\partial s_{it}}{\partial \theta_2}, \tag{C.15}
\]

\[
\sum_{r,t} \lambda_{rt} \frac{\partial^2 [\eta_2 - \tilde{s}_{rt}]}{\partial \delta_t \theta_2} = \sum_{r,t} \lambda_{rt} \int_{i \in r} s_{it} [s_{it} s_{it} X_{it}^{rc} \text{diag}(v_i) - \frac{\partial s_{it}}{\partial \theta_2}], \tag{C.16}
\]

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

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

\[
\sum_{r,t} \lambda_{rt} \frac{\partial^2 [\eta_2 - \tilde{s}_{rt}]}{\partial \delta_t \delta_t} = \sum_{r,t} \lambda_{rt} \int_{i \in r} s_{it} [2 s_{it} s_{it} - \text{diag}(s_{it})], \tag{C.18}
\]

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

After the optimization converges, we use (C.3) to obtain standard errors of the parameter estimates. The Jacobian matrix of the two sets of moments with respect to \( \theta_1 \) and \( \theta_2 \) is
\[ J = \begin{pmatrix} \frac{\partial g}{\partial \theta_1} & \frac{\partial g}{\partial \theta_2} \\ \frac{\partial \tilde{s}_{rt}}{\partial \theta_1} & \frac{\partial \tilde{s}_{rt}}{\partial \theta_2} \end{pmatrix}, \tag{C.19} \]

where

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

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

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

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

The second moments \( \Phi \) is

\[ \begin{pmatrix} \Phi_1 & 0 \\ 0 & \Phi_1 \end{pmatrix}, \tag{C.24} \]

where

\[ \Phi_1 = \frac{1}{N_d} \sum_{j,t} \xi_{jt}^2 Z_{jt} Z_{jt}', \tag{C.25} \]

\[ \Phi_2 = \frac{1}{I} \text{diag} \left( \sum_{i} \left( \tilde{s} - \tilde{S} \right)^2 \right). \tag{C.26} \]
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 share but the highest profits compared to other scenarios.

Table D.1: Counterfactual Market Shares before B Exits

<table>
<thead>
<tr>
<th>Chain B</th>
<th>Local</th>
<th>National</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chain A</td>
<td>(64.97%, 22.61%)</td>
<td>(59.87%, 22.74%)</td>
</tr>
<tr>
<td>National</td>
<td>(62.93%, 21.15%)</td>
<td>(57.47%, 20.17%)</td>
</tr>
</tbody>
</table>

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

Table D.2: Counterfactual Market Shares after B Exits

<table>
<thead>
<tr>
<th>Chain A</th>
<th>Local</th>
<th>National</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chain D</td>
<td>(81.43%, 12.62%)</td>
<td>(78.61%, 10.74%)</td>
</tr>
</tbody>
</table>

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.

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

<table>
<thead>
<tr>
<th></th>
<th>Observed National Pricing Policies</th>
<th>Local Pricing in Five Largest Areas</th>
<th>Local Pricing in Top 10% Uncontested SSAs</th>
<th>Local Pricing in Top 20% Uncontested SSAs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chain A</td>
<td>57.82%</td>
<td>58.41%</td>
<td>58.77%</td>
<td>59.34%</td>
</tr>
<tr>
<td>Chain B</td>
<td>20.33%</td>
<td>20.79%</td>
<td>20.56%</td>
<td>20.71%</td>
</tr>
</tbody>
</table>

As can be seen across these analyses, when Chains A and B go national, their market shares decrease due to increased prices, but their overall profits also improve.

References


Web Appendix

E Sales of Major Chains over Time

Table E.1 reports annual units sales of the three retailers A, B and D, the dummy chain L, the internet channel, as well as market size. We can see the overall sales were relatively flat during the data period, with a slight decline after 2008. This pattern largely agrees with other external industry analysis such as IC Insights (2014).

Table E.1: Annual Sales in Million Unites

<table>
<thead>
<tr>
<th>Year</th>
<th>Chain A</th>
<th>Chain B</th>
<th>Chain D</th>
<th>Chain L</th>
<th>Online</th>
<th>Non-buyers</th>
<th>Market Size</th>
</tr>
</thead>
<tbody>
<tr>
<td>2007</td>
<td>5.07</td>
<td>2.13</td>
<td>1.35</td>
<td>0.91</td>
<td>0.92</td>
<td>10.75</td>
<td>21.13</td>
</tr>
<tr>
<td>2008</td>
<td>5.21</td>
<td>1.80</td>
<td>1.59</td>
<td>0.92</td>
<td>0.94</td>
<td>11.05</td>
<td>21.51</td>
</tr>
<tr>
<td>2009</td>
<td>5.81</td>
<td>0.30</td>
<td>1.57</td>
<td>0.89</td>
<td>0.89</td>
<td>10.05</td>
<td>19.51</td>
</tr>
</tbody>
</table>

F Scaling of the PMA Survey for the Micro Moments

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

Assume a survey gives average purchase probabilities for four income segments, A, B, C, and D, at the national level. Then, we must obtain purchase probabilities a, b, c, and d for the corresponding four income segments in each local market. First, from the market-specific income distribution P(yi), we obtain the weight of each segments in this market by

\[ w_r = \int_{y \in r} dP(y_i), \]

where \( r = 1, 2, 3, 4 \). Denoting \( \tilde{S}_i = \sum_{j=1}^J s_{jt} \), the sum of shares of all inside options observed in the sales data, we solve the following equations to obtain a, b, c, and d:
\[
\tilde{S}_t = w_1 a + w_2 b + w_3 c + w_4 d
\]
\[
a/b = A/B
\]
\[
b/c = B/C
\]
\[
c/d = C/D.
\]

G  **Additional Estimation Results**

G.1  **Pooled Demand Estimation**

<table>
<thead>
<tr>
<th>Variable</th>
<th>OLS</th>
<th>2SLS</th>
<th>Random Coefficients &amp; Microdata</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Price Coefficients (α’s)</td>
<td>Random Coefficients &amp; Microdata</td>
<td></td>
</tr>
<tr>
<td>α₁</td>
<td>5.014 (0.021)</td>
<td>18.162 (0.027)</td>
<td>32.005 (0.806)</td>
</tr>
<tr>
<td>α₂</td>
<td>29.689 (6.781)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>α₃</td>
<td>63.408 (8.467)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>α₄</td>
<td>82.339 (12.296)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Resolution</td>
<td>0.049 (0.000)</td>
<td>0.055 (0.000)</td>
<td>0.247 (0.023)</td>
</tr>
<tr>
<td>Resolution s.d.</td>
<td>0.119 (0.005)</td>
<td>0.996 (0.068)</td>
<td></td>
</tr>
<tr>
<td>Optical Zoom</td>
<td>0.043 (0.010)</td>
<td>0.161 (0.007)</td>
<td>0.227 (0.051)</td>
</tr>
<tr>
<td>Thickness</td>
<td>-0.159 (0.003)</td>
<td>-0.183 (0.001)</td>
<td>-0.177 (0.002)</td>
</tr>
<tr>
<td>Display Size</td>
<td>0.340 (0.002)</td>
<td>0.457 (0.000)</td>
<td>0.564 (0.002)</td>
</tr>
<tr>
<td>Nov-Dec</td>
<td>-0.137 (0.002)</td>
<td>-0.159 (0.002)</td>
<td>-0.361 (0.000)</td>
</tr>
<tr>
<td>June</td>
<td>0.100 (0.003)</td>
<td>0.117 (0.000)</td>
<td>0.056 (0.000)</td>
</tr>
<tr>
<td>Congestion</td>
<td>-0.898 (0.001)</td>
<td>-1.002 (0.000)</td>
<td>-0.934 (0.021)</td>
</tr>
</tbody>
</table>

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

Table G.1 reports parameter estimates from the pooled demand model. The price coef-
ficient triples when moving from OLS to 2SLS with instrumental variables, suggesting price endogeneity is present in the demand specification. The random coefficients model with micro data shows the price coefficients vary substantially across income tiers. Similar to the findings in Petrin (2002), in our analysis, the marginal utility of expenditures on other goods and services increases with income. Consumers on average favor cameras with higher resolution, longer optical zooms, larger displays, and dislike cameras that are thick in size, and yet the taste for resolution is highly heterogeneous across households. Some consumers in the market appear to have little valuation for resolution, consistent with the industry trend that the pursuit of higher resolution in the compact point-and-shoot sector has declined since 2007 (Euromonitor 2010).

G.2 Including Camera “Age” in the Demand Model

Because consumers generally prefer newer to older digital products, we test an alternative demand model with an additional “age” term. We want to see, conditional on the variation in product attributes and the product entries and exits, whether the age of a camera affects its demand. Table G.2 reports the estimates of a homogeneous logit demand model with such an age term that reflects the number of months for which a camera has been available on the market. Although its coefficient is statistically significant, the inclusion of the age variable results in little change in other parameter estimates. Specifically, relevant to our analysis, the price sensitivity coefficient is very similar across the two models. Thus, the preference for “newness” is already picked up by the enhanced quality levels on the new cameras (e.g., higher resolution, smaller size).

Table G.2: Homogeneous Logit Demand Estimation with Age Variable

<table>
<thead>
<tr>
<th>Variables</th>
<th>Without Age</th>
<th>With Age</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha_1$</td>
<td>5.014</td>
<td>5.021</td>
</tr>
<tr>
<td></td>
<td>(-0.021)</td>
<td>(-0.026)</td>
</tr>
<tr>
<td>Resolution</td>
<td>0.049</td>
<td>0.048</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Optical Zoom</td>
<td>0.043</td>
<td>0.042</td>
</tr>
<tr>
<td></td>
<td>(-0.010)</td>
<td>(-0.008)</td>
</tr>
<tr>
<td>Thickness</td>
<td>-0.159</td>
<td>-0.159</td>
</tr>
<tr>
<td></td>
<td>(-0.003)</td>
<td>(-0.003)</td>
</tr>
<tr>
<td>Display Size</td>
<td>0.340</td>
<td>0.335</td>
</tr>
<tr>
<td></td>
<td>(-0.002)</td>
<td>(-0.003)</td>
</tr>
<tr>
<td>Nov-Dec</td>
<td>-0.137</td>
<td>-0.140</td>
</tr>
<tr>
<td></td>
<td>(-0.002)</td>
<td>(-0.002)</td>
</tr>
<tr>
<td>June</td>
<td>0.100</td>
<td>0.102</td>
</tr>
<tr>
<td></td>
<td>-0.003</td>
<td>-0.003</td>
</tr>
<tr>
<td>Age</td>
<td>-0.012</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td></td>
</tr>
</tbody>
</table>
G.3 Estimates of Margins

Table G.3 reports the margins of Chain A before and after B exits, under the separate demand estimation with random coefficients and micro data. The table shows Chain A had slightly higher price margins following Chain B’s exit, mostly due to the eased competition in previously competitive markets.

Table G.3: Inferred Margins of Chain A before and after B’s Exit

<table>
<thead>
<tr>
<th>Margin</th>
<th>Before Exit</th>
<th>After Exit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>33.76%</td>
<td>36.29%</td>
</tr>
<tr>
<td>Median</td>
<td>28.64%</td>
<td>31.51%</td>
</tr>
<tr>
<td>10%-percentile</td>
<td>21.83%</td>
<td>22.25%</td>
</tr>
<tr>
<td>90%-percentile</td>
<td>42.58%</td>
<td>44.13%</td>
</tr>
</tbody>
</table>