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Donald Ngwe

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Why Outlet Stores Exist: Averting Cannibalization in Product Line Extensions

Donald Ngwe^a

^aHarvard Business School, Boston, Massachusetts 02163

Contact: dngwe@hbs.edu,  <http://orcid.org/0000-0002-9264-5070> (DN)

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Abstract. Outlet stores offer attractive prices at locations far from central shopping districts. They form a large and growing component of many firms' retailing strategies, particularly in the fashion industry. I use a structural demand model to show that consumers are segmented according to their sensitivity to travel distance and taste for product newness. I then develop a supply model to predict product development responses to changes in store locations. Through policy simulations, I discover that the firm uses outlet stores to serve lower-value consumers who self-select by traveling to outlet stores from central shopping districts. The firm sells older, less desirable merchandise through outlet stores to prevent cannibalization of regular store revenues by means of exploiting the positive correlation between consumers' travel sensitivity and taste for new products. I find that the rate of new product introduction in regular stores would fall by 16% if outlet stores were closed down, while variable profits would decline by 23%. These results imply that the existence of outlet stores may enable firms to improve quality in their regular channels, thus counteracting brand dilution effects.

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1. Introduction

Outlet stores are a fixture of the American retail landscape. These brick-and-mortar stores offer deep discounts in locations far away from most consumers. Firms operate outlet stores in addition to regular stores, which are located in central shopping districts. Outlet stores operated by different firms are often agglomerated in sprawling outlet malls off interstate highways. As of March 2014, there were 201 outlet malls in North America, which generated an estimated \$31–\$42 billion in annual revenues (Humphers 2014). This is a large and growing portion of the total retail sales in clothing and clothing accessories, which amounted to \$241 billion in 2012.¹

There are several perspectives on why outlet stores have become a widely adopted selling strategy. One concerns *inventory management*: outlet stores provide firms with a cost-efficient way to dispose of excess inventory. Another is *geographic segmentation*: outlet stores cater to lower-value consumers that reside near outlet malls. A third is *consumer self-selection*: lower-value consumers are more willing to travel greater distances to avail of discounted products.²

The multiplicity of views on why outlet stores exist corresponds to the variety of ways in which firms sell

through outlet stores, a sense of which is provided by a report from ConsumerReports.org:

When we asked outlet-store employees and customer-service reps for differences between goods at their chain's outlet and retail stores, they were candid, and it's clear that every company has its own strategy. Staff at Under Armour told us that the outlets sell older merchandise from regular stores and goods made just for the outlets. A Guess employee explained it fills its shelves with discontinued items, while a worker at Gap said the chain offers apparel that never saw the light of day in a regular store. At Black and Decker Factory Stores, you'll find fully warranted demo and refurbished equipment and brand-new goods. Lands' End "Inlets" carry year-old inventory, clearance items, and returns. Harry & David outlets sell a lot of the food and gifts in the company's catalog and on its website (though not always fruit), but prices and promotions differ. Sunglass Hut offers a mix of old and new glasses at "prices not necessarily cheaper" than those at its mall-based stores, a customer-service representative told us. Some retailers don't draw any line between outlet and regular merchandise. A customer-service rep for Dress Barn told us that in all the company's stores, "it's the exact same stuff, just different prices and promotions."³

In this paper, I evaluate the relevance of several possible reasons for selling through outlet stores in the

case of a major fashion goods firm with a heavy outlet store presence. Using newly available and highly granular data, I am able to observe both inventory flows between store formats, and locations and sales records of individual consumers—rich sources of model-free evidence. I then use a structural model of demand and supply to predict consumer behavior and firm product decisions under counterfactual distribution schemes.

It is evident from observing product flows and production runs that inventory management is not the sole function of the firm's outlet stores. The firm sells a significant fraction of units of each style through the outlet channel. It is also immediately clear that outlet stores do not mainly serve consumers who reside in their vicinity—the majority of each outlet store's revenues are attributed to consumers for whom a regular store is closer to home. This suggests that the firm's main motivation for operating outlet stores might be to price discriminate between its consumers by forcing the most price-sensitive among them to travel to obtain discounts.

Notably, consumers who shop at outlet stores do not differ significantly from consumers who shop at regular stores in terms of observable characteristics such as income. They make purchases at roughly the same frequency, and have had about the same time elapse since their first purchase of the brand. Taking these factors into account, I propose a demand model that characterizes how consumers make their purchase decisions. I use the demand model to estimate the extent to which consumers vary in their unobservable characteristics, and to show that outlet store consumers significantly differ from regular store consumers in two ways: their sensitivity to travel distance and their taste for product newness. In addition, I find a strong positive correlation between these two values.

I hypothesize that the firm exploits the positive correlation between consumer travel sensitivity and taste for new products by selling older products in its outlet stores. I test this notion by setting the correlation to zero and simulating the corresponding purchase behavior. I find that the resulting advantage to operating outlet stores is diminished, owing to the fact that outlet stores would cannibalize a larger portion of regular store revenues.

To better characterize the consumer's choice set in the absence of outlet stores, I build a supply model in which the firm optimally sets prices and product introduction rates given store locations. While prices can be adequately modeled using a standard monopoly pricing assumption, modeling the firm's product choice presents a nontrivial challenge. I address the problem by developing a probabilistic model of product choice. Rather than requiring the firm to choose characteristics individually for hundreds of products, I describe the firm's choice set in terms of a joint probability

distribution of characteristics. The firm's problem can then be reduced to choosing the parameters of this distribution. Since product ages are of particular importance to consumers, I focus on the firm's choice of the rate of product introductions and reassignment to outlets, which are arguably the components of product quality over which the firm has the highest degree of control.

I find that the firm is able to serve a much narrower range of consumers in the absence of outlet stores. With only its regular distribution channel available, the firm would expand its regular retail audience by lowering prices and the rate of product introduction (and hence the average age) of its products, but would be unable to attain the same level of coverage without the geographic differentiation enabled by outlets. This reveals an additional benefit of having outlet stores: they enable the firm to increase its rate of product introduction in the regular format. I find that the firm introduces 16% more new styles with dual distribution than with only regular stores. This result implies that the existence of outlet stores may enable firms to improve quality in their regular channels, thus counteracting brand dilution effects.

The paper proceeds as follows. I review the related literature in Section 2. In Section 3, I describe the data. In Section 4, I provide preliminary evidence of how outlet stores work. In Section 5, I describe the demand model I use to estimate preferences, discuss the estimation procedure, and present the estimates. In Section 6, I describe the supply model I use to represent firm product choice, and present the implied marginal and product development costs. In Section 7, I perform policy simulations that highlight the benefit of operating outlet stores. Section 8 concludes.

2. Related Literature

Prior research puts forth several theories about why firms sell goods through outlet stores. Deneckere and McAfee (1996) derive conditions under which a firm would damage or "crimp" a portion of its goods to increase profits by expanding its market coverage, and offer outlet stores as an example of such a damaged goods strategy. Coughlan and Soberman (2005) show that dual distribution (i.e., having both regular and outlet stores) is more profitable than single channel distribution when the range of service sensitivity is low relative to the range of price sensitivity. Qian et al. (2013) show that the opening of an outlet store had substantial positive spillovers for a retailer's catalog and online channels, whereas Soysal and Krishnamurthi (2016) show that regular physical channels experience these benefits as well. My work complements this literature by applying insights from multidimensional screening in assessing the relevance to dual distribution of consumer travel costs and taste for quality.

Additionally, I show how having outlet stores impacts overall product assortment.

More generally, this paper offers a new point of view on how product lines should be designed to effectively segment consumers. Previous work on product line design has explored the benefits of broadening product lines (Kekre and Srinivasan 1990, Bayus and Putsis 1999), methods for selecting optimal product lines (Moorthy 1984, Green and Krieger 1985, McBride and Zufryden 1988, Dobson and Kalish 1988, Netessine and Taylor 2007), cannibalization between product lines (Desai 2001), pricing (Reibstein and Gatignon 1984, Draganska and Jain 2006), and the effects on brand equity of product line extensions (Randall et al. 1998). My paper contributes to this body of work by demonstrating the importance of correlations in consumer tastes in making product line decisions. It also shows how cannibalization can be mitigated by appropriately combining product line attributes.

I develop an explicit model of product line choice that corresponds to the institutional details of the fashion goods industry. The large number of products in each product line poses a particular challenge. While existing work has modeled endogenous product choice for a single multidimensional good (Fan 2010) or for several single-dimensional goods (Draganska et al. 2009, Crawford et al. 2011), none has addressed the product choice problem of a firm with several multidimensional products. I introduce a simple and tractable method of describing this choice. Modeling the firm as choosing the parameters of a distribution of product characteristics, rather than the characteristics that make up each individual product, dramatically reduces the number of choice variables for the firm. It is also a more realistic representation of decision making in many sectors.

This paper's central premise is that the choice of whether to open outlet stores and what to stock them with is a type of multidimensional screening problem. Empirical models of multidimensional product choice are particularly useful because they can be used to complement lessons from theoretical work in multidimensional screening. The obstacles to obtaining general results in multidimensional screening are well documented by Rochet and Stole (2003). Full solutions to this problem are available for the discrete two-type case (Armstrong and Rochet 1999) and other cases for which the form of consumer heterogeneity is severely restricted (e.g., Armstrong 1996). It is difficult to see how these models' predictions would manifest in actual product decisions, such as those in my empirical setting. By using empirical models that are not anchored to any particular screening model, I am able to provide evidence for the applicability of existing results to real-world settings and the significance of multidimensional screening for firms in general.

3. Data and Industry Background

The first outlet stores appeared in the United States in the 1930s. These stores were attached to factories and sold overruns, irregulars, and slightly damaged goods. Outlet stores initially catered to only the firm's employees, but the stores' market audience quickly expanded to include regular consumers. Until the 1970s, firms continued to use outlet stores primarily to dispose of excess inventory, even as they began to be established independently of manufacturing centers (Coughlan and Soberman 2004).

The modern outlet store has evolved into a considerably different format from its earlier incarnations. In many ways, outlet store goods now constitute distinct product lines, rather than mere excess inventory. Many firms design products exclusively for sale in outlet stores (though they may prefer to limit awareness of the practice among consumers). Revenues from outlet stores often rival, and sometimes exceed, revenues from a firm's regular retail formats.

One feature of the outlet store that remains unchanged is its distance from central shopping districts. In fact, an entire industry of outlet mall operators owes its existence to the prevalence of this selling strategy among clothing and fashion goods retailers. The practice of selling goods in hard-to-access locations would seem curious were it not so common. Yet many firms choose not to sell through outlet stores; adoption is variable even within narrowly defined categories. For instance, premium apparel brands Brooks Brothers, Hugo Boss, and Ralph Lauren have several outlet store locations, but Chanel, Burberry, and Zegna have few or none.

Data for this project are provided by a major fashion manufacturer and retailer based in the United States. The firm's main product line belongs to a category that generates annual revenues of about \$9 billion in the United States. The firm is the market leader, with between 30% and 40% market share. About 60% of the firm's revenues are sourced from sales of its main product line. The data used for this study consists of transaction-level records from July 2006 to March 2011. The sample includes all purchases of products made by U.S. consumers in firm-operated channels. Excluded from this sample are online and department store transactions, which according to the firm's managers accounted for less than 10% of the total revenue.

The firm is able to track repeat purchase behavior by consumers. Available information on consumers includes their billing zip codes, date of first purchase within the brand, and their total lifetime expenditures on the firm's products. Each record contains detailed information on the consumer, the product, and the store. Product attributes include color, silhouette, materials, collection, release date, and a code that

Table 1. Data Set Summary Statistics

Sample duration	July 2, 2006–March 13, 2011
Number of unique consumers	16,019,140
Number of unique transactions	27,532,116
Number of units sold	80,020,960
of which main category	28,581,504
of which out of outlet store	53,947,984

uniquely identifies each style. Store attributes include their location, weekly foot traffic, and format type.

For the analysis in this paper, I focus on main category purchases in physical stores. While this excludes a considerable number of nonmain category purchases, those observations are used to proxy for the number of consumers who visit a store but do not make a purchase in the main category. Table 1 lists summary statistics of the data set.

The firm's overall distribution strategy is fairly common among brands with outlet store locations. The firm introduces most of its new products in its regular stores, which are located in central shopping districts. After a few months, these products are removed from the regular stores and transferred to the outlet stores. The firm also produces styles that are sold exclusively in outlet stores.

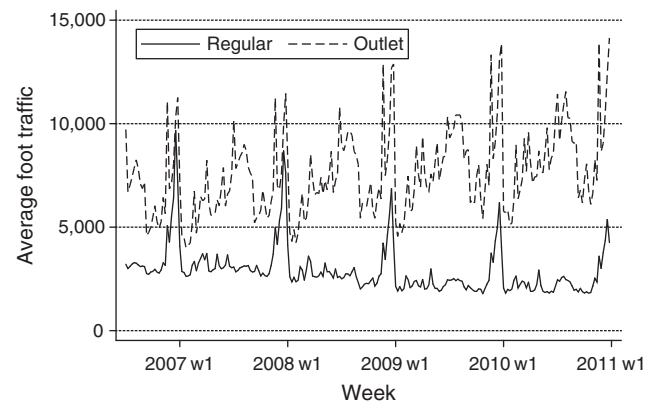
Table 2 summarizes the differences between the firm's two store formats. The most obvious difference is price: the typical product goes for about \$300 in regular retail stores, while most outlet store products sell for less than half that. Outlet stores are also bigger than regular retail stores in terms of square footage and the number of styles on the shelf; however, each market is typically served by several regular retail stores and a single outlet store. Figure 1 shows average weekly foot traffic according to format type over time; the pattern has the expected seasonality as well as a downward trend that corresponds to the opening of more outlet stores than regular stores during the sample period.

Table 2. Average Store Characteristics

Store format	Regular	Std. dev.	Outlet	Std. dev.
Transacted price	298.14	108.03	125.45	44.31
Number of styles on shelf ^a	87.11	27.22	223.51	69.19
% premium material ^b	21.22	40.88	18.48	38.82
% basic material	8.61	28.05	5.35	22.50
Months since product intro	5.36	13.63	7.27	15.60
Weekly foot traffic	2,845.19	2,219.42	7,677.44	5,763.83

^aInformation on stocking is unavailable. Throughout the paper, a style is assumed to be available for purchase during a period if and only if it is observed as purchased during that period. The polling frequency used is monthly.

^b"Premium" and "basic" materials correspond exactly to the two most common values in the corresponding product-specific data field. Actual material names are omitted to prevent identification of the product category.

Figure 1. Average Weekly Foot Traffic

The composition of available product choices in the two formats do not differ greatly according to stylistic characteristics. Most products are made of either a basic or a premium material and the two formats carry about the same percent of each type. Where the assortments do differ greatly is in product age—time that has elapsed since the products were introduced. A fashion good's age is likely an important determinant of its attractiveness in an industry that is marked by constant product updating.

4. Preliminary Evidence

In this section I use a descriptive analysis of the data to offer preliminary evidence of the value to the firm of having outlet stores. In each section, I provide model-free evidence that speaks to each of the three main possible purposes: inventory management, geographic segmentation, and consumer self-selection.

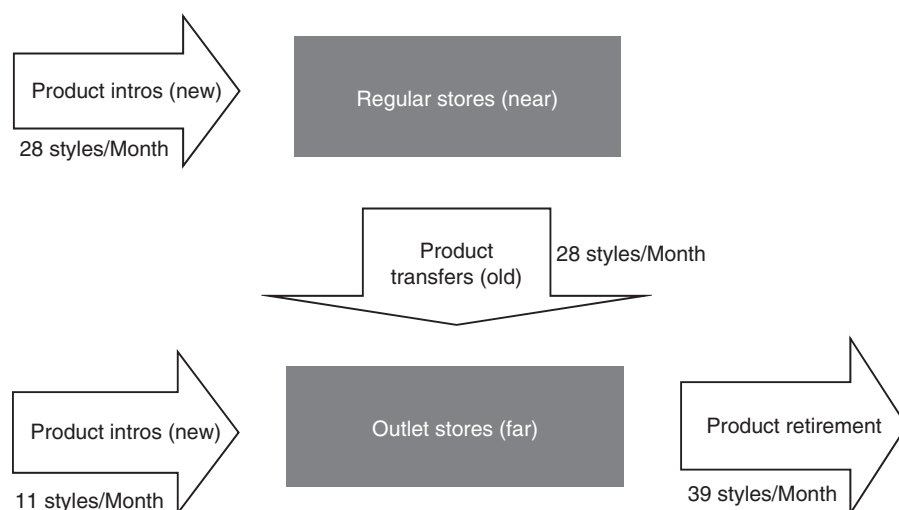
4.1. Inventory Management

I first consider the relevance of outlet stores in managing the firm's inventory: particularly the disposal of excess supply. This purpose is the historical basis for the emergence of outlet stores, and continues to be relevant for many firms.

At the most basic level, the firm manufactures two types of products, which I name *original* and *factory*. Original products are introduced in regular stores, and after a few months, taken out of regular stores and sold in outlet stores. Factory products are sold only in outlet stores. Figure 2 summarizes these flows. At any given point, an outlet store offers about as many original products as factory products. While original products are typically thought of as more desirable than factory products, anecdotal evidence suggests that consumers are seldom able to distinguish one from another, or are even aware of the distinction. Table 3 contains information on the flows of these product types.

Inspecting product flows alone suggests that the firm does not use outlet stores for the traditional purpose of

Figure 2. Product Flows



disposing excess inventory. First, it is not the firm’s policy to sell defective merchandise in either of its channels; these items are destroyed. Second, the firm manufactures a product line that is meant for exclusive sale in its outlet stores. Third, close to half of the units of each style that is introduced in regular stores are sold in outlet stores. This implies that the life of original products in outlet stores represents a deliberate aging strategy rather than a dump of excess inventory.

Another possibility relating to inventory management is that the firm faces uncertainty about the demand for each of its products and uses the outlet store as a dumping ground for original products that are revealed to have low demand after being introduced in the regular channel. I address this possibility by estimating product quality in Section 5 and find some support for this mechanism.

4.2. Geographic Segmentation

Given how the firm uses location to differentiate product lines, a natural hypothesis is that outlet stores are designed to segment consumers according to geography. Outlet stores are located in areas that have a lower population density and lower household income than the areas around regular stores.

Table 4(a) catalogues average consumer characteristics in each format that are observable in the data. The

averages are taken over all purchases in each format. Median household incomes by zip code from the 2010 American Community Survey are used to proxy for a consumer’s income. The consumer’s travel distance is the distance between centroids of the consumer’s billing zip code and the store’s zip code.

Noteworthy in Table 4(a) is the absence of an appreciable difference in observable characteristics between consumers who buy from the two formats. They resemble each other not only in income but also in their level of experience with the firm’s products. The difference in travel distance reflects the fact that consumers in both formats live in the same areas, but must travel farther to access outlet stores.

Table 4(a). Average Consumer Characteristics

Store format	Regular	Outlet
Annual income	71,231 (27,780)	65,226 (23,670)
Years since first purchase	2.51 (3.40)	2.25 (3.08)
Lifetime expenditures on brand	4,071 (12,757)	2,475 (11,425)
Travel distance	9.53 (8.49)	20.44 (15.65)

Note. Standard deviations are in parentheses.

Table 3. Inventory Flows

Product type	Original goods	Factory goods
Average styles introduced per year	336	132
Average months sold in regular format	10.32	N/A
Average months sold in outlet format	6.97	11.03
Average total units per style sold in regular format	3,103	N/A
Average total units per style sold in outlet format	2,707	12,725
Average composition of styles in outlet format (%)	42.71	57.29

Table 4(b). Consumer Behavior

	Only regular store	Only outlet store	Multihome
Share (%)	13.2	56.8	30.0
Outlet closer (%)	7.0	29.5	15.3
Average income (\$)	73,489	64,554	69,294

Table 5. Average Market Characteristics

	Mean	Std. dev.
Number of regular stores	1.96	3.52
Number of outlet stores	0.66	0.66
Market size (No. of consumers)	92,870.51	186,769.80

Note. A market is a CBSA-month.

An alternative way of thinking about different classes of consumers is presented in Table 4(b). In this table, I consider consumers who have made at least two purchases in the sample and group them according to the store formats at which they made the transactions. Consumers either shopped exclusively at one format, or at both formats. *Share* refers to what percent of all consumers belongs to each class. *Outlet closer* is the percent of each class of consumers for whom the closest store is an outlet. The main takeaway from Table 4(b) is that even within the class of consumers who shop exclusively at outlet stores, 70.5% live closer to regular stores.

I take a core-based statistical area (CBSA) to be a reasonable geographic market definition.⁴ I choose months as a temporal market definition. While perhaps a shorter time period than actual consumers take to return to the market, rapidly changing choice sets necessitate a tightly defined market period. Table 5 has descriptive statistics for the average market according to my definition.

By inspecting the data alone, it can reasonably be inferred that geographic market segmentation is not a driver of the outlet store strategy. The two store formats serve shoppers from nearly identical locations, and often attract the same consumers. This leaves one last hypothesis to consider: that the firm's selling strategy is designed to implement price discrimination through consumer self-selection.⁵

4.3. Consumer Self-Selection

This paper focuses on illustrating how outlet stores induce a segment of consumers to travel for discounts. While, as Tables 4(a) and 4(b) show, consumers do not differ markedly in their observable attributes by format choice, this does not preclude them from differing in their preferences. In Section 5, I lay out a demand model that permits heterogeneity in unobserved consumer tastes. Among other uses, estimation of the model's parameters will allow me to better characterize the differences between regular store and outlet store shoppers. This step illustrates how the firm's selling strategy achieves a sorting of consumers according to their preferences.

5. Demand

I present a model of consumer demand that describes store and product choice. I proceed to discuss how

I estimate model parameters using transaction data from the firm. Finally, I present the results of demand estimation and discuss what they imply about the function of outlet stores as a tool for price discrimination.

Demand model. Since the typical consumer chooses between multiple store locations, it is natural to think of her purchase decision as consisting of a store choice followed by a product choice. Conditional on her store choice, the indirect utility that a consumer i derives from purchasing product j at store k in month t is

$$u_{ijkt} = (1 + \gamma \times \text{outlet}_k \times \text{original}_j) \xi_j - (\alpha + \zeta_i) p_{jt} - (\beta + \eta_i) \text{age}_{jt} + \sum_{m=2}^{12} \delta_m m_t + \epsilon_{ijkt}. \quad (1)$$

That is, her utility is determined by the following: the intrinsic quality of the product, ξ_j ; the product's price p_{jt} ; time that has elapsed since the product was first introduced, denoted by age_{jt} ; outlet store dummy outlet_k ; original product dummy original_j ; month dummies m_t ; and an idiosyncratic demand shock ϵ_{ijkt} . I allow for quality perceptions of original products to adjust by a factor of γ when stocked in an outlet store. I assume that consumers vary in their price sensitivity according to deviations ζ_i from the mean level α , and in their taste for new products according to deviations η_i from the mean level β . Utility from the outside good is normalized to $u_{i0kt} = \epsilon_{i0kt}$. I also assume that ϵ_{ijkt} is i.i.d. type-I extreme value.

At the store, the consumer chooses the product that gives her the highest utility.⁶ Given the distributional assumption on ϵ_{ijkt} , this implies that the expected utility consumer i derives from a store k 's product assortment in period t , J_{kt} is the inclusive value

$$IV_{ikt} = \log \left(\sum_{h \in J_{kt}} \exp \left((1 + \gamma \times \text{outlet}_k \times \text{original}_h) \xi_h - (\alpha + \zeta_i) p_{ht} - (\beta + \eta_i) \text{age}_{ht} + \sum_{m=2}^{12} \delta_m m_t \right) \right). \quad (2)$$

Consumers choose which store to visit based on store characteristics in addition to their expected utility from the available products. Consumer i 's utility from visiting store k is

$$\tilde{u}_{ikt} = \tilde{\xi}_k + \lambda IV_{ikt} + \psi_{ikt} - (\gamma + v_i) \text{distance}_{ik} + \sum_{m=2}^{12} \tilde{\delta}_m m_t + \tilde{\epsilon}_{ikt}. \quad (3)$$

A desirable feature of the data is that each consumer's billing zip code is observed, allowing for a focus on the role of travel distance in consumer choices. In addition, I allow for individual deviations v_i from the mean level of sensitivity to travel γ . The parameter λ governs substitution patterns between products and stores

by indicating the correlation in unobserved product characteristics within each store. The fixed effect $\tilde{\xi}_k$ captures the attractiveness of features of store k that are unrelated to the products within it or its distance from consumers. I include month dummies in the store choice level of demand in addition to those in the product choice level.⁷ I normalize utility from no store visit to $\tilde{u}_{i0t} = \tilde{\epsilon}_{i0t}$ and again assume that $\tilde{\epsilon}_{ikt}$ is i.i.d. type-I extreme value.

I account for imperfect information on store and product attributes with a mean-zero shock $\psi_{ikt} \sim N(0, \sigma_{\psi_{ikt}})$, where $\sigma_{\psi_{ikt}} = X_{ikt}\beta_{\psi}$ is a linear combination of store- and shopper-specific attributes: an outlet store dummy, travel distance, and time since store opening.⁸ I choose this functional form and these covariates based on data availability and computational tractability. The true form of shopper uncertainty is likely to be more complex, with information depending on various reference points (such as competitors' offerings, prior exposure, and advertising messages), varying over attributes, and decaying over time.⁹ I find that within the current model specification, accounting for individual-level heterogeneity in shopping experience does not significantly affect the degree of uncertainty (see Appendix E).

The distributional assumptions on ϵ_{ijkt} and $\tilde{\epsilon}_{ikt}$ above imply that the probability that consumer i purchases product j in store k is

$$P_{it}(j_k) = P_{it}(j | k)P_{it}(k) \quad (4)$$

$$= \frac{\exp(u_{ijkt} - \epsilon_{ijkt})}{1 + \sum_{h \in J_{kt}} \exp(u_{ihkt} - \epsilon_{ihkt})} \times \frac{\exp(\tilde{u}_{ikt} - \tilde{\epsilon}_{ikt})}{1 + \sum_{l \in K_i} \exp(\tilde{u}_{ilt} - \tilde{\epsilon}_{ilt})}, \quad (5)$$

where K_i is the set of stores in consumer i 's market.

I further assume that $\zeta_i \sim N(0, \sigma)$ and $[\eta_i \ v_i]' \sim N(0, \Sigma)$. This allows for an arbitrary correlation between sensitivity to travel and taste for new products. Correlations between these values and price sensitivity are restricted to zero. This restriction is made (i) to correspond with analytical models of multi-dimensional screening, e.g., that in Armstrong and Rochet (1999), and (ii) to allow for sharper counterfactual simulations.¹⁰

Note that, based on the specified model and the granularity of the data, consumers are identical up to their billing zip codes. Consequently, the predicted market share of product j in store k at the zip code z where consumer i resides is

$$s_{zt}(j_k) = \int_i P_{it}(j_k) df(\eta_i, v_i, \psi_{ikt}; \sigma, \Sigma, \sigma_{\psi_{ikt}}), \quad (6)$$

where f is a multivariate normal probability density function.

Let n_{zjkt} be the number of consumers in zip code z that purchase product j at store k in month t . The

log-likelihood function given a set of parameter values and fixed effects $\Theta = (\alpha, \beta, \gamma, \lambda, \sigma, \Sigma, \sigma_{\psi_{ikt}}, \{\xi_j\}, \{\tilde{\xi}_k\}, \{\delta_m\}, \{\tilde{\delta}_m\})$ is

$$l(\Theta) = \sum_t \sum_{k \in K_z} \sum_{j \in J_{kt}} \sum_z n_{zjkt} \log s_{zt}(j_k), \quad (7)$$

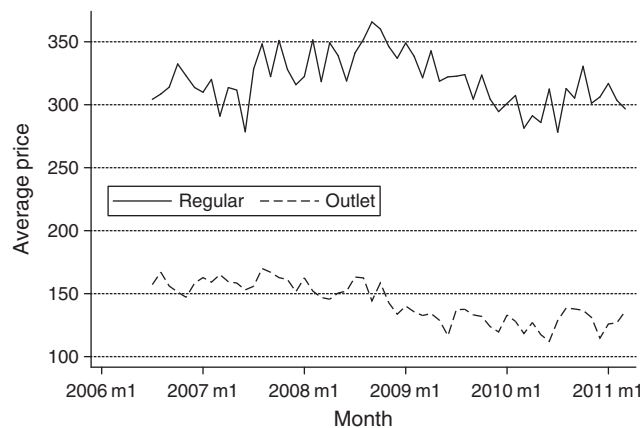
where K_z is the set of stores geographically accessible from zip code z .

Market sizes and outside options. For estimation purposes, the market size for each zip code is the total number of unique consumers who made a purchase within the entire sample. The assumption is that consumers who do not make any purchases within the five-year period are not part of the market. If a consumer purchases a nonmain category product from store k , then she is counted as visiting store k and choosing the outside option. If a consumer is not observed during a period, then she is counted as not having visited a store.

Since store visits that do not result in any purchase are not observed, there is a possibility that estimated store fixed effects may be biased. However, the available data suggest that this bias may be limited. To the extent that nonmain category purchases are proportional to true nonpurchase store visits, the rates are similar between formats: 32.2% of purchases in regular stores and 36.7% in outlet stores are nonmain category.

Identification. The firm's pricing practices allow for the consistent estimation of α and σ without the use of instrumental variables. To begin, the firm implements a national pricing regime, thereby eliminating any systematic pricing differences between markets. Within-product variation in prices is generated by two sources. The first is randomly implemented storewide promotions. These typically take the form of discounts that apply to all of the products in-store.¹¹ The second is a general marking down of products over time. While all products exhibit a downward trend in price, the shape of this trend differs markedly between products, with many exhibiting a nonmonotonic pattern. It is also helpful that the firm does not adopt seasonal discounting; as seen in Figure 3 average prices are mostly flat through the year. Table 6 shows through a projection of prices on product fixed effects, an outlet dummy, month dummies, and age that most of the variation in prices is accounted for by the included variables, while the leftover variation falls within the scope of the randomized promotions.

The inclusion of product and store fixed effects in the estimation absorbs all unobserved quality differences between products and stores outside of age and distance. This also addresses potential endogeneity concerns with respect to the assignment of products to particular stores.

Figure 3. Average Monthly Prices by Channel

Although outlet stores have older products on average than regular stores, the large number of stock-keeping units (SKUs) in each channel and the wide variation in product introduction dates within each channel allows for the identification of the full covariance matrix Σ of tastes for travel distance and product newness. As illustrated in Figures 4 and 5, there are at all times very new and very old products in either channel; the assortment allows for the full range of covariance to be estimated depending on the realized market shares.¹²

Table 7(a) outlines the result of the estimation procedure. All estimated coefficients have the expected sign: higher prices, older ages, and farther distances adversely affect utility. The Choleski decomposition of covariance matrix Σ is precisely estimated and implies a large variance in travel sensitivity and taste for new products. The estimates indicate a high correlation between travel sensitivity and taste for new products: consumers who highly dislike traveling also dislike buying old merchandise.¹³

An interpretation of the estimated coefficients for price, age, and distance is that the average consumer would have to be compensated roughly \$100 to maintain her level of utility given a one-year increase in the age of a product or a 20-mile increase in travel distance. The λ estimate implies a moderate correlation in demand shocks within each store.

Table 6. Pricing Equation

Variable	Coefficient	Std. dev.
Constant	6.90	0.47
Outlet	−0.34	0.0071
log(age)	−0.53	0.012
Depvar	log(price)	
Product FE	Yes	
Month FE	Yes	
R ²	0.9089	

Estimates of the utility uncertainty term $\sigma_{\psi_{ikt}}$ suggest a significant role for imperfect information in store choice. Perturbations around the perfect-information expected utility are higher for outlet stores than for regular stores, and for stores that are farther away from the shopper. Time since store opening, meanwhile, does not appear to mitigate imperfect information.

Market segmentation. Estimating the underlying parameters of consumer preference allows for a description of consumers based on unobservable characteristics. Here I use the estimates to expound on the differences between consumers who buy goods from regular stores and those who buy goods from the outlet stores. I do this by using my demand model to predict purchase behavior given the available products for different types of consumers. Recall that consumers and their choices differ in multiple ways: (1) within each market, they vary by home zip code and thus perceive relative travel distances differently, (2) store availability and assortment differ between markets, and (3) consumers in all locations differ in their travel sensitivity and taste for new products.

Table 7(b) augments the information in Table 4(a) through demand estimation. Consumer values are computed by predicting purchase behavior for all consumers given estimated parameters, then backing out average values according to predicted purchase instance by format. Whereas the data show that consumers do not significantly differ by income and other purchase behavior depending on which format they choose, estimation reveals that they differ greatly in travel sensitivity and taste for new products.

The analysis in this section provides supportive evidence that through the firm's outlet store strategy, it segments consumers according to their underlying preferences for travel and newness. Discounts in outlet stores seem deep enough to cater to lower-value consumers, but not enough to cater to consumers who place a high premium on convenience and new arrivals.

A complete argument for these conclusions requires studying counterfactual store configurations and the associated consumer responses. The natural counterfactual scenario is one in which the firm chooses not to open locations in outlet malls. It would be insufficient, however, to simply remove these locations from the data and simulate purchase behavior. The firm would presumably charge different prices in its regular stores in the absence of outlet stores. Since outlet stores form an integral part of the firm's distribution strategy, removing them would also motivate changes in how the firm stocks its regular stores.

Section 6 provides a framework for thinking about how the firm chooses prices and product assortments given its dual distribution strategy. The purpose of

Figure 4. Product Age Densities in Regular Format

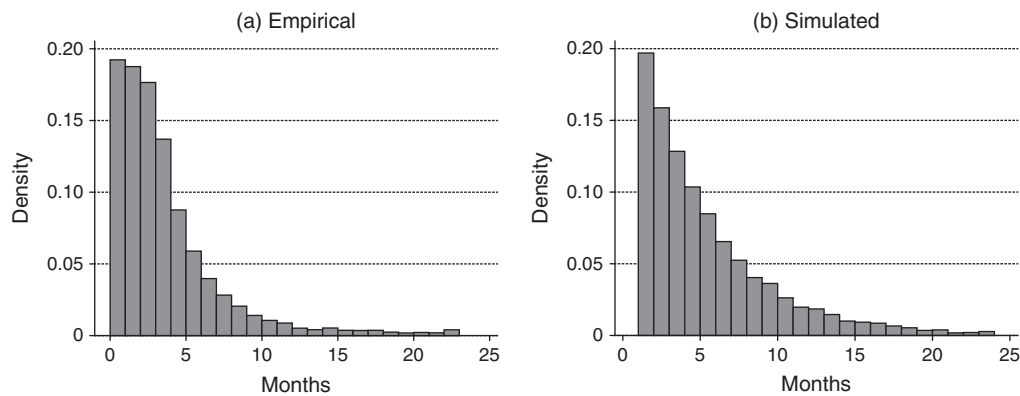


Figure 5. Product Age Densities in Outlet Format

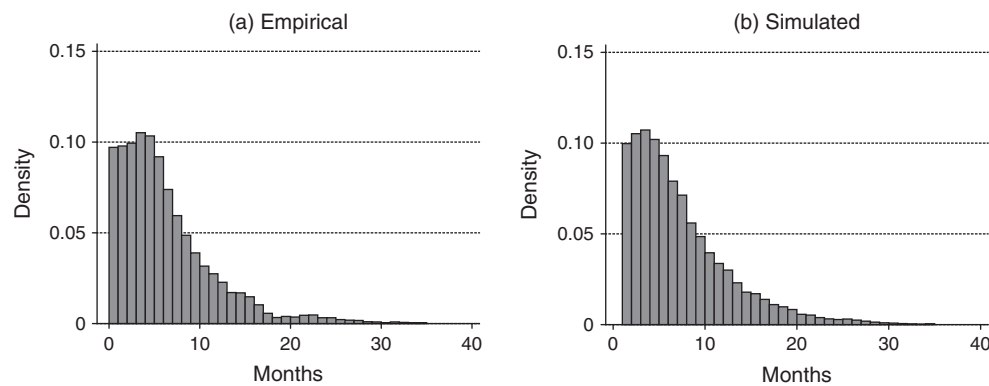


Table 7(a). Demand Estimates

	Coeff.	SE
Product level		
Price	-2.644	0.782
σ_{price}	0.353	0.128
Age	-2.205	0.555
Outlet decay (γ)	-0.140	0.020
Store level		
$IV(\lambda)$	0.579	0.214
Distance	-1.217	0.098
Store utility uncertainty $\sigma_{\psi_{ikt}}$		
Outlet dummy	0.327	0.185
Distance	0.034	0.022
Time since store opening	0.036	0.183
chol(Σ)		
(1,1)	0.859	0.329
(2,1)	0.620	0.208
(2,2)	0.028	0.012
Implied covariances		
σ_{age}	0.859	
σ_{dist}	0.621	
$\rho_{\text{age,dist}}$	0.730	
$N(\text{observations})$	7,302,841	
$N(\text{product fixed effects})$	4,626	
$N(\text{store fixed effects})$	500	
$N(\text{month fixed effects})$	11	
Log-likelihood	1,749.54	

Table 7(b). Market Segmentation by Consumer Tastes

Consumer values (\$)	Regular stores	Outlet stores
20-mile travel distance increase	73.10 (14.64)	33.74 (13.05)
One-year product age increase	50.89 (16.99)	31.23 (14.86)

Notes. This table lists consumer values in dollars for changes in store and product attributes. Standard deviations are in parentheses.

modeling supply is to form a basis, together with the demand model, for predicting firm performance given a counterfactual distribution strategy.

6. Supply

In this section I develop a model of firm behavior with respect to price-setting and product assortment choice. This model permits a careful comparison of firm performance under counterfactual consumer characteristics and alternative distribution strategies, and hence sheds light on the profitability of outlet stores. This also allows an examination of the firm's costs, which serve as both a basis for the policy simulations and an indicator of the validity of the model's assumptions.

Two major assumptions are maintained throughout this section. The first is that the firm behaves like a

monopolist, setting prices and product characteristics without strategic considerations. The second is that the firm's prices and product choices maximize profits conditional on store locations. I discuss each of these assumptions before describing the model.

The monopoly assumption is motivated by the firm's unique position in the industry. It has a 30%–40% share of total industry revenues, and an even larger share in its particular psychographic segment. The next largest brand accounts for about 10% of industry revenues. Their products, however, retail at about the \$1,000 price point—much higher than the data provider's average price of \$300. There is arguably little overlap between the market for the data provider's products and the market for higher-end products such as those carried by the number two brand.¹⁴

The firm's dominant position also motivates the assumption that the firm is profit maximizing. There may be very few firms for which this is a more appropriate assumption to make, given the firm's reputation not only in its category but also across industries. The firm consistently ranks among the top 10 firms across all industries in revenue per square foot of retail space, which is a standard performance metric among retailers.

I categorize firm decisions according to long- and short-term horizons. Long-term decisions concern store locations, stylistic product characteristics, and store capacities. Short-term decisions consist of pricing and the choice of product introduction rates. In my supply model, I take the firm's long-term decisions as exogenous, and treat the short-term decisions as endogenous.

I now proceed to describe the supply model in detail. First I discuss pricing. The monopoly pricing assumption, combined with the previous section's demand model, implies marginal costs for each product. I show how these marginal costs relate to observed product characteristics. Next I add endogenous product choice. The added features, combined with the pricing and demand models, pin down product development costs.

Prices. The firm sets prices in each period to maximize profit given store locations and product characteristics. The firm's profit function, conditional on product characteristics, is

$$\pi(\mathbf{p}_t) = \sum_{z,t} \left(M_z \sum_{k \in K_z} \sum_{j \in J_{kt}} s_{zt}(j_k) (p_{jt} - mc_{jt}) \right). \quad (8)$$

That is, per-product (j) profit in each zip code z and month t is price p_{jt} minus marginal cost mc_{jt} times quantity sold $M_z s_{zt}(j_k)$, where M_z is market size and $s_{zt}(j_k)$ is market share as determined by Equation (6). Total profit is the sum over all products, periods, and geographical markets, where the set of products in each store is J_{kt} and the set of stores assigned to each zip

code is K_z . Profit-maximizing prices satisfy the first-order conditions

$$\frac{d\pi}{dp_{ht}} = \sum_{z,t} M_z \sum_{k|h \in J_{kt}} \left(s_{zt}(h_k) + \sum_{j \in J_{kt}} \frac{\partial s_{zt}(j_k)}{\partial p_{ht}} (p_{jt} - mc_{jt}) \right) = 0, \quad (9)$$

for each product h and month t . Rewriting the conditions for each period (and suppressing time subscripts) as $\mathbf{s} + \Delta(\mathbf{p} - \mathbf{mc}) = 0$, where $\mathbf{s}_j = \sum_z \sum_{k|h \in J_{kt}} M_z s_{zt}(j_k)$ and $\Delta_{h,j} = \sum_z \sum_{k|h \in J_{kt}} (\partial s_{zt}(j_k) / \partial p_h)$, the marginal cost of each product in a given period is exactly identified using estimated demand coefficients

$$\mathbf{mc} = \mathbf{p} + \Delta^{-1} \mathbf{s}. \quad (10)$$

I use Equation (10) to compute marginal costs for each product. Recall that observed prices are “contaminated” by randomized promotions, which conceivably cause departures from strict profit maximization. I make the operational assumption that the estimated parameters in Table 6 are profit-maximizing choices by the firm. I use the pricing equation from Table 6 to find predicted prices for each product, which I interpret as the fully endogenous component of prices that adheres to profit maximization. These are the prices I use to compute marginal costs for each period.

For descriptive purposes I project these marginal costs linearly onto product characteristics, and present the coefficients in Table 8.¹⁵ Product characteristics include material dummies and silhouette (shape) dummies, ordered by size from the smallest silhouette 1 to the largest silhouette 8. The implied average marginal cost over all products closely resembles figures from industry reports and suggestions from the firm's executives. The estimated relationships between characteristics and marginal cost are also sensible: premium material costs more than basic, and larger silhouettes tend to cost more to manufacture than smaller ones. This provides an indication of the validity of the pricing equation.

Table 8. Marginal Cost Estimates

Characteristic	Coefficient	SE
Constant	44.04	13.82
Premium material	21.39	11.54
Basic material	−9.53	0.26
Silhouette 1	−13.59	7.26
Silhouette 2	−22.71	13.90
Silhouette 3	0.94	6.75
Silhouette 4	−5.56	2.93
Silhouette 5	−6.83	0.63
Silhouette 6	24.85	10.73
Silhouette 7	22.84	3.66
Silhouette 8	26.29	8.57
OLS depvar		Mcost
N		848
R^2		0.46

Product choice. The overall product design process is exceptionally complex for firms that produce fashion goods. There is an expansive number of dimensions to determine for each of a huge number of products to generate periodically. It is infeasible to model product choice as it applies to every individual good. This necessitates a means of drastically reducing the number of choice variables for the firm while focusing on the most relevant decisions to the research question.

An important dimension of product choice for the firm that is salient to studying the outlet store strategy is that of product lifespans in each format. By lifespan, I mean the amount of time a product is available for purchase in each format. Figure 2 shows how product lifespans are determined by the flow of inventory into, between, and out of store formats. New products flow into both formats when “original” and “factory” products are born (see Table 3). All products in the regular store are eventually transferred to the outlet store, where the last units of each style are sold.

One advantage of using the current data set to study firm product choice is that the outlet store strategy provides a structure that delimits the firm’s choice set. The technology that the firm uses to create product age-distance combinations—physically transferring products between formats—is completely transparent and can mostly be considered cost neutral. This is in contrast to most other cases, where both product assembly technologies and cost structures are more complex.

Although the number of new products in each format can conceivably be modeled using existing techniques, the selection of which products to transfer or discontinue presents a different challenge. Because the firm offers such a large number of products, an attractive option is to think of the firm as targeting a joint probability of product characteristics rather than individual product attributes. A primary contribution of this paper is a demonstration of this novel approach to modeling multidimensional product differentiation.

Specifically, I assume that store locations and capacities are given. Let C_k be the number of items that store k can display on its shelves. I assume that in each period, each store k of format $f_{mt} \in \{\text{regular}, \text{outlet}\}$ takes C_k draws from the corresponding master set of products, described by the distribution of product characteristics $\phi_{f_{mt}}$. Let $\phi_{f_{mt}} = f_{f_{mt}} \times g_{f_{mt}}$, where $f_{f_{mt}}$ is the distribution of endogenous product characteristics (product ages in this setting) and $g_{f_{mt}}$ governs the exogenous characteristics (summarized here by ξ_j).¹⁶ The firm’s objective is to choose the profit-maximizing shapes of f_{regular} and f_{outlet} .

To make this problem tractable, I propose to construct $f_{f_{mt}}$ using a set of parametric distributions. Industry logistics and the data suggest a natural choice

for these distributions and a direct interpretation of their parameters. Consider these assumptions on product assortment:

1. Original products in the regular format have an average probability x of being transferred to the outlet format in the next period.

2. Factory products in the outlet format have an average probability y of being retired in the next period.

3. Original products in the outlet format have an average probability z of being retired in the next period.

4. Factory goods make up a proportion α of goods in the outlet format.

These assumptions imply that if X is product age in the regular format and Y is product age in the outlet format then

$$X \sim \text{Geometric}(x), \quad (11)$$

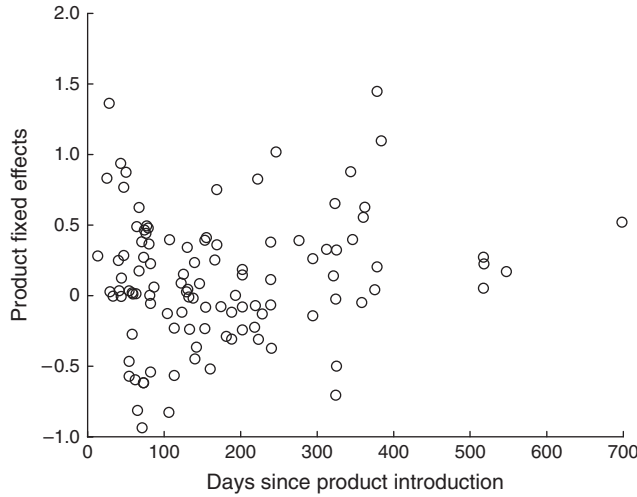
$$Y = \begin{cases} W & \text{with probability } \alpha, \\ X + Z & \text{with probability } 1 - \alpha, \end{cases} \quad (12)$$

where $W \sim \text{Geometric}(y)$ and $Z \sim \text{Geometric}(z)$.

By adjusting the stopping probabilities x , y , and z , the firm can control the relative distributions of product age in each store format. These probabilities also pin down the portion of products that are new introductions in each period: the share of original products that are newly introduced in a period is simply x and the share of new factory products is y . Figures 4 and 5 illustrate how closely this parameterization resembles the observed distribution of product characteristics. The simulated densities (right) are generated using moments of the empirical densities (left).

Original products in the regular format are not transferred to outlet stores at random. Products that perform better in sales, and thus are presumably of higher quality, have longer lifespans in regular stores. Figure 6 plots ξ_j against age_{jt} for the regular store offerings in a representative market, which serves as the test market in Section 7. In the language of the exposition above, the distribution of endogenous characteristics f_{regular} is dependent on that of exogenous characteristics g_{regular} . I keep the form of this dependence fixed by allowing the firm to adjust the speed of product turnover but not the order by which products are transferred according to their ξ_j .

The preceding assumptions on the distribution of product characteristics are made both for convenience and realism. Convenience arises from the small number of parameters that govern the joint distribution, and from the fact that these parameters relate directly to product ages, whereas store locations are held fixed. For the same reasons the modeling choices are realistic, since product differences between formats are made at senior management levels, while store locations are

Figure 6. Better Products Are Longer Lived in Regular Stores

much less flexible than product characteristics over the short to medium terms. At the same time the specification is general enough to allow for the counterintuitive case in which outlet stores have newer products on average.

Adjusting the restocking probabilities, and consequently the rate of new product introduction, has implications on per-period costs. Assuming that the firm chooses to maintain a fixed number of products in its universal offer set (i.e., the set from which store k draws C_k products), the cost per period $C(x, y)$ of implementing a given age distribution must depend on the number of new product introductions it requires. I use a linear function¹⁷

$$C(x, y) = ax + by \quad (13)$$

to represent these costs.

I assume that the firm chooses product choice parameters x , y , z , and α once to maximize expected profit

$$\begin{aligned} E(\pi | x, y, z, \alpha, \mathbf{p}_t) \\ = \sum_{f_{mt}} \int \sum_{z,t} M_z \sum_k \sum_{j \in J_{kt}} s_{zt}(j_k) \\ \cdot (p_{jt} - mc_{jt}) df_{mt}(x, y, z, \alpha) - C(x, y), \end{aligned} \quad (14)$$

where \mathbf{p}_t is a vector of optimal prices for any realization of product characteristics.

This allows me to identify cost parameters a and b exactly through the first-order conditions of profit maximization: $\partial E(\pi)/\partial x = \partial E(\pi)/\partial y = 0$. I solve these equations numerically for a and b . For each perturbation around x and y , product age draws are taken from the implied distribution. I assign these draws to the actual products such that their ordering from newest to oldest is preserved. I present the implied product development costs in Table 9.

Table 9. Implied Product Development Costs

Product class	Parameter value	Average stock	Fixed cost per unit
Original (a)	7,276,180	151	48,187
Factory (b)	18,541,993	433	42,822

Before proceeding to discuss the fixed cost solutions, I describe how I compute the expected profit for perturbations around the observed x and y . First, I sort the C_k products according to age within each store k . This allows me to fix the dependence of the stocking priorities on ξ_j . Given stocking probabilities x and y , I make ns sets of C_k draws from the distributions specified in Equations (11) and (12).¹⁸ I replace the ages in the data with these draws, keeping the original order according to age constant. I then compute the average over corresponding profits for each of the ns draws.

The parameter values in Table 9 indicate the cost of replacing the entire stock of products, i.e., when $x = 1$ or $y = 1$.¹⁹ Dividing these values by the average stock of each class of product gives the fixed costs associated with developing each unit.²⁰ “Original” and “factory” products in Table 9 refer to product types and not to different formats, hence dividing by the average stock of each product type is consistent with the supply model. Although there are more original designs produced per period, there is more space allotted for factory products at outlet stores. Hence $b > a$ since it would cost the firm more to replace the entire stock every period. I find that producing each style of product carries a fixed cost of about \$50,000, and that the fixed cost of producing an original product is significantly higher than the fixed cost of a factory product.

With the model of price-setting and product introduction discussed in this section, together with the fixed and marginal costs that they imply, counterfactual store configurations can now be properly evaluated.

7. Policy Simulations

The basic question that this paper addresses is, Why do outlet stores exist? In this section, I explore this question by simulating situations in which the firm pursues selling strategies that exclude some aspect of outlet store retail. For each of these policy simulations, I use the supply side model in Section 6 to predict how the firm would change its pricing and product introduction rates in response to changes in other store attributes. The demand model from Section 5 then shows how consumers would react to these changes. Specifically, I simulate four scenarios: the removal of outlet stores, random assortment of styles between regular and outlet stores, relocating outlet stores to city centers, and improvements in outlet store service and

Table 10(a). Test Market Store Characteristics

Store	Regular 1	Regular 2	Outlet
Number of products	60	72	165
Average price	313.46	329.39	154.28
Average product age (mo)	13.14	13.49	20.04
Average distance (mi)	11.34	9.39	30.60
Units sold	148	217	967
Revenue	29,861.96	50,083.60	119,057.12

promotion. I find that outlet stores serve to expand the firm's market to include consumers who are more sensitive to prices, less averse to travel, and less particular about product ages. Furthermore, the assortment in outlet stores is chosen to prevent higher-value consumers from preferring to visit outlet stores over regular stores.

Test market. To clearly demonstrate the effects of each experiment, I use a representative market over which to perform policy simulations. The test market is the Indianapolis–Carmel Metropolitan Statistical Area in July 2007.²¹ This market is representative of the firm's markets both in terms of the demand profile and the firm's store and product configurations. Table 10(a) lists the store attributes and some performance measures in this market.

7.1. No Outlet Stores

The most natural policy experiment to run involves simply removing the outlet stores.²² Many large retail firms choose not to operate outlet stores. Although a careful comparison between firms is hard to make, it can be argued that these firms' selling strategies are similar to the firm's regular store strategy taken alone in several respects. For instance, the firm's regular stores are of similar size, configuration, and location to those of a competitor, even though the competitor does not sell through outlet stores.

Columns 1a to 1c of Table 10(b) contain the results of this counterfactual as they pertain to the supply side and demand side responses. Column 1a shows that revenues in regular stores increase compared to the baseline when the outlet store is closed, even when prices and assortment in the regular stores remain the same. Column 1b shows that the firm would lower prices in regular stores in the absence of outlet stores, even if it could not change the assortment (see Appendix B for details on finding optimal prices). Column 1c shows that the firm would choose to make fewer product introductions if outlet stores did not exist, resulting in an increase in average product age in these stores.

The story is rounded out by looking at details of the demand side response. Closing the outlet store initially results in a very small increase in regular store revenues because very few consumers who shopped at

the outlet store switch to regular stores. When allowed to change product characteristics, the firm lowers the quality and price in the regular stores to cater to the lower-value consumers. However, even given this flexibility, the firm is unable to serve the full range of consumers that it can with the outlet stores present.

An important caveat to this analysis is that brand image effects are not modeled.²³ Removing outlet stores in the overall market may enhance the brand's overall image among certain clients, mitigating the negative results found here. In addition Qian et al. (2013) find that outlet stores can have positive brand awareness effects in both channels. The case considered in Section 7.3, in which the outlet store is maintained but transferred to the city center, provides a setting that is less prone to these concerns.

7.2. Random Assortment

The assignment of products to either regular stores or outlet stores forms an important part of the firm's selling strategy. In this section, I show the value of the firm's observed assortment strategy by comparing its observed performance with that achieved by a counterfactual assortment strategy in which products are randomly assigned to stores. This random assignment results in a configuration in which regular and outlet stores contain roughly identical assortments.^{24, 25} This counterfactual strategy resembles that of firms that open stores in outlet malls, but does not distinguish the assortment in these stores from those in their nonoutlet locations.

Column 2a in Table 10(b) describes the resulting average product characteristics in these stores. Here I allow the firm to adjust prices, so that in both cases prices are profit maximizing, conditional on product assortments. Jumbling the products results in near-identical average product qualities between stores, but prices are still much lower in the outlet store. This suggests that the bulk of discounting in outlet stores is to compensate for the inconvenience associated with longer travel times.

The firm's performance suffers under a random assignment of products to stores. Revenues in all stores decrease, and consumers do not differ as much between formats. This should be unsurprising, given that the products are less different between formats. My hypothesis is that sorting works exceptionally well because there is a positive correlation between consumer travel sensitivity and taste for newness. To test this hypothesis, I run the same counterfactual but under a supposed form of consumer heterogeneity in which there is zero correlation between travel sensitivity and tastes for newness.

Columns 2b and 2c in Table 10(b) have the results of this experiment. As anticipated, randomizing assortment has less of an effect when consumer tastes for the

Table 10(b). Results of Counterfactual Simulations

		No outlet store			Random assortment			Central	Improvements	
	Baseline	1a	1b	1c	2a	2b	2c	3	4a	4b
Supply										
Regular 1										
Price	313.46	313.46	278.73	218.27	297.23	277.32	274.83	309.84	309.52	332.82
Age	13.14	13.14	13.14	15.56	16.92	13.14	16.92	12.24	13.02	13.12
Revenue	29,862	33,254	36,990	37,384	25,858	22,742	22,682	21,113	30,853	31,842
Regular 2										
Price	329.39	329.39	301.00	250.03	300.13	282.98	279.78	312.38	312.64	346.01
Age	13.49	13.49	13.49	15.56	17.43	13.49	17.43	12.57	13.22	13.42
Revenue	50,084	57,101	64,857	69,386	43,215	37,211	36,849	38,896	51,489	52,366
Outlet										
Price	154.28				172.96	150.07	163.75	202.16	165.39	157.27
Age	20.04				17.18	20.04	17.18	24.30	22.82	20.03
Revenue	119,057				103,509	95,044	93,390	101,850	125,118	119,010
Total revenue	199,003	90,355	101,847	106,770	172,582	154,997	152,921	161,859	207,460	202,858
Variable profit	106,728	62,347	75,367	82,213	83,658	75,324	73,098	70,183	114,103	115,629
Demand										
Regular 1										
Distance aversion	75.78	71.55	66.89	65.39	72.13	55.15	54.78	67.31	75.79	75.66
Age aversion	44.91	42.21	38.92	34.83	41.13	40.02	39.08	35.92	46.55	44.86
Regular 2										
Distance aversion	83.62	82.75	74.23	72.17	78.37	63.69	61.84	74.18	83.92	83.43
Age aversion	42.12	41.05	36.68	32.42	38.96	36.19	36.23	33.98	43.78	41.87
Outlet										
Distance aversion	35.94				42.08	43.60	44.64	56.73	35.73	37.93
Age aversion	24.44				36.87	31.92	33.47	28.59	23.34	25.56

Notes. Consumer values presented as demand results are averages over each store. Distance aversion is the dollar equivalent of a 20-mile increase in travel distance. Age aversion is equivalent to a one-year increase in product age. Columns denote cases in which there is the following:

1a: The outlet store is closed and prices and product ages in the regular stores are unchanged.

1b: The outlet store is closed and prices in the regular stores are reoptimized.

1c: The outlet store is closed and prices and product ages in the regular stores are reoptimized.

2a: Products are randomly assigned and prices are reoptimized.

2b: Demand side correlation between product age and travel sensitivity is set to zero; prices are reoptimized.

2c: Demand side correlation between product age and travel sensitivity is set to zero; products are randomly assigned and prices are reoptimized.

3: The outlet store is moved to the city center.

4a: Outlet store multiplier on original product fixed effects is set to zero.

4b: Outlet store effect on store utility uncertainty is set to zero.

two attributes are uncorrelated. There was little sorting to begin with, so the decrease does not come with a very big cost. Optimal prices between the two formats approach each other as the assortment becomes more similar.

7.3. Centrally Located Outlet Stores

One viewpoint is that the firm implements a “damaged goods” strategy by selling a portion of its goods in distant locations. To consider this hypothesis, I run a third set of counterfactuals in which outlet stores are moved to central locations. I show that (i) revenues decrease, (ii) the firm would make fewer product introductions in the outlet format, and (iii) it would cater to a narrower range of consumers.

An alternative explanation to damaged goods is that firms locate in outlet malls to take advantage of lower rents. Outlet malls on average set a monthly rent of

\$29.76 per square foot, which can be dwarfed by rents in the most prestigious retail locations (Humphers 2012). However, this rent is close to the average for retail space in many urban centers—implying that the firm could choose (without cost) to relocate its outlet stores closer to its target market. These locations may not be as attractive and brand consistent as the more expensive areas of the city, but neither are the areas in which most outlet malls are located.

Column 3 of Table 10(b) presents the results of the experiment in which the outlet store is moved into the central shopping district. Notably, while prices are less variable now (regular store products are cheaper and outlet store products are more expensive), quality along the age dimension is more variable (regular store products are slightly newer and outlet store products are much older). Denied the ability to differentiate products according to location, the firm increases the

level of differentiation according to age. The range of consumers that the firm is able to reach, nevertheless, is similar to the case in which the outlet store is simply shut down.

7.4. Improved Outlet Stores

Outlet stores differ from regular stores in more ways than simply location and product assortment. They receive less promotional support, are typically less attractively designed, and offer lower service levels. For these reasons shopping at an outlet store may offer lower utility apart from that caused by a less desirable assortment. The demand side of the model used in this paper accounts for these differences by allowing outlet stores to have negative format effects on perceived product quality, and a lower awareness among shoppers of the product assortment. In the following pair of counterfactuals, I investigate the potential benefits to the firm of improving outlet stores along these dimensions. In particular, I set the outlet adjustment γ on perceived original product quality and the outlet component of imperfect information shocks ψ_{ik} to zero and predict firm and consumer reactions. Columns 4a and 4b in Table 10(b) present the supply side responses and outcomes.

Both improvements to the outlet store experience result in higher revenues and profits. In column 4a, the firm adjusts by increasing the product age difference but decreasing the price differential between formats. The intuition is that removing the outlet store multiplier diminishes the quality differences between formats and therefore the firm compensates by adjusting the product age difference. Because consumers are heterogeneous in their taste for product newness but not in the intrinsic quality (fixed effects) of the products, the price difference can be relaxed in favor of higher revenues without the danger of excess cannibalization.

In column 4b, increased consumer certainty about outlet store utility also improves firm performance, even though optimal prices and product ages are similar to the baseline. The reason is that consumers who receive negative shocks disproportionately opt for nonpurchase, while consumers who receive positive shocks disproportionately trade down from visiting the regular store. While variable profits improve in both of these cases, it is possible that the level of investment required to implement such improvements may prove too high to justify. However, it is clear that in the management of outlet stores, service and promotion effects are nontrivial relative to that of product assortment and pricing.

This section's counterfactuals show that adopting outlet stores helps the firm in many ways. It extends the firm's market to include consumers who are not averse to traveling and less desirous of new products. Since these are the same people in the data, it makes

sense for the firm to populate its outlet stores with older products. This has the additional benefit of making outlet store products less attractive to higher-value consumers, thus preventing cannibalization.

8. Conclusion

Owning and operating outlet stores constitutes a major component of many firms' distribution strategies, particularly in the clothing and fashion industries. It is an interesting practice that continues to evolve and gain popularity. Yet there has been little written in the marketing and economics literatures that speaks to the reasons for the success of outlet stores, or the mechanisms by which they improve firm performance. The availability of new sales data from a major fashion goods manufacturer and retailer offers a unique opportunity to empirically investigate how outlet stores work.

This paper shows that outlet stores provide several benefits as a tool of price discrimination. Outlet stores allow the firm to serve lower-value consumers without lowering prices faced by its regular store clientele. By stocking outlet stores with less desirable products, the firm exploits the positive correlation between consumers' travel sensitivity and taste for quality. Prices are low in outlet stores, but not low enough to attract consumers who value quality and convenience the most.

The model of product choice in this paper suggests a benefit of running outlet stores apart from its price discrimination use: it allows the firm to make more frequent new product introductions in its regular format. The firm offers more new products every period in its regular stores both to increase the attractiveness of regular store offerings relative to those in outlet stores and because it stocks outlet stores with older, less attractive products from the regular stores. This can conceivably counter the threat that is most associated with outlet stores: that it results in the dilution of prestige brands. Outlet stores may actually enable the firm to improve its regular store products, which typically form the basis of a fashion brand's image.

Lessons from outlet store retail have wide applicability to questions of product line design and price discrimination. Outlet stores are a specific response to the apparent heterogeneity in tastes for quality and convenience among fashion shoppers. Similar responses by firms to consumer tastes can be observed in the electronics and travel industries. The notion that the correlation of characteristics in a firm's product space ought to resemble the correlation of consumer tastes for them may be useful to many firms.

The key insight is that multidimensionality in consumer preference heterogeneity matters for product line design. Firms that seek to optimize their product offerings must take into account how tastes vary

for different product characteristics, and what the correlations between those tastes are. This is not a new discovery: the existing theoretical literature on multidimensional screening emphasizes the sensitivity of the optimal allocation set by the principal to the agent's value correlations. This is, however, the first demonstration of its importance in an actual business setting. The choice of whether to operate outlet stores hinges on a market landscape in which consumers who are most willing to travel to outlet malls value quality the least.

While the static framework adopted in this paper is sufficient for the specific research questions, it does impose limitations on aspects of firm and consumer behavior that can be incorporated. Some consumers may, for instance, forego the purchase of a particular original product in the hope of eventually finding it in the outlet store. The firm may correspondingly adopt strategies to induce uncertainty around the availability of original goods in the outlet store. A fully specified dynamic model is needed to incorporate such interactions.

Another limitation arises from the focus of this work on specific product and store characteristics. There are other unobserved aspects of outlet stores that are potentially relevant, e.g., service levels, subjective product evaluations, and experiential factors—some of which have been studied in previous work (e.g., Coughlan and Soberman 2005). There may also be scope for firms to optimize over dimensions of product assortment apart from product age. Accounting for these strategic choices may attenuate the losses measured in the counterfactual simulations in Section 7. Given the diversity in selling strategies even among firms that operate outlet stores, there is likely to be much variation in the relevance of each of these factors between different cases.

There are many possible directions for future research. Outlet stores constitute a single aspect of a consolidated selling strategy that has become standard among fashion goods firms. Other parts of this strategy include price skimming, targeted coupons, and loyalty programs. Many of these components operate on the intertemporal dimension of durable goods demand. It would be interesting to see how they build on the firm's overall product lining strategy by adding additional dimensions.

This setting is also a prime vehicle for exploring alternative theories of consumer behavior with respect to fashion goods demand. Consumers, for instance, may conceivably choose products based on their capacity to signal status. Meanwhile, fashion goods may have characteristics that are discernible to some consumers but not others (for instance, whether a product is sold exclusively in outlet stores). This presents a unique product design challenge to firms that wish to exploit these consumer preferences.

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Appendix A. Estimation Details

Maximization of the likelihood in Equation (7) is performed numerically in Matlab using Knitro's interior-point direct algorithm. Efficient integration over $f(\eta_i, v_i, \psi_{ikt}; \sigma, \Sigma, \sigma_{\psi_{ikt}})$ of each share $s_{zt}(j_k)$ in Equation (6) is achieved through quadrature on sparse grids (Heiss and Winschel 2008). For each guess of Σ , its Choleski decomposition $chol(\Sigma)$ is taken and multiplied by the matrix of uncorrelated nodes to generate nodes with the corresponding covariance structure.

Appendix B. Finding Optimal Prices

The policy simulations in Section 7 involve generating optimal prices given counterfactual product characteristics. This presents a nontrivial computational task given the large number of products and markets. Morrow and Skerlos (2011) provide a fixed-point approach to finding these prices that dramatically reduces the computational burden. In particular, they demonstrate that iteration on a rearrangement of Equation (10)

$$\mathbf{p} = \mathbf{mc} - \Delta^{-1} \mathbf{s} \quad (\text{B.1})$$

results in convergence to profit-maximizing prices for mixed-logit demand systems.

Appendix C. Purchase Outcomes in Regular Stores Following an Outlet Store Opening in the Same Market

Figure C.1 contains kernel densities of sold/transacted prices (denoting purchase outcomes) and available prices (denoting product availability) in regular retail stores pre and post the opening of an outlet store within the same market. There are

Figure C.1. Kernel Densities for Available and Transacted Prices

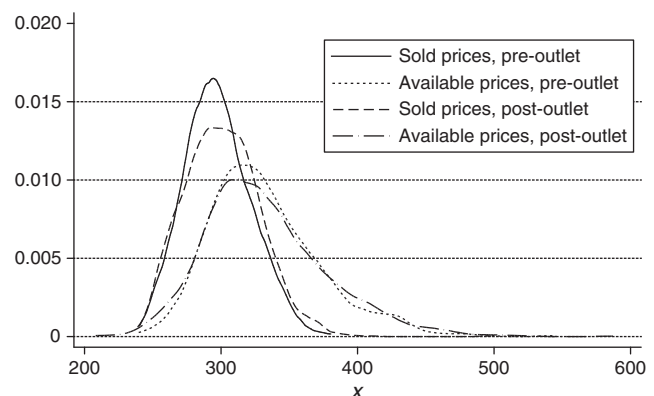
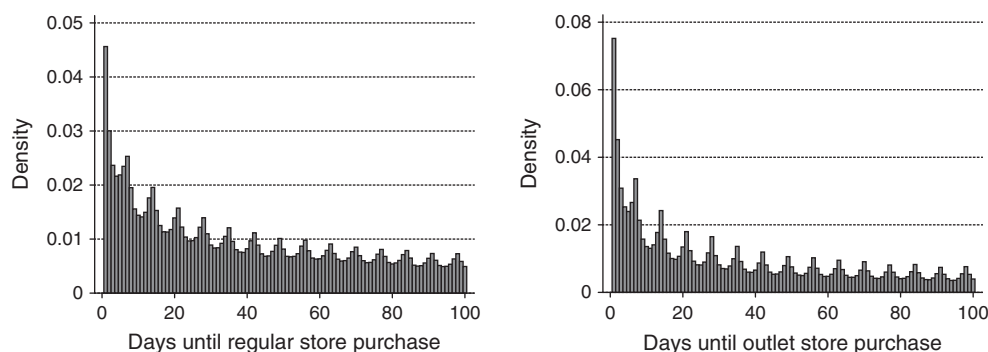


Figure D.1. Histograms of Days Between Conversion Events



a number of useful observations to arise from inspecting this slice of the data. First, products bought in regular stores tend to be more expensive (despite relatively stable assortment) after an outlet store opens—consistent with some cannibalization of the lower end by the outlet store. Second, the magnitude of this shift is moderate—supporting the idea that outlet stores primarily expand the market. Finally, the stability of available prices regardless of outlet store presence is consistent with nationally determined assortment policies.

Appendix D. Conversion at Regular and Outlet Stores Following Purchase at Outlet Store

Figure D.1 is a comparison of histograms of days between a purchase at an outlet store and (i) a purchase at a regular

store and (ii) another purchase at an outlet store, truncated at 100 days. I observe that the right-hand side distribution is more skewed to the left, suggesting that outlet stores do not disproportionately drive consumers to regular stores.

Appendix E. Incorporating Individual Visit Data Into Uncertainty Over Store Utility

In an alternative specification of demand, I include the average number of prior purchases as an explanatory variable for $\sigma_{\psi_{ikt}}$, the consumer's degree of uncertainty associated with a store's product assortment. Because I aggregate purchase data to the zip code level, I operationalize this variable as the average number of past purchases per consumer within the zip code. The demand estimates are in Table E.1.

Endnotes

¹ A second, mutually exclusive comparison is to annual department store sales, which was \$183 billion in 2012. Both figures are from the 2012 U.S. Economic Census.

² Yet another perspective is that outlet stores lower search costs for consumers through collocation. While this is likely to be true, collocation is also a common feature among regular stores. This paper focuses on features of outlet stores that distinguish them from regular stores.

³ "Outlet Malls Then and Now." <http://www.consumerreports.org/cro/magazine-archive/2011/november/shopping/outlet-stores/outlet-malls-then-and-now/index.htm> (accessed September 13, 2015).

⁴ CBSAs consist of metropolitan statistical areas and micropolitan areas—collectively areas based on urban centers of at least 10,000 people and economically relevant adjoining areas.

⁵ Here "geographic segmentation" is taken to be synonymous with third-degree price discrimination, and "self-selection" with second-degree price discrimination.

⁶ A total of 92.25% of purchase instances in the regular store that include a main category product purchase include exactly one main category product; and 87.42% of these purchases in the outlet store include exactly one main category product.

⁷ The two sets of month dummies are separately identified by relative variations in outside shares on the product- and store-choice levels of demand. The outside good on the product level is a nonmain category purchase, whereas on the store choice level it is no store visit (operationalized as no purchase of any category). These shares can vary in movement quite substantially; for instance, store visits spike during December whereas main category "inside shares" spike during other points of the year.

⁸ An alternative means of accounting for the consumer's imperfect information about product assortment might be to alter expected

Table E.1. Alternative Demand Estimation Results

	Coeff.	SE
Product level		
Price	−2.644	0.784
σ_{price}	0.356	0.131
Age	−2.183	0.556
Outlet decay (γ)	−0.141	0.02
Store level		
$IV(\lambda)$	0.577	0.224
Distance	−1.245	0.101
Store utility uncertainty $\sigma_{\psi_{ikt}}$		
Outlet dummy	0.323	0.188
Distance	0.035	0.024
Time since store opening	0.041	0.295
Number of past purchases	−1.282	2.429
Chol (Σ)		
(1, 1)	0.861	0.419
(2, 1)	0.619	0.213
(2, 2)	0.028	0.011
Implied covariances		
σ_{age}	0.861	
σ_{dist}	0.620	
$\rho_{\text{age, dist}}$	0.730	
$N(\text{observations})$	7,302,841	
$N(\text{product fixed effects})$	4,626	
$N(\text{store fixed effects})$	500	
$N(\text{month fixed effects})$	11	
Log-likelihood	1,749.54	

utility IV_{ikt} . However, this would break the nested logit form for which consistency with random utility maximization (RUM) has been established (McFadden 1978). For instance, the model is consistent with RUM only when the log-sum coefficient λ is between 0 and 1. No such result exists for alternative forms of IV_{ikt} . Given this modeling limitation, I include the uncertainty term ψ_{ikt} to represent departures from perfect information that may vary systematically with shopper and format attributes. Note that an additional source of uncertainty lies in lower model shocks ϵ_{ijkt} , which are unobserved by the consumer on the store-choice level.

⁹Much of the literature that formally accounts for consumer expectations in store and product choice focuses on uncertainty over prices in settings with frequently purchased products. For instance, Bell and Lattin (1998) model price expectations in grocery store choice where sellers vary in the cadence of pricing over time, and Erdem et al. (2003) account for consumer inventory in addition to more flexible forms of price uncertainty. By contrast, the current context features infrequent store visits and format choices within the same brand.

¹⁰Models of multidimensional screening have traditionally taken price sensitivity as homogeneous and focused on correlations between consumer values for nonprice attributes. The benefit of this focus in that literature, as well as in this paper, is to allow for sharper and more easily interpretable comparative statics concerning counterfactual correlations than would be possible if, say, all correlations between price sensitivity, travel sensitivity, and taste for newness were allowed to vary.

¹¹The firm continuously implements A/B testing on discount campaigns; these campaigns are necessarily randomly occurring between markets and are never product specific. Such testing might, for instance, be meant to measure the relative effectiveness of different promotional messaging. This creates price variation not between control and treatment groups, but between markets included and excluded from testing. Local store managers have very little input on promotions.

¹²As a robustness check, demand parameters are estimated using data from the few markets with only one store format. This estimation also produces a significantly negative correlation between preferences for travel distance and product newness.

¹³Interestingly, estimated fixed effects for outlet stores are consistently higher than those for regular stores. This possibly points to additional agglomeration and lower search cost motivations for visiting outlet malls.

¹⁴There is little publicly available information with more precise figures; however, these market shares are confirmed by the firm's managers. They also agree with the notion that competitors' pricing trends have little or no impact on the firm's pricing decisions.

¹⁵These marginal costs are computed for the last period in the sample.

¹⁶Treating ξ_j as exogenous can be rationalized by the fact that the firm usually cannot ascertain the appeal of a product to consumers before it is taken to market.

¹⁷As a robustness check, I add quadratic terms to the cost function. I find no meaningful difference in the implied relative costs between product classes.

¹⁸The sampling size is $ns = 50$ in this version of the paper.

¹⁹The empirical values of x and y are 0.19 and 0.09, respectively.

²⁰The average stock is defined as the average number of styles in the entire product universe (across all stores) observed in a month.

²¹As a robustness check I perform the same analysis on the Charlotte–Concord–Gastonia CBSA in December 2009. Results are directionally equivalent and similar in magnitude.

²²Although some markets in the data contain only regular stores, there is some difficulty in using this information toward addressing

the research question. Product assortment in stores in markets with single-format distribution are not measurably different (i.e., a regular retail store has about the same assortment regardless of whether there is an outlet store in the same market) owing to the firms commitment to keeping product assortment consistent within the same format type across markets. However, which markets have only one format type may also be endogenous to market-specific tastes and demographics. Appendix C presents some data on regular store prices before and after outlet store openings in the same market.

²³In an effort to detect such effects I compared the estimated store fixed effects for regular stores in markets with and without outlet stores; however, no meaningful systematic difference exists.

²⁴Recall that a product is unique only up to its fixed effect ξ_j , its price p_j , and its vintage age_j .

²⁵Outlet stores will still have more shelf space than regular stores.

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