ESSAYS ON PRICE DISCRIMINATION

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ABSTRACT

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The increasing availability of detailed, individual-level data from retail settings presents new opportunities to study fundamental issues in product design, price discrimination, and consumer behavior. In this set of essays I use a particularly rich data set provided by a major fashion goods manufacturer and retailer to illustrate how observed firm strategies correspond to predictions from producer theory. I present evidence on the importance of multidimensionality in consumer preferences, both within the theory of price discrimination and as a factor in actual firm decisions. Finally, I explore the applicability of concepts from signaling theory and behavioral economics in explaining consumer purchase decisions.

The first chapter describes the empirical setting used throughout the entire dissertation. Data is provided by a luxury goods firm that dominates its category of fashion goods in the United States. The firm operates hundreds of stores in the US, with different types of stores differing markedly in their geographic accessibility to consumers. I present and estimate a model of demand that admits consumer heterogeneity in two dimensions: travel sensitivity and product age sensitivity. I show that consumer heterogeneity in these two dimensions outweigh that in observable characteristics, such as household income. Furthermore, I estimate a high correlation in the two dimensions, such that consumers who are most averse to travel are also those for whom product newness is most valuable.

The second chapter focuses on the firm's store location and product introduction strategies. I introduce a model of product introduction wherein the firm selects only the parameters of the distribution of product characteristics, rather than the characteristics of each new product. This dramatically simplifies the firm's optimization program. I use this model

to simulate counterfactual product assortments given alternative store location decisions. I show that the optimality of observed store locations depends substantially on the correlation in consumer values for travel distance and product quality. I also show that increased differentiation in geographic accessibility enables the firm to profitably increase differentiation in product quality.

The third chapter studies how consumers respond to different price signals conditional on store visitation. Many firms employ price comparisons as a selling strategy, in which actual prices are framed as discounted from a high list price, occasionally even when no units are sold at list prices. I show that high list prices enhance demand both on product and store levels. I present evidence that suggests that consumers infer quality from list prices. I also demonstrate that these demand-enhancing effects are dependent on characteristics of the retail context, such as the general level and dispersion of discounting.

These essays study in isolation components of consolidated selling strategies that have been widely adopted by US manufacturers and retailers across a wide variety of categories. My hope is to achieve a deeper understanding of the aspects of consumer behavior and firm incentives that have led to the prevalence of these selling strategies. This understanding is central in forming prescriptions for managers as well as measuring welfare implications, both of which I leave for future work.

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Chapter 1

Why Outlet Stores Exist: Market Segmentation in Unobservable Consumer Attributes

1.1 Introduction

Outlet stores are a fixture of the American retail landscape. These are brick-and-mortar stores that offer deep discounts in locations far away from most consumers. Firms operate outlet stores in addition to primary stores, which are located in central shopping districts. Outlet stores operated by different firms are often agglomerated in sprawling outlet malls off interstate highways. In 2012 there were 185 outlet malls in the US, which generated an estimated $25.4 billion in revenues (Humphers 2012).

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

In this and the following chapter, I evaluate the relevance of each of these proposed explanations to the case of a major fashion goods firm with a heavy outlet store presence. Using new 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 make use of structural models of demand and supply to predict consumer behavior and firm product decisions under counterfactual store configurations.

It is evident from observing product flows alone that inventory management is not an essential 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 primarily serve the communities in their vicinity—most of each outlet store's revenues are attributed to consumers for whom a primary store is closer to home. This suggests that the firm's main motivation for operating outlet stores might be to price discriminate among its consumers by forcing the most price-sensitive among them to travel to obtain discounts.

Surprisingly, consumers who shop at outlet stores do not differ significantly from consumers who shop at primary 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 differ from primary 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.

This chapter proceeds as follows. I review the related literature in Section 1.2. In Section 1.3, I describe the data. In Section 1.4, I provide preliminary evidence of how outlet stores work. In section 1.5, I outline the demand model I use to estimate preferences, discuss the estimation procedure, and present the estimates. Section 1.6 concludes.

1.2 Related literature

This work contributes to several literatures in marketing and economics. It is the first empirical study to study the incentives behind outlet store retail. It builds on existing work on product line decisions. It proposes a technique to model endogenous product choice for cases in which a large number of products comprise each product line. The underlying structure of the firm's problem that I model belongs to the class of multidimensional screening models, for which few general results are available and no empirical work has been performed. Finally, this and the next chapter demonstrate that outlet stores allow the firm to improve quality in its primary stores, which may countervail brand dilution.

Several theories exist about how why firms build and 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 share, and put forth outlet stores as an example of such a damaged goods strategy. This work picks up this example and provides the first empirical demonstration of a successful damaged goods policy. Coughlan and Soberman (2005) show that dual distribution (i.e. having both primary 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. While these sensitivities were independent in their model, I look chiefly at how the correlation between consumer sensitivities matters. In recent empirical work, Qian et al. (2013) show that the opening of an outlet store had substantial positive spillovers for a retailer's primary channel, and ascribe this spillover to the advertising effects of a new store opening. This essay goes further by studying how the firm's optimal product line choices are influenced by its store locations—thereby offering an alternative mechanism by which outlet stores can have positive spillovers.

More generally, this work 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, Ulrich, and Reibstein 1998). These essays contribute to this body of work by demonstrating the importance of accounting for the full extent of consumer heterogeneity in making product line decisions. It also shows how concerns like cannibalization can be ameliorated by a careful design of 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, Mazzeo, and Seim 2010; Crawford, Shcherbakov and Shum 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 may also be a more realistic representation of decision-making in many sectors.

The importance of allowing product design to be endogenously determined in equilibrium has been emphasized in many recent papers. Kuksov (2004) shows that firms may respond to lower buyer search costs by increasing product differentiation and thus diminishing price competition. There are many other instances in which allowing for endogenous product differentiation changes the sign of welfare effects.

This and the next chapter'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-by-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 demand and supply 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.

1.3 Data and industry background

The first outlet stores appeared in the Eastern 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 established them independently of manufacturing centers.

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 primary 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. Deneckere and McAfee (1996) provide a relevant argument in this regard by showing that a firm may profit from "damaging" a portion of its goods. They also point out that the practice is widespread: certain slower microprocessors, student editions of software, and outlet store offerings can all be considered damaged goods.

Yet many firms choose not to sell through outlet stores; adoption is variable even within narrowly-defined categories. For instance, premium apparel manufacturers Brooks Brothers, Hugo Boss, and Ralph Lauren have several outlet store locations, but Chanel, Burberry and Zegna have few or none. Coughlan and Soberman (2005) provide an explanation for this fact that rests on the form of consumer heterogeneity. They show that firms find single-channel distribution superior when the range of service sensitivity among consumers is high relative to the range of price sensitivity.

The data used for this study consists of transaction-level records from July 2006 to March 2011. About 60% of the firm's revenues are sales of its main category; the remainder is from sales of other categories. The sample includes all purchases of products made by US consumers in firm-operated channels. Excluded from this sample are online and department store sales, which according to the firm's managers accounted for less than 10% of 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 at a store, 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 uniquely identifies each style. Store attributes include their location, weeklong foot traffic, and format type.

For the analysis in this essay, I focus on main category purchases in physical stores. While this excludes a considerable number of other-category purchases, those observations are used to proxy for the number of consumers who visit a store but do not make a main category purchase.

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

Table 1.1 summarizes the differences between the firm's two store formats. The most obvious difference is in price: the typical product goes for about $300 in primary retail stores, while most outlet store products sell for less than half that price. Outlet stores are also bigger than primary retail stores in terms of square footage and the number of styles on shelf; however, each market is typically served by several primary retail stores and a single outlet store.

Table 1.1: Average Store Characteristics

Store format:	Primary	Outlet
Transacted price	299	126
Number of products on shelf	150	432
% premium material products	29.3	24.4
% standard material products	35.8	39.3
Months since product intro	11.9	15.1
Square footage	2,718	4,536
Weekly foot traffic	2,845	7,677
Annual revenue	1,267,480	5,048,774
Total revenue in format	461M	722M
Total number of stores	367	143

The composition of available product choices in the two formats do not differ greatly according to stylistic characteristics. Most products are made of one of two materials and the two formats carry about the same percent of each type. Where the assortments do differ greatly is in 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.

1.4 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 subsection, I provide model-free evidence that speaks to each of three main possible purposes: inventory management, geographic segmentation, and consumer self-selection.

1.4.1 Inventory management

I first consider the relevance of outlet stores in managing the firm's inventory: particularly the disposal of excess supply. This purpose serves as the historical basis for outlet stores' emergence, and continues to be relevant for many firms. As I show in the following discussion, however, inventory management does not appear to be a primary purpose of the firm's outlet stores.

At the most basic level, the firm manufactures two types of products, which I term *original* and *factory*. Original products are introduced in the primary stores, and after a few months, taken out of primary stores and sold in outlet stores. Factory products are sold only in outlet stores. Figure 1.1 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 the other, or even aware of the distinction. Table 1.2 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 disposing of excess inventory. First, it is not the firm's policy to sell defective merchandise in either of its channels. Second, the firm manufactures a product line that is meant for exclusive sale in its outlet stores. And third, close to half of the units of

Figure 1.1: Product flows

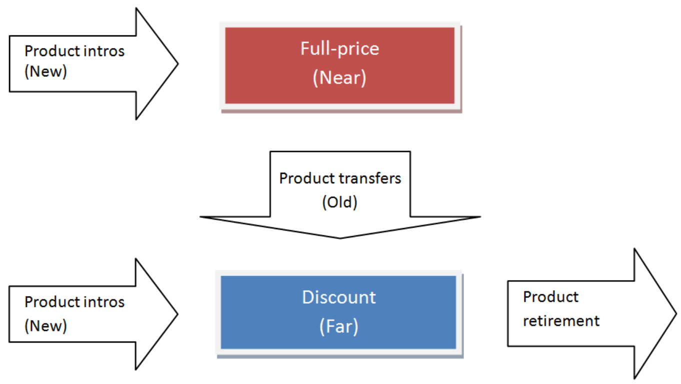


Table 1.2: Inventory Flows

Product type:	Original	Factory
Average styles introduced per year	336	132
Average months sold in primary format	10.32	N/A
Average months sold in outlet format	6.97	11.03
Average total units per style sold in primary 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

each style that is introduced in primary stores is 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.

1.4.2 Geographic segmentation

Given how the firm uses location to distinguish each product line, a natural hypothesis is that outlet stores are designed to segment consumers according to geography. In fact, outlet stores are located in areas that have lower population density and lower income than the areas around primary stores.

Table 1.3 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 1.3 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. As will be clear from the succeeding discussion, 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.

An alternative way of thinking about classes of consumers is presented in Table 1.4. 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 at exclusively 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

Table 1.3: Average Consumer Characteristics by Store Format

Store format:	Primary	Outlet
Income	71,231	65,226
	(27,780)	(23,670)
Years since first purchase	2.51	2.25
	(3.40)	(3.08)
Travel distance	9.53	20.44
	(8.49)	(15.65)

Standard deviations are in parentheses.

for whom the closest store is an outlet. The main takeaway from Table 1.4 is that even within the class of consumers who shop exclusively at outlet stores, 70.5 percent live closer to primary stores.

Table 1.4: Consumer behavior

	Only primary retail	Only outlet store	Multi-home
Share (%)	13.2	56.8	30.0
Outlet closer (%)	7.0	29.5	15.3
Average income ($)	73,489	64,554	69,294

I take a core-based statistical area (CBSA) to be a reasonable geographic market definition.[1] 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 1.5 has descriptive statistics for the average market according to my definition.

Figure 1.2 identifies where the firm's consumers live in Indianapolis, Indiana and shows the market population density by zip code. Indianapolis is a typical market for the firm, which it serves with two primary store locations and one outlet store. For the purposes

[1]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.

Table 1.5: Average Market Characteristics

	Mean	St Dev
Number of primary stores	1.96	3.52
Number of outlet stores	0.66	0.66
Revenue	186,666.00	371,510.50
Market size (#consumers)	92,870.51	186,769.80

A market is a CBSA-month.

of this figure, a 'consumer' is an individual who purchased at least one item from the firm within the five-year sample.

Figure 1.2 highlights the fact that the outlet store is located in an area where very few consumers reside. This agrees with what is found in the national sample, where there is a relatively small group of consumers for whom the closest store is an outlet store.

Figure 1.3 shows from where revenues at the outlet store are sourced. The shading of the regions closely resembles the market population density shown in Figure 1.2. Most of the outlet store's revenues are attributed to consumers who live in the central shopping district where the primary stores are located. As before, this is a pattern that is also seen in the national sample.

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 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.[2]

[2]Here 'geographic segmentation' is taken to be synonymous with third-degree price discrimination, and 'self-selection' with second-degree price discrimination.

Figure 1.2: Consumers in Indianapolis, IN

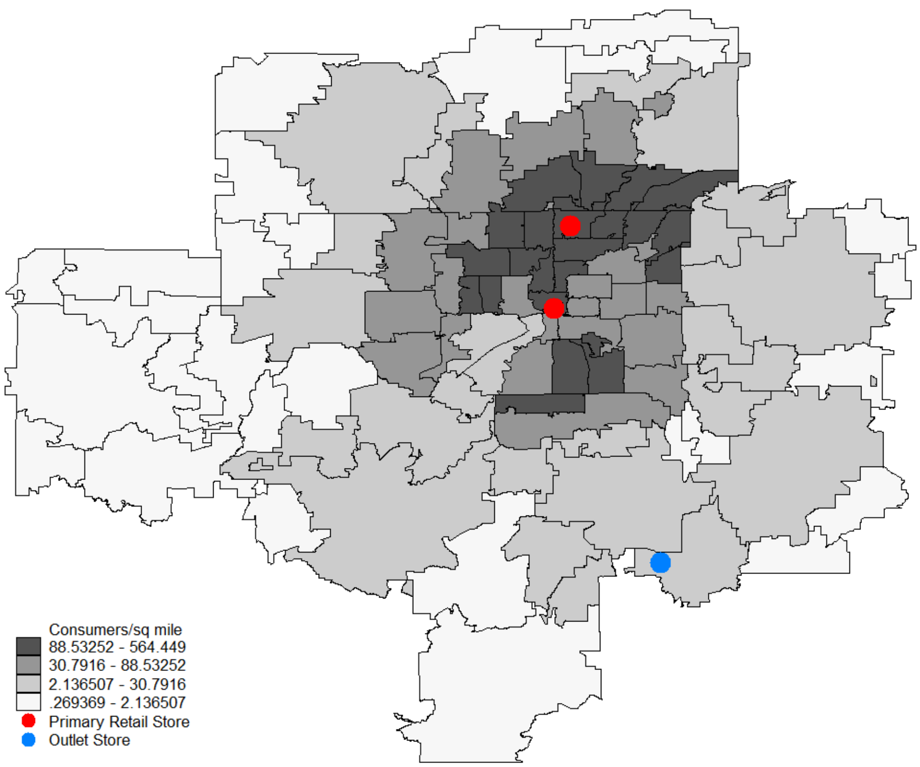
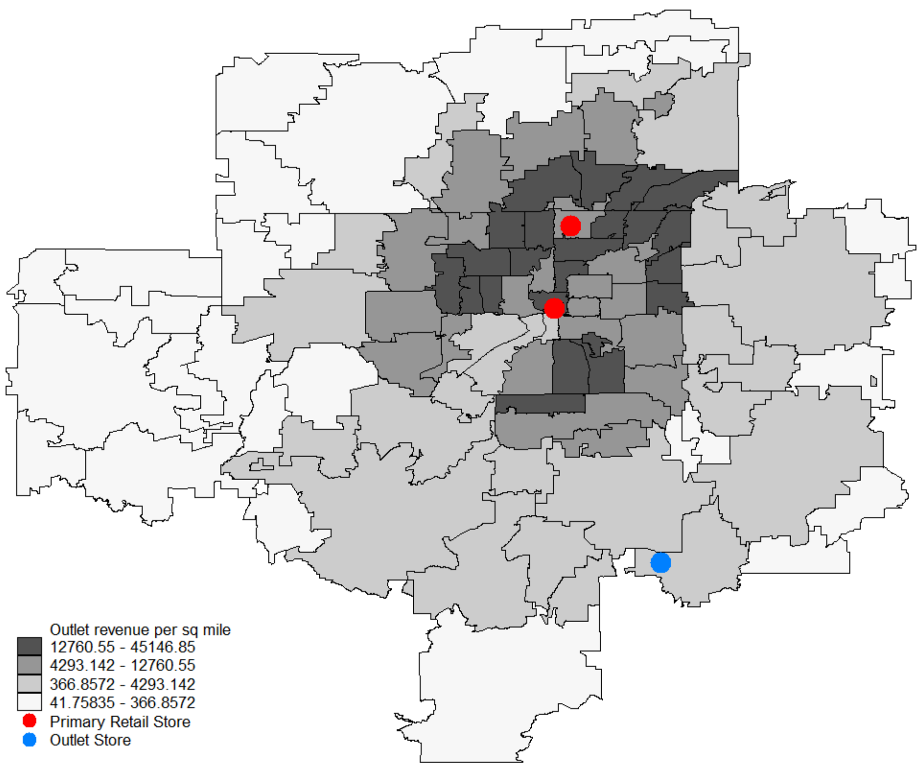


Figure 1.3: Outlet store revenues in Indianapolis, IN



1.4.3 Consumer self-selection

This chapter focuses on illustrating how outlet stores induce a segment of consumers to travel for discounts. While, as Tables 1.3 and 1.4 show, consumers do not markedly differ in their observable attributes by format choice, this does not preclude them from differing in their preferences. In the following section, 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 more fully characterize the differences in primary store and outlet store patrons. This step illustrates how the firm's selling strategy achieves a sorting of consumers according to their preferences.

1.5 Demand

In this section, I present a model of demand for the firm's main category, which takes on a nested mixed logit form. I proceed to discuss how I estimate the parameters of the model using transactions 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 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 in month t is

$$u_{ijt} = \xi_j - (\alpha + \zeta_i)p_{jt} - (\beta + \eta_i)age_{jt} + \epsilon_{ijt}. \tag{1.1}$$

That is, her utility is determined by: the intrinsic quality of the product, ξ_j; the product's price p_{jt} at time t; time that has elapsed since the product was introduced, denoted age_{jt}; and an idiosyncratic demand shock ϵ_{ijt}. 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 $u_{i0t} = \epsilon_{i0t}$. I also assume that ϵ_{ijt} is i.i.d. type-I extreme value.

At the store, the consumer chooses the product that gives her the highest utility.[3] Given the distributional assumption on ϵ_{ijt}, this implies that the expected utility consumer i derives from a store k's product assortment in month t, J_{kt}, is the inclusive value

$$IV_{ikt} = \log\left(\sum_{h \in J_{kt}} \exp(\xi_h - (\alpha + \zeta_i)p_{ht} - (\beta + \eta_i)age_{ht})\right). \tag{1.2}$$

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 in month t is

$$\tilde{u}_{ikt} = \tilde{\xi}_k + \lambda IV_{ikt} - (\gamma + \nu_i)distance_{ik} + \tilde{\epsilon}_{ikt}. \tag{1.3}$$

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 ν_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 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.

These distributional assumptions imply that the probability that consumer i purchases

[3] Unit demand is appropriate given that 99.4% of all transactions in the data are single-unit purchases.

product j in store k in month t is

$$\begin{aligned} P_{it}(j_k) &= P_{it}(j|k)P_{it}(k) && (1.4)\\ &= \frac{\exp(\xi_j - (\alpha+\zeta_i)p_{jt} - (\beta+\eta_i)age_{jt})}{1+\sum_{h\in J_{kt}}\exp(\xi_h - (\alpha+\zeta_i)p_{ht} - (\beta+\eta_i)age_{ht})} && (1.5)\\ &\quad \times\frac{\exp(\tilde{\xi}_k + \lambda IV_{ikt} - (\gamma+\nu_i)distance_{ik})}{1+\sum_{l\in K_i}\exp(\tilde{\xi}_l + \lambda IV_{ilt} - (\gamma+\nu_i)distance_{il})} && (1.6)\end{aligned}$$

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

I further assume that $\zeta_i \sim N(0,\sigma)$ and $[\ \eta_i \quad \nu_i\ ]' \sim N(0,\Sigma)$. This allows for a nonzero correlation between sensitivity to travel and taste for new products. In this version of the model, correlations with the price coefficient are restricted to zero. These restrictions are partially relaxed in the appendix, which also contains a discussion of possible implications of these assumptions (*see Section A.2*).

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

$$s_{zt}(j_k) = \int_i P_{it}(j_k)df(\zeta_i,\eta_i,\nu_i;\sigma,\Sigma), \qquad (1.7)$$

where f is a multivariate normal pdf.

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 $\Theta = (\alpha,\beta,\gamma,\lambda,\sigma,\Sigma,\{\xi_j\},\{\tilde{\xi}_k\})$ is

$$l(\Theta) = \sum_t \sum_{k\in K_z} \sum_{j\in J_{kt}} \sum_z n_{zjkt}\log s_{zt}(j_k), \qquad (1.8)$$

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. That assumption is that consumers who do not make a purchase over a five-year period are not part of the market. If a consumer purchases an other-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.

Identification. The firm's pricing practices allows for the consistent estimation of α and σ without the use of instrumental variables techniques. To begin with, 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 store-wide promotions. These typically take the form of discounts that apply to all of the products in-store. The second is a systematic marking down of products over time. Table 1.6 shows through a projection of prices on product fixed effects, an outlet dummy, 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.

Table 1.6: Pricing equation

Variable	Coefficient	St Dev
constant	5.33	0.15
outlet	-0.42	0.0029
log(age)	-0.43	0.0022
depvar	log(price)	
product FE	yes	
R2	0.8965	

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.

Table 1.7 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.

Table 1.7: Demand estimates

		coef	se
Product level			
	price	-2.327	0.503
	σ_{price}	0.344	0.109
	age	-2.621	0.681
Store level			
	IV	0.442	0.183
	distance	-0.912	0.079
chol(Σ)			
	(1,1)	0.908	0.297
	(2,1)	0.435	0.178
	(2,2)	0.209	0.172
Implied covariances			
	σ_{age}	0.908	
	σ_{dist}	0.483	
	$\rho_{age,dist}$	0.629	
	N	7,566,195	
	l	1,832.09	
	product fixed effects	yes	
	store fixed effects	yes	

An interpretation of the estimated coefficients for price, age, and distance is that the average consumer would have to be compensated roughly $100 in order 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.

Market segmentation. Estimating the underlying parameters of consumer preferences 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 primary 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 1.8 adds to the information in Table 1.3 through demand estimation. Whereas the data shows 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.

Table 1.8: Market segmentation by consumer tastes

Consumer values ($) for:	Primary Stores	Outlet Stores
20-mile travel distance increase	71.83	36.21
	(12.47)	(11.08)
1-year product age increase	51.97	33.45
	(14.22)	(12.76)

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

1.6 Conclusion

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 product 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.

The demand estimates suggest an important role for estimation of unobservable consumer characteristics in evaluating market segmentation efforts. In the current setting, mere inspection of consumer income underestimates the extent of consumer heterogeneity between retail channels. Demand estimation can also conceivably provide retailers with guidance as to which of several consumer attributes drives heterogeneity in their particular markets, and consequently, which product characteristics can most effectively maximize product differentiation.

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 primary 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 the how the firm stocks its primary stores.

The following chapter provides a framework for thinking about how the firm chooses prices and product assortments given its dual distribution strategy. The purpose of these models is to form a basis, together with the demand model, for predicting firm performance given a counterfactual distribution strategy.

Chapter 2

Why Outlet Stores Exist: Store Location and Product Assortment

2.1 Introduction

As in many other retail settings, there is a clear relationship between store and product attributes in the current setting's dual distribution framework. Primary stores stock new arrivals, while older products are sold in outlet stores. 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 much diminished, owing to the fact that outlet stores would cannibalize a larger portion of primary store revenues.

In order 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 each of 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 primary distribution channel available, the firm would expand its primary 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 primary format. I find that the firm introduces 13% more new styles with dual distribution than with only primary stores.

In Section 2.2, I outline the supply model I use to describe firm product choice, and present the implied marginal and product development costs. In Section 2.3, I perform policy simulations that highlight the benefit of operating outlet stores. Section 2.4 concludes.

2.2 Supply

In this section I develop a model of firm behavior concerning price-setting and product choice. This model permits a careful comparison of firm performance under counterfactual distribution strategies, and hence sheds light on the operational benefits 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 models' underlying assumptions.

There are two major assumptions that are maintained throughout this section. The first is that the firm behaves like a monopolist, setting prices and product characteristics without regard for any competitor's strategies. The second is that the firm's prices and product choices maximize profits. I discuss each of these assumptions before going into the models.

The monopoly assumption is motivated by the firm's unique position in the industry. It has a dominant share of total industry revenues, and an even larger share in its psychographic segment. The next largest brand in the category accounts for only about a third of our firm's revenues. Products by the number two brand, however, retail at around the $1,000 price point—much higher than our firm's average price of $300. There is arguably little overlap between the market for the firm's products and the market for higher-end products such as those carrying the number two brand's label.[1]

The firm's dominant position 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.

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 discuss the supply model. 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, implies 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

$$\pi(\mathbf{p}) = \sum_m \left(M_m \sum_{h \in J_m} s_h (p_h - mc_h) \right). \tag{2.1}$$

That is, per-product (h) profit in each market m[2] is price p_h minus marginal cost mc_h times quantity sold $M_m s_h$, where M_m is market size and s_h is market share as determined by Equation 1.7. These are summed over markets, where the set of products in each market

[1] There is little publicly available information with more precise figures–these market shares were relayed by the firm's executives. They also agree with the notion that competitors' pricing trends have little or no impact on the firm's pricing decisions.

[2] A market m is a zip code-month.

is J_m. Profit-maximizing prices satisfy the first-order conditions

$$\frac{d\pi}{dp_j} = \sum_{m|j\in J_m} M_m \left(s_j + \sum_{h\in J_m} \frac{\partial s_h}{\partial p_j}(p_h - mc_h) \right) = 0 \tag{2.2}$$

for each product j. Rewriting the conditions as $\mathbf{s}+\Delta(\mathbf{p}-\mathbf{mc}) = 0$ where $\mathbf{s}_j = \sum_{m|j\in J_m} M_m s_j$, $\Delta_{j,h} = \sum_m \frac{\partial s_h}{\partial p_j}$, and $\mathbf{p}_j = p_j$, the marginal cost of each product in a single period is exactly identified using estimated demand coefficients:

$$\mathbf{mc} = \mathbf{p} + \Delta^{-1}\mathbf{s}. \tag{2.3}$$

I use Equation 2.3 to compute marginal costs for each product. Recall that observed prices are "contaminated" by randomized promotions, which conceivably cause departures from strict profit maximization. The operational assumption must therefore be that the estimated parameters in Table 1.6 are profit-maximizing choices by the firm. I use the pricing equation from Table 1.6 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 calculate marginal costs for each period.

This static pricing equation and its implied marginal costs embeds several assumptions. It follows the demand model in Chapter 1 in precluding the possibility of intertemporal substitution by consumers. It also implies that all within-product variation in optimal prices depends on the product's age and the overall assortment of products. Meanwhile, the simulations conducted in Section 2.3 concern only a single period in a single geographic market, and hence do not rely on assumptions about how costs vary over time.[3]

The implied average marginal cost over all products closely resembles figures from indus-

[3] In future versions, constant marginal costs may be estimated using multi-period data by adding an i.i.d. error to the first order condition and applying GMM methods.

try reports and suggestions from the firm's executives. The estimated relationships between characteristics and marginal cost are also sensible: premium material costs more than standard, and larger shapes cost more to manufacture than smaller ones. This provides an indication of the validity of the pricing equation.

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 1.1 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 1.2). All products in the primary store are eventually transferred to the outlet store, where the last units of all styles are sold.

One advantage of using this data to study product choice is that the outlet strategy provides a structure that delimits the firm's choice set. The technology that the firm uses to create 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 work 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 takes C_k draws from a master set of products, represented by the distribution of product characteristics h. Let $h = f \times g$, where f is the joint distribution of endogenous product characteristics (product ages by format) and g governs the set of exogenous characteristics (summarized by ξ_j).[4] The firm's objective is to choose the profit-maximizing shape of f.

In order to make this problem tractable, I propose to construct f 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. The average original product in the primary format has a probability x of being transferred to discount in the next period.

2. The average factory product that is introduced in the outlet format has a probability y of being retired in the next period.

3. The average original product that has been transferred to the outlet format has a probability z of being retired in the next period.

4. The proportion of products in the outlet format that are factory goods is α.

These assumptions imply that if X is product age in the full-price format and Y is product age in the discount format then

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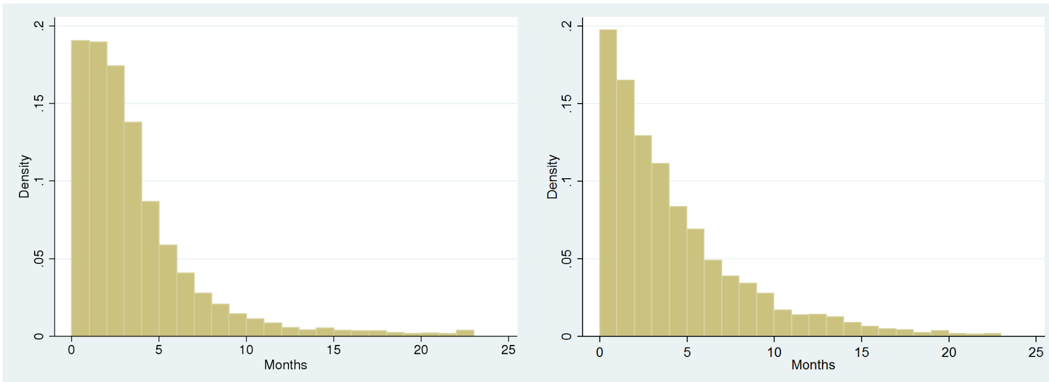
[4]Treating ξ_j as exogenous can be rationalized by the fact that the firm usually cannot ascertain the appeal of a product to consumers until it is actually on shelves.

Figure 2.1: Empirical versus simulated age densities in primary format



$$X \sim Geometric(x) \tag{2.4}$$

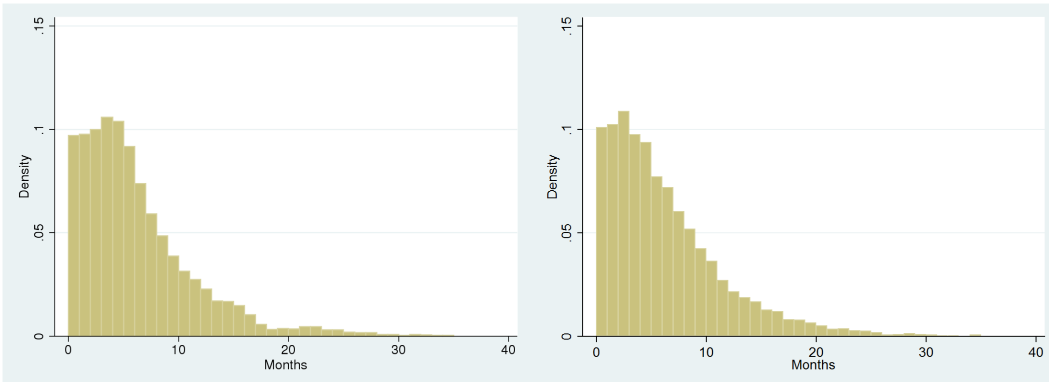
$$Y = \begin{cases} W & \text{with probability } \alpha \\ X + Z & \text{with probability } 1 - \alpha \end{cases} \tag{2.5}$$

where $W \sim Geometric(y)$ and $Z \sim Geometric(z)$

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 full-price products that are newly introduced in a period is simply x and the share of new made-for-discount products y. Figures 2.1 and 2.2 illustrates how closely this parameterization resembles the observed distribution of product characteristics.

Products in the primary format, however, are not transferred to outlets at random. Products that perform better in sales, and thus presumably are of higher quality, have longer lifespans in primary stores. Figure C.3 plots the ξ_j against age_j for the primary store selections in the Indianapolis example from Figure 1.2. In the language of the exposition

Figure 2.2: Empirical versus simulated age densities in outlet format



above, the distribution of endogenous characteristics f is dependent on that of exogenous characteristics g. I keep the form of this dependence fixed by allowing the firm to adjust the speed of product turnover but not the order at which products are transferred according to their ξ_j.

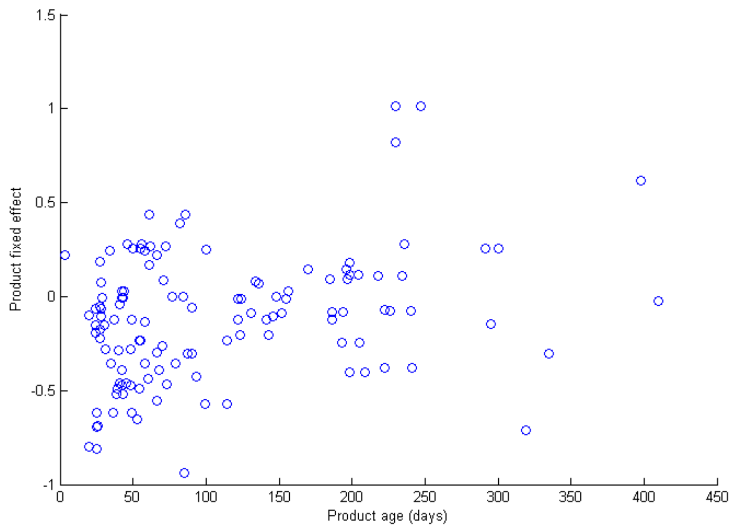
Clearly, adjusting the stocking probabilities, and thus the rate of new product introductions, is not cost-neutral. Assuming that the firm chooses to maintain a fixed number of products in its universal offer set, the cost per period $C(x, y)$ of implementing a given age distribution must depend on the number of new product introductions it requires. I use the simple cost function

$$C(x, y) = ax + by \tag{2.6}$$

to represent these costs.

To summarize, the firm chooses product choice parameters x, y, z, and α and prices $\mathbf{p}$ to maximize expected profit

Figure 2.3: Better products are longer-lived in primary stores



$$E(\pi|x, y, z, \alpha) = \int \sum_m M_m \sum_{j \in J_m} s_j(p_j - mc_j) df(x, y, z, \alpha) - C(x, y) \tag{2.7}$$

In line with the earlier assumption that prices are profit-maximizing conditional on product characteristics, I also assume that the firm chooses x and y optimally. 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, and present the implied product development costs in Table 2.1.

Note that this solution implies that the firm chooses its supply parameters once and for all, precluding the possibility of making adjustments dynamically in response to demand shocks. This simplifying assumption is made to keep the problem computationally feasible. Conclusions drawn from counterfactuals performed in the next section pertain to static results, and hence are robust to this assumption.

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 2.4 and 2.5.[5] 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.

Table 2.1: Implied product development costs

Product class	Parameter Value	Average stock	Fixed cost per unit
Original (a)	7,779,203	151	51,518
Factory (b)	19,034,202	433	43,959

The parameter values in Table 2.1 indicate the cost of replacing the entire stock of products, i.e., when $x = 1$ or $y = 1$. Dividing these values by the average stock of each class of product gives the fixed costs associated with developing each unit. 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.

2.3 Policy Simulations

The basic question that this chapter addresses is: Why do outlet stores exist? In this section, I answer this question by simulating situations in which the firm pursues selling

[5]$ns = 50$ in this version.

strategies that exclude outlet store retail. For each of these policy simulations, I use the supply-side model in Section 2.2 to specify how the firm would change its pricing and product introduction rates in response to changes in store locations. The demand model from Chapter 1 then shows how consumers would react to these changes in firm strategy.

While the ideal exercise would be to generate optimal store locations in response to changing demand conditions, such an endeavor would entail substantially more complex, possibly infeasible, computation. Instead, I describe the shape of the firm's objective function by solving for optimal product assortment parameters given store locations. As such, the results I derive are a conservative measure of the importance of the variables of interest.

Through the following counterfactuals, 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 primary stores.

Test market. I use a representative market over which to perform policy simulations, in order to clearly demonstrate the effects of each experiment. The test market is the Indianapolis-Carmel Metropolitan Statistical Area in July 2007, maps of which were presented in Chapter 1. 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 2.2 lists store attributes and some performance measures in this market.

2.3.1 No outlet stores

The most natural policy experiment to perform involves simply removing the outlet store. 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 primary store strategy taken alone in several respects. For instance, the current

Table 2.2: Test market store characteristics

Store:	Primary 1	Primary 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

firm's primary stores are of similar size, configuration, and location to those of the second biggest firm in the category, even though the other firm has no outlet stores.

Table 2.3 contains the results of this counterfactual as they pertain to the supply-side responses. Column 1 contains the actual average prices, product ages, and revenues, which are used as a baseline. Column 2 shows that revenues in primary stores increase when the outlet store is closed, even when prices and assortment in the primary stores remain the same. Column 3 shows that the firm would lower prices in primary 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 4 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, which are listed in Table 2.4. Closing the outlet store initially results in a very small increase in primary store revenues because few of the consumers who shopped at the outlet store switch to primary stores. When allowed to change product characteristics, the firm lowers quality and price in the primary 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

Table 2.3: No outlet stores (supply response)

	1	2	3	4
Primary 1				
Price	313.46	313.46	280.21	220.73
Age	13.14	13.14	13.14	15.12
Revenue	29,862	32,771	35,911	36,125
Primary 2				
Price	329.39	329.39	302.51	250.03
Age	13.49	13.49	13.49	15.12
Revenue	50,084	55,831	62,200	67,830
Outlet				
Price	154.28	-	-	-
Age	20.04	-	-	-
Revenue	119,057	-	-	-
Total revenue	199,003	88,602	98,111	103,955
Variable profit	106,728	62,042	71,389	73,518

Prices and product ages are averages over each store.
Columns indicate:
1 - Baseline
2 - Outlet store closed
3 - Prices reoptimized
4 - Prices and product ages reoptimized

outlet stores present.[6]

Table 2.4: No outlet stores (demand response)

	1	2	3	4
Primary 1				
Distance aversion	73.98	70.04	65.32	63.42
Age aversion	45.17	42.99	39.13	35.16
Primary 2				
Distance aversion	81.09	80.82	72.15	70.21
Age aversion	42.65	41.53	37.26	32.88
Outlet				
Distance aversion	32.55	-	-	-
Age aversion	25.90	-	-	-

Consumer values are averages over each store. Distance aversion is the dollar equivalent to a consumer of a 20-mile increase in travel distance. Age aversion is equivalent to a 1-year increase in product age.
Columns indicate:
1 - Baseline
2 - Outlet store closed
3 - Prices reoptimized
4 - Prices and product ages reoptimized

2.3.2 Random assortment

The assignment of products to either primary stores or outlet stores forms an important part of the firm's selling strategy. In this subsection, 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 primary and retail stores contain

[6] A clearer picture of which consumers are served can be presented through heat maps in consumer taste space.

roughly identical assortments.[7,8] This counterfactual strategy resembles that of firms that open stores in outlet malls, but do not distinguish the assortment in these stores from those in their non-outlet locations.

Table 2.5 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.

Table 2.5: Randomized product distribution–supply

Assortment:	Actual	Randomized
Primary 1		
Age	13.14	16.92
Price	313.46	300.12
Primary 2		
Age	13.49	17.43
Price	329.39	302.18
Outlet		
Age	20.04	17.18
Price	154.28	170.48

As reported in Table 2.6, the firm's performance suffers under a random assignment of products to stores. Revenues in all stores decrease, and consumers are less different 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

[7] Recall that a product is unique only up to its fixed effect ξ_j, its price p_{jt}, and its vintage age_{jt}.

[8] Outlet stores will still have more shelf space than primary stores.

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.

Table 2.6: Randomized product distribution (actual tastes)

Assortment:	Actual	Randomized
Primary 1		
Distance aversion	73.98	70.87
Age aversion	45.17	41.74
Primary 2		
Distance aversion	81.09	75.42
Age aversion	42.65	39.21
Outlet		
Distance aversion	32.55	41.53
Age aversion	25.90	35.23
Total revenue	199,003	173,374
Variable profit	106,728	85,150

Table 2.7 has the results of this experiment. As anticipated, randomizing assortment has less of an effect when consumer tastes for the two attributes are uncorrelated. There was little sorting to begin with, so the decrease does not come with very big a cost. This result directly contradicts that of Armstrong and Rochet (1999). In their solution of a simple model of multidimensional screening, they find that when consumer values for two product attributes are highly correlated, the optimal menu features no dependence between the two attributes. The authors point out in their paper that this result is counterintuitive; this result confirms their intuition.

2.3.3 Centrally-located outlet stores

It seems plain to see that the firm pursues a "damaged goods" strategy by selling a portion of its goods in distant locations. In order to confirm this hypothesis, I run a third set of

Table 2.7: Randomized product distribution (uncorrelated tastes)

Assortment:	Actual	Randomized
Primary 1		
Distance aversion	54.82	53.88
Age aversion	40.84	39.15
Primary 2		
Distance aversion	62.46	60.32
Age aversion	37.28	36.71
Outlet		
Distance aversion	41.38	43.28
Age aversion	31.84	33.18
Total revenue	153,432	151,883
Variable profit	73,648	71,832

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) cater to a narrower range of consumers. I also show that the benefit of damaging goods in this fashion is increasing in the taste correlation.

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 to costlessly relocate its outlet stores closer to its target market.

Table 2.8 presents the supply-side results of the experiment in which the outlet store is moved into the central shopping district. Notably, while prices are less variable now (primary store products are cheaper and outlet store products are more expensive), quality along the age dimension is more variable (primary 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.

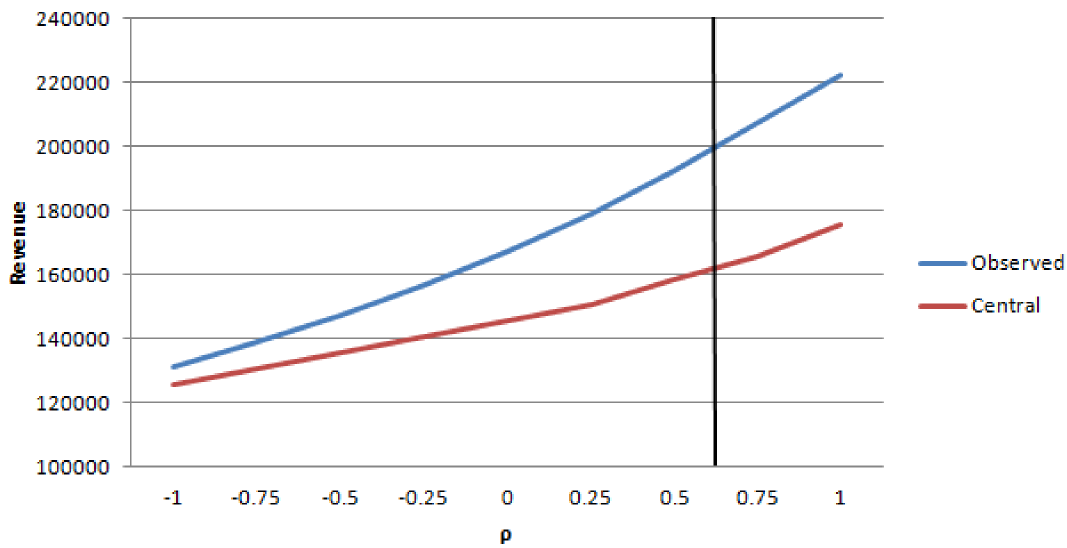
Table 2.8: Outlet moved to center (supply response)

Outlet location:	Actual	Central
Primary 1		
Age	13.14	12.78
Price	313.46	308.21
Distance	11.34	11.34
Primary 2		
Age	13.49	13.00
Price	329.39	314.77
Distance	9.39	9.39
Outlet		
Age	20.04	23.89
Price	154.28	204.76
Distance	30.60	10.69
Total revenue	199,003	162,601
Variable profit	106,728	70,419

Figure 2.4 shows the relationship between the relative profitability of outlet store retail and the correlation between consumer tastes for quality and convenience. It is additional evidence for the idea that the firm exploits the correlation in consumer attributes through its outlet store strategy. It also suggests a plausible reason for why outlet stores have become so popular among clothing and fashion firms, but not so much in other industries: tastes for quality and convenience may not be so strongly correlated elsewhere.

These counterfactuals show that adding outlet stores helps the firm in many ways. First, it extends the firm's market to include consumers who are not averse to traveling and less desirous of new things. 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

Figure 2.4: Central outlet policy vs taste correlation



cannibalization.

2.4 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 chapter 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 primary store clientèle. 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 essay suggests a benefit of running outlet stores apart from its price discrimination uses: it allows the firm to make more frequent new product introductions in its primary format. The firm offers more new products every period in its primary stores both to increase the attractiveness of primary store offerings relative to those in outlet stores and because it stocks outlet stores with older, less attractive products from the primary 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 primary 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 extant 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.

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 yet 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.

Chapter 3

Discount Pricing in Retail

3.1 Introduction

Firms often engage in discount pricing, in which prices are listed as a discount from an original price. There are several reasons for which firms might drop the price of a good over time, such as when it seeks to discriminate between consumers according to their willingness to pay, as a means of managing its inventory, or when it faces less demand uncertainty after the good's introductory phase. In many of these instances, consumers can be thought of as having nearly full information and making rational responses to price incentives. This essay, on the other hand, focuses on motivations for discount pricing that arise from consumers having imperfect information, or exhibiting irrational behavior. These are motivations that might encourage firms to post high "original" prices at which products are never actually available for purchase.

In this chapter, I identify patterns in how consumers respond to discounts. I use data from a dominant fashion goods retailer that makes heavy use of this strategy in its outlet stores. This data set offers a rare opportunity to study this pricing strategy because it records both original and transacted prices, as well as repeat purchases. A portion of these original prices are observably genuine, while the remainder are suggested. As with most outlet stores, the firm implements random discounts across both time and products in store, providing much variation in the transacted prices.

I find that consumer responses to suggested prices are consistent with several theories both of prices as a signal of quality and of reference-dependent behavior. Controlling for transactional prices and other product characteristics, a higher "original" price increases a good's purchase probability. While this effect is larger for products for which original prices are genuine, it is also substantial for products with suggested original prices. Moreover, this effect seems to be invariant to the consumer's level of information.

Somewhat puzzlingly, this positive effect increases exponentially in the original price (and equivalently, the discount amount). One might expect this effect to exhibit diminishing marginal returns if consumers are less likely to put much stock in overly inflated original prices. In addition, optimal behavior by firms would suggest concave returns to higher suggested prices since increasing these prices is costless. I find that reference dependence offers a partial explanation of this phenomenon. Consumers take the average discount level in a store as the reference point, and are more likely to purchase goods that are more highly discounted than this benchmark.

This reference dependence is in line with the idea that firms exploit bargain-hunting behavior through suggested pricing. This effect may be particularly potent in outlet stores, in which most items are discounted. Yet the attractiveness of a bargain must go hand-in-hand with original prices being a reliable signal of quality. This implies that the firm must maintain the credibility of these prices even as it employs them to manipulate consumer behavior.

Setting suggested prices is a unique problem for the firm, as suggested prices can be thought of as a signal of quality akin to certain forms of advertising. Yet unlike advertising, setting higher suggested prices is costless to the firm. Setting optimal suggested prices, therefore, involves balancing their (initially) demand-enhancing effects versus the possibility that consumers may eventually lend less credibility to these signals.

This chapter proceeds as follows. Section 3.2 reviews the related literatures on pricing and reference dependence. Section 3.3 describes the data used for the empirical analysis and provides some descriptive statistics. Section 3.4 outlines a demand model and presents parameter estimates. Section 3.5 concludes and points to directions for future work.

3.2 Related literature

Suggested pricing can occur in a wide variety of circumstances. The environment I consider has the following features: a single seller that produces goods of varying quality, a weak regulatory environment, consumers that have less information than the firm about product quality and past prices, and the possibility of repeat purchases. An additional, novel characteristic is that the marginal cost of production may not be monotonically increasing with quality. This occurs, for instance, in the manufacture of fashion goods for which the attractiveness of the final product may have little relationship with the processes involved in its production.

Several authors have recognized the importance of price as a signal of quality for uninformed consumers. Bagwell and Riordan (1991) argue that high and declining prices can indicate that a product is of high quality. In their framework, high prices are a credible signal of quality because high quality, high-cost firms are more willing to restrict sales volume than low-cost firms. Over time, as the proportion of uninformed consumers decreases, it becomes easier for the high-cost firm to signal its quality and thus its price lowers toward the full-information monopoly price.

Armstrong and Chen (2013) examine a similar environment, but one in which quality is endogenously determined and consumers can potentially be misled by false price announcements. They find that when consumers are ignorant of the initial price, the firm finds it profitable to produce a high quality good and announce the initial price when it is constrained to tell the truth. However, it does even better by producing a low quality good, and subsequently misleading consumers by announcing a high initial price. Therefore, a key empirical question of particular interest to regulators is: Are consumers deceived by suggested prices?

Results from behavioral economics provide additional and alternative explanations for why high suggested prices might be effective in driving demand. Bordalo, Gennaioli and Shleifer (2013) argue that salient attributes are overweighted by consumers when choosing between goods. They proceed to show how this logic can explain "misleading sales," which are mostly identical to what I term suggested pricing. The difference is that retailers inflate original prices during misleading sales, instead of maintaining the same false original price throughout a product's lifetime.

Recently authors have begun to reconcile anomalous patterns in field data using concepts generated in behavioral economics. One such example is Hastings and Shapiro (2012), who find that consumers switch from premium to regular gasoline given a uniform price increase to an extent that cannot be accounted for by wealth effects. They present this as evidence of mental accounting, which manifests itself through the infungibility of money between an individual's different purposes (Thaler 1985).

The above-mentioned theories frequently have conflicting predictions on both consumer behavior and firm decisions, owing to difference in fundamental assumptions. Perhaps because of the rareness of obtaining data with suggested prices, there has been no related empirical work on actual retail settings. Thus, this is a valuable opportunity to test and measure the relative importance of analytic results on both discount pricing and suggested pricing.

Models of price as a signal of quality and those of reference dependence have different predictions of how consumers react to false list prices and provide different motivations for the firm to post suggested prices. Following Bagwell & Riordan (1991) and Armstrong & Chen (2013), suppose that a monopolist supplies one good over two periods, setting prices p_t for periods $t = 1, 2$. Quality may be high or low, with marginal costs being c_i, $i \in \{H, L\}$ respectively. Marginal costs are common knowledge. Consumers are heterogeneous in their patience and there level of information about the quality of the good. A portion x of consumers are *trendy*: they are eager to buy the good, can ascertain its quality, and are in the market in period 1. The remaining $1 - x$ of consumers are *casual*: buyers who are uncertain about the good's quality and enter the market in period 2.

In Bagwell & Riordan (1991), casual consumers do not observe the purchasing decisions of trendy consumers, and the firm is constrained to set $p_1 = p_2$. Casual consumers infer product quality from price, their knowledge of the firm's cost function and the proportion of trendy consumers. If x is small enough, and under equilibrium refinements, casual consumers accept a high price as a credible signal of high quality. Over time, as x increases, the firm can signal high quality with less effort, and thus high quality goods exhibit prices that are initially high but decline over time.

Armstrong & Chen (2013) relax the problem along several dimensions. First, the firm is allowed to choose quality and set $p_1 \neq p_2$. They show that if x is large enough, then the firm chooses to provide high quality and set high prices in both periods if casual consumers do not observe p_1. The condition on x weakens when casual consumer can observe p_1, which provides an incentive for the firm to (credibly) inform casual consumers about past prices. However, when casual consumers can be fooled into believing a false announcement about p_1, then the firm maximizes its profits by producing low quality goods, setting low prices in period 1, and misinforming casual consumers about p_1.

An alternative explanation of why suggested prices exist is provided by Bordalo et al. (2013). They conceptualize salience as it applies to a discrete choice setting. Suppose the consumer's choice set is $\mathbf{C} \equiv (q_j, p_j)_{j=1,\ldots,N}$. Each good j has quality q_j and price p_j. Without salience effects, a consumers values good j with a utility function that assigns equal weights to quality and price:

$$u_j = q_j - p_j.$$

Salient thinking, meanwhile, puts more weight on attributes that stand out for each good. Denote by $(\bar{q}, \bar{p})$ the reference good consisting of average attributes $\bar{q} =\equiv \sum_j q_j/N$ and $\bar{p} =\equiv \sum_j p_j/N$. The salience of quality for good j is then $\sigma(q_j, \bar{q})$ and the salience of price is $\sigma(p_j, \bar{p})$.

The salience function $\sigma(\cdot, \cdot)$ is symmetric and continuous and satisfies the following conditions:

1. *Ordering.* Let $\mu = \text{sgn}(a_j - \bar{a})$. Then for any $\epsilon, \epsilon' \geq 0$ with $\epsilon + \epsilon' > 0$, we have

$$\sigma(a_j + \mu\epsilon, \bar{a} - \mu\epsilon') > \sigma(a_j, \bar{a}).$$

2. *Diminishing sensitivity.* For any $a_j, \bar{a} \geq 0$ and all $\epsilon > 0$, we have

$$\sigma(a_j + \epsilon, \bar{a} + \epsilon) < \sigma(a_j, \bar{a}).$$

In choice set $\mathbf{C}$, quality is salient for good j when $\sigma(q_j, \bar{q}) > \sigma(p_j, \bar{p})$, price is salient for good j when $\sigma(q_j, \bar{q}) < \sigma(p_j < \bar{p})$, and price and quality are equally salient when $\sigma(q_j, \bar{q}) = \sigma(p_j, \bar{p})$.

An example of a salience function is

$$\sigma(a_j, \bar{a}) = \frac{|a_j - \bar{a}|}{a_j + \bar{a}} \tag{3.1}$$

for $a_j, \bar{a} \neq 0$, and $\sigma(0, 0) = 0$.[1]

(Bordalo et al, 2013) The salient thinker's evaluation of good j enhances the relative utility weight attached to the salient attribute (keeping constant the sum of weights attached

[1] This function is also homogeneous of degree 0, which implies diminishing sensitivity.

to quality and price). Formally,

$$u_j^S = \begin{cases} \frac{2}{1+\delta} \cdot q_j + \frac{2\delta}{1+\delta} \cdot p_j & \text{if } \sigma(q_j, \bar{q}) > \sigma(p_j, \bar{p}) \\ \frac{2\delta}{1+\delta} \cdot q_j + \frac{2}{1+\delta} \cdot p_j & \text{if } \sigma(q_j, \bar{q}) < \sigma(p_j, \bar{p}) \\ q_j - p_j & \text{if } \sigma(q_j, \bar{q}) = \sigma(p_j, \bar{p}) \end{cases}$$

where $\delta \in (0, 1]$ decreases in the severity of salient thinking.

Using the definitions in this subsection I illustrate how a demand model that incorporates salient thinking would predict different purchase decisions from a standard demand model.

Let $\mathbf{C_1} = \{(q_0 = 0, p_0 = 0), (q_1 = 15, p_1 = 3), (q_2 = 20, p_2 = 4)\}$. A non-salient thinker would assign values $u_1 = 12$ and $u_2 = 16$, and would thus opt for the high-quality product. Applying the salience function in Eq. 3.1, quality and price are equally salient for both goods, and thus a salient thinker would also opt for high quality.

Now consider a uniform price decrease so that $\mathbf{C_2} = \{(q_0 = 0, p_0 = 0), (q_1 = 15, p_1 = 2), (q_2 = 20, p_2 = 3)\}$. Since utility is linear in quality and price, a non-salient thinker would still choose the high quality product. However, quality is now salient for good 1 and price is salient for good 2. Some algebra shows that a salient thinker would opt for the low quality good if $\delta < 0.82$.

Finally, we account for price expectations. Price expectations affect salience rankings by influencing the reference good. The reference price is now taken by averaging transactional together with expected prices. Taking expected prices as $p_1 = 3$ and $p_2 = 4$, quality becomes salient for both goods in $\mathbf{C_2}$, so that the salient thinker continues to opt for the high quality good for any $\delta \in (0, 1]$.

Thus, emphasizing the importance of salience in consumer decision-making, as well as the primacy of price expectations, results in different predictions for how a firm should apply suggested pricing in retail environments. At a basic level, the relevance of these competing theories (price as a signal of quality versus salience) can be compared by examining how consumers react to suggested prices, and measuring how this depends on consumer characteristics and the choice sets.

3.3 Data and industry background

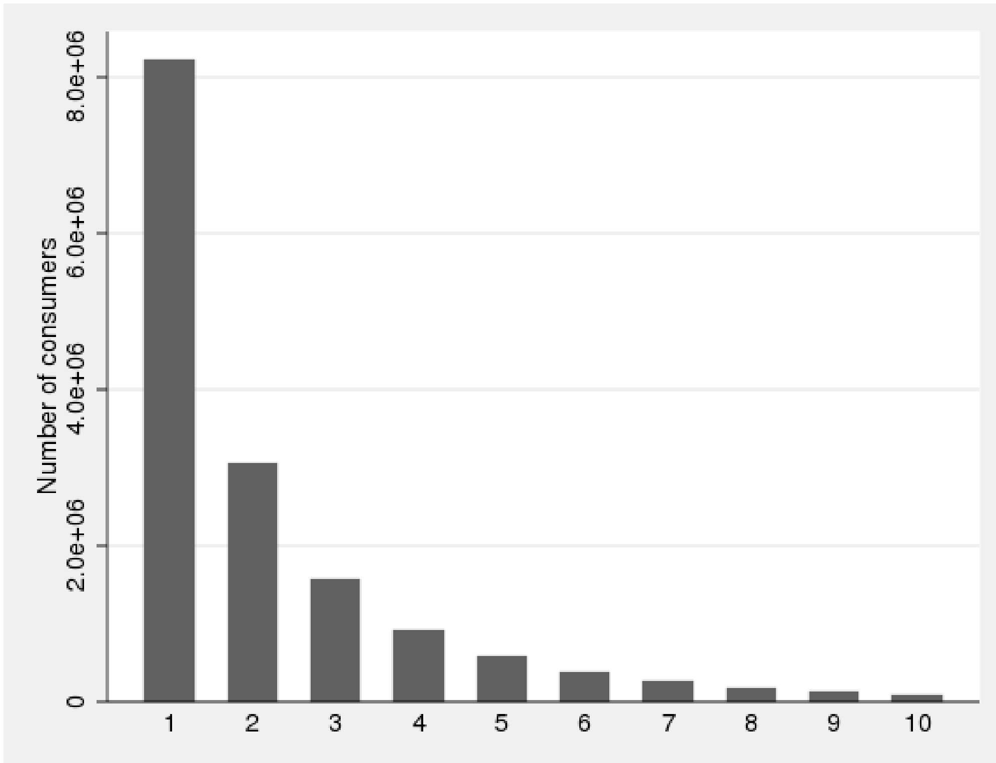
Data is provided by a major fashion goods manufacturer and retailer in the United States. The firm sells above 90% of its products by revenue through its own physical stores. The firm derives more than 60% of its revenue from a single product type, which is a fashion good. All of the data and analysis in this chapter concerns this single product category. The firm dominates as a market leader in this category, controlling about 40% of the market.

The firm operates two types of stores: regular and outlet. Regular stores are centrally located and do not typically offer discounts on products. Outlet stores are typically located an hour away from city centers and offer deep discounts (both actual and suggested). The firm offers two main types of goods: original and factory. Original goods are first sold at full price in regular stores and then sold at a discount in outlet stores. Factory goods are only sold in outlet stores. The firm implements suggested pricing through its factory goods, which carry original prices that are never transacted.

The data consists of transaction-level records over a 5-year period. Each record has the original price of each item and any applied discount. Also included are consumer observables, including billing zip code, date of first purchase from the firm, and household ID.

Consumers. Repeat purchases by consumers are observable in the data. A total of 16,019,140 unique consumers are observed to make purchases within the sample. The proportion of purchases that are made by return consumers is significant (*see* Figure 3.1). In the firm's outlet channel, 24% of purchases are made by return consumers. Of this group,

Figure 3.1: Consumers by number of within-sample purchase instances



38% have made purchases in the regular channel.

Prices. Table 3.1 describes the pricing differences between original and factory goods in outlet stores. Original goods are more expensive than factory goods on average, both in terms of list prices and transactional prices. However, there is much variation in these prices over time; and factory goods occasionally carry higher prices than original goods (*see* Figure C.4).

Figure 3.2 graphs the average percent discount over time for original goods and factory goods in the firm's outlet channel. Recall that original goods are sold at full price in the regular channel, while factory goods are sold exclusively in the outlet channel. The similar trend in discount increase over time for these two product classes reflects the firm's policy of trimming prices at even rates across all products over time, regardless of sales performance.

Table 3.1: Average prices in outlet format

	Original goods	Factory goods
List price	349.03	308.87
	[177.45]	[85.50]
Discount percent	50.84	58.90
	[13.81]	[11.74]
Transactional price	165.76	123.20
	[85.82]	[38.03]
On-shelf composition	69.64%	30.36%
Revenue composition	30.90%	69.10%

Figure 3.2: Discounting pattern in outlet channel

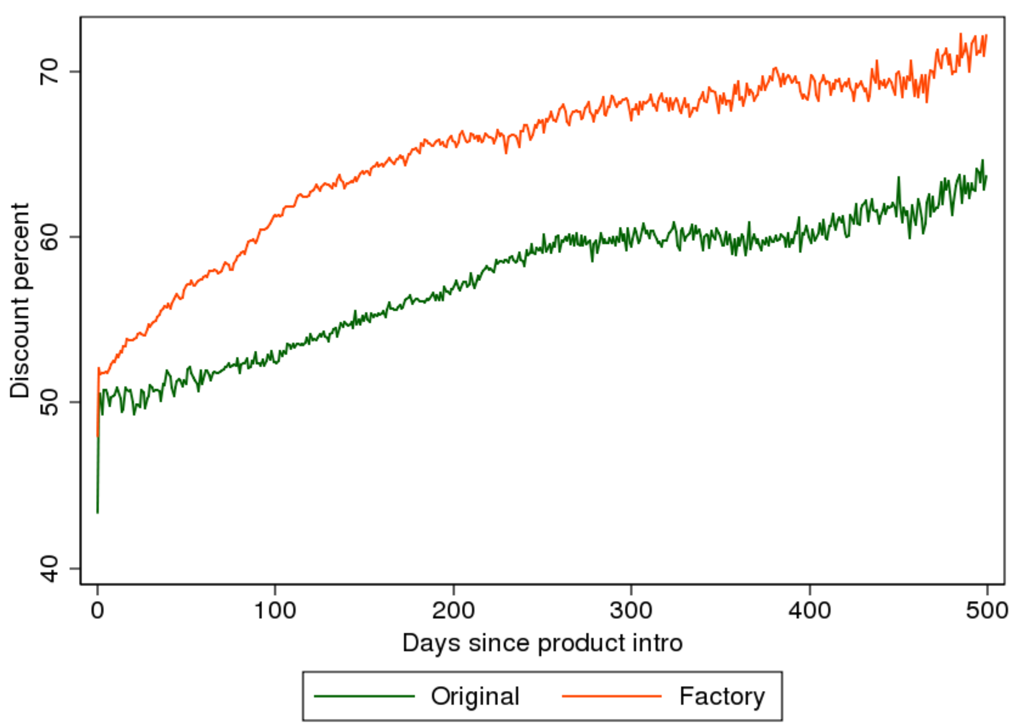
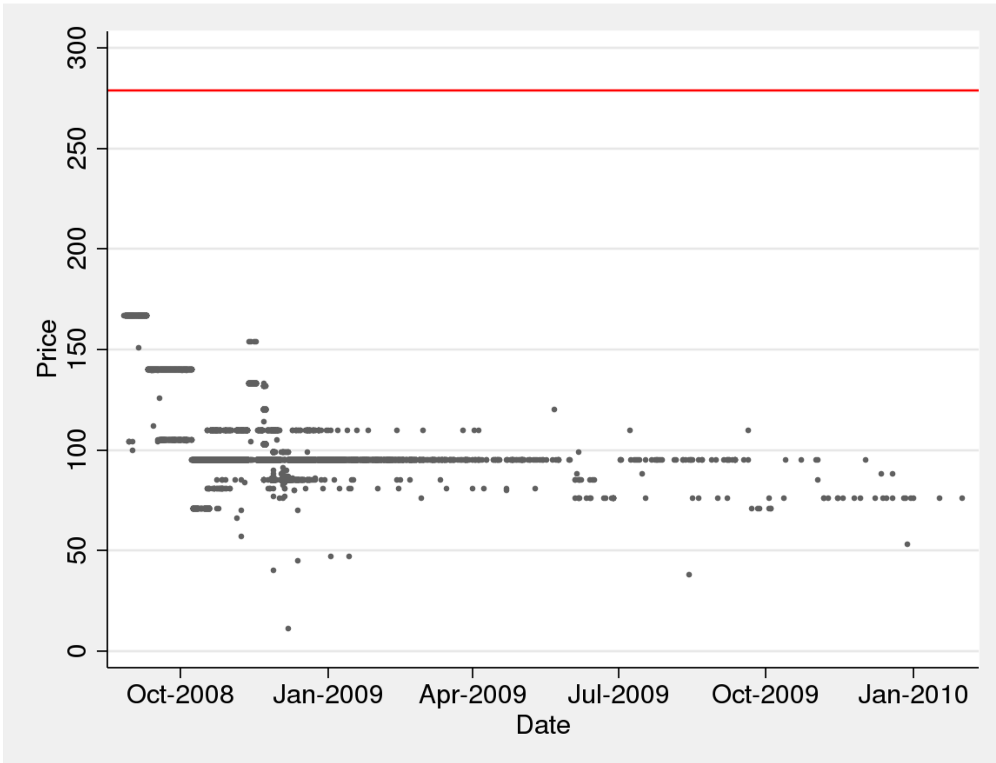


Figure 3.3: Discounting pattern of a typical good



The pattern of discounting implemented by the firm in its outlet stores has store, period, and product-specific components. Across stores and time periods, the firm implements randomized discounting within certain parameters. Occasionally these discounts are also affected by outlet mall-wide events. The product-specific component of discounting is highly correlated with the product's design age, i.e. the time since its introduction. Older-lived products are discounted more heavily. Figure 3.3 plots the list price and observed transactional prices for a single factory good over time, displaying the resulting discount pattern for a typical product.

The red line on Figure 3.3 marks the original price assigned to this particular product. Every single purchase instance over the product's lifetime is plotted on the graph; obviously not a single unit was sold anywhere near the original price. Not immediately observable from the graph is that 94% of units were sold by the end of 2008. This is consistent with high consumer values for a product's newness in this industry. The remaining purchase observations show that the firm does not use discounting in order to clear inventory.

Figure C.2 in the appendix shows that the firm has increased the average discount level over time. This shift provides an opportunity to study the effect on purchase decisions of discount pricing. It also demands an explanation as to why such a pricing strategy is effective.

3.4 Demand model

In this section I present a discrete choice model of consumer purchase behavior and estimate its parameters using data from a major fashion goods retailer. The main objective of estimation is to verify that list prices affect purchase behavior keeping all other product attributes, including the actual selling price, constant. I measure how this effect varies across consumer types. I proceed to decompose consumer sensitivity to different components and ranges of discounting in order to identify the margins in which suggested pricing is most effective. Finally, I test for the significance of certain reference points that may influence the salience of discounting.

The model presented below differs slightly from the demand model estimated in Chapter 1. The first main difference is that instead of including both store and product choice, the model below concerns only product choice conditional on store choice. The rationale for this focus is that discount pricing is exercised most heavily in the outlet channel. Additionally, this allows me to use store foot traffic as a measure of market size. The second main difference is that, rather than estimating product fixed effects, I include product characteristics in the utility function. This is necessary given that there is no within-product variation in list prices.

Let product j in store m and time t be defined by observable characteristics X_{jt}, unobserved quality ξ_j, list price LP_j, and transactional price p_{jmt}. The utility of consumer i from purchasing product j in market m is

$$u_{ijmt} = \alpha p_{jmt} + X_{jt}\beta + \gamma LP_j + \xi_j + \epsilon_{ijmt} \tag{3.2}$$

where α, β, and γ, are parameters, and ϵ_{ijmt} are idiosyncratic demand shocks. (Allowing for greater consumer heterogeneity is left for future work. In what follows the model is estimated within subsets of the data, which is indicative of the importance of consumer heterogeneity.)

Letting ϵ_{ijmt} be iid Type-I extreme value, and inverting the resulting system of market share equations (Berry 1994), we have that mean utilities can be written as

$$\log(s_{jmt}) - \log(s_{0mt}) = \delta_{jmt} \equiv \alpha p_{jmt} + X_{jt}\beta + \gamma LP_j + \xi_j$$

where s_{jmt} are market shares and s_{0mt} is the share of the outside good. A consumer is considered to have chosen the outside good if she has visited a store but has not made a purchase. Availability of foot traffic counts for each store-week enables direct observation of these outside shares.

Initial estimation of demand parameters is by OLS regression of mean utility levels on observables. A market is defined as a store-week. The market size is taken to be the foot traffic recorded in each store-week. Product characteristics X_{jt} include product age and categorical variables relating to shape, color, material, and *collection*.[2] Store and week fixed effects are also included. Descriptive statistics for these variables in the estimation sample

[2] A collection is a set of products that share the same general aesthetic. Products are presented in shelves according to their collection in the firm's regular channel. In the firm's outlet channel, products are grouped according to other physical characteristics.

are reported in Table 3.2.[3]

Table 3.2: Sample descriptive statistics

	Mean	St. Dev.		Count
Market size	9303.74	6442.74	Stores	124
Market share	0.00074	0.00065	Weeks	27
Price	120.80	32.84	Colors	350
List price	337.73	63.37	Materials	29
Age (days)	305.30	152.74	Silhouettes	20
Factory	0.89	0.31	Collections	47

Estimates from the OLS regression are reported in column 1 of Table 3.3. Dummies for each categorical variable, as well as for stores and weeks, are included in this and all succeeding regressions. As anticipated, purchase probability is positively correlated with original price, and negatively with the product's design age. However, these estimates are likely biased and inconsistent owing to a dependence of p_{jmt} and LP_j on ξ_j.

As discussed in previous chapters, the general level of p_{jmt} is determined via a national pricing strategy. Within-product variation in p_{jmt} arises from randomized experiments undertaken by the firm in order to gauge the effectiveness of planned promotions, as well as by a systematic decline over product age as summarized in Table 1.6. Therefore, any correlation between p_{jmt} and ξ_j must follow the same mechanism as that between LP_j and ξ_j.

Instruments for p_{jmt} comprise the average discount percent in a store-week, selected collection dummies, and their interactions. The average discount percent in a store-week reflects store- instead of product-specific departures from full price, and are assumed to be uncorrelated with ξ_j. The collection to which a product belongs may be a suitable instrument because while p_{jmt} and LP_j are highly correlated with collection (see Table C.3), most collections themselves have no bearing on product quality controlling for physical

[3]In this version, the estimation sample includes 27 weeks and 124 stores.

Table 3.3: Demand estimates

dep var: δ_{jmt}	(1) OLS	(2) IV
actual price	-0.00788***	-0.0108***
	[5.05e-05]	[0.000119]
list price	0.00118***	0.00198***
	[2.73e-05]	[7.44e-05]
product age	-0.000166***	-0.000297***
	[1.05e-05]	[1.17e-05]
factory	-0.194***	-0.289***
	[0.00841]	[0.00918]
constant	-5.855***	-5.815***
	[0.512]	[0.514]
Observations	429,730	429,730
R-squared	0.536	0.532

Standard errors in brackets
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

characteristics.

Instruments for LP_j are constructed from list prices of products in the same collection as product j but in other categories. The operative assumption is that, while the relative magnitude of list prices are largely determined by collection across product categories, there is no relationship between the unobserved quality of the main product category and that of list prices of products in other categories within the same collection.

From the total number of collections, I select the most prominently advertised and widely purchased collections as regressors in the second stage, and use the remaining collections as instruments in the first stage. The reasoning is that, apart from the most popular among them, collections in the outlet channel mainly serve as record-keeping devices for the firm, that while related to pricing, are difficult for consumers to distinguish.

As a means of verifying that this subset of product collections are valid instruments, I estimate product intercepts for each of the 3,360 unique styles in the sample using this alternative demand model:

$$u_{ijmt} = \alpha p_{jmt} + \tilde{\xi}_j + \epsilon_{ijmt}$$

Figure C.3 in the appendix plots the estimated $\tilde{\xi}_j$ against LP_j. I assume that $\tilde{\xi}_j$ incorporates both observed and unobserved components of quality. I project $\tilde{\xi}_j$ on regressors X_j, excluding collection dummies, and LP_j and collect the residuals. These residuals, then, comprise the unobserved component of quality. I regress the residuals on collection dummies, and select the 42 collections for which t-stat is less than 2 as instruments for LP_j in the main model. The results of the IV estimation are in column 2 of Table 3.3.

Instrumenting for LP_j eliminates the bias resulting from objectively higher quality products having higher original prices; the magnitude of the IV estimate suggests a large scope for LP_j's influence on purchase behavior controlling for actual product quality. The estimated price coefficient in Table 3.3 implies an average price elasticity of 1.24. Comparing coefficients suggests that each dollar reduction in transactional price has about the same effect on utility as a $5-6 dollar increase in list price.

This simple demand model implies that consumers consider list prices when making their purchase decisions, but does not offer an interpretation as to why consumers do so. Possible reasons are that (i) consumers delay purchases to take advantage of discounts, (ii) consumers take list prices as a signal of quality, (iii) consumers enjoy receiving discounts, or (iv) the firm more aggressively markets products with deeper discounts. Each of these hypotheses, if valid, would correspond to certain patterns in purchase behavior. In the remainder of this section, I extend the basic demand model from Equation 3.2 to verify if these patterns exist in the data.

Price as a signal of quality. Consumers who lack full information may take price as a signal of quality. Demand data, coupled with transactional and list prices, offer an opportunity to measure this signaling effect separately from the more common price sensitivity. If less-informed consumers are more reliant on this signal, then they should demonstrate more sensitivity to list prices.

To check whether this holds true in the data, I bucket the purchase observations according to first-time and repeat consumers.[4] The assumption is that repeat consumers are better informed about product quality owing to their greater experience with the brand. I estimate the regression model for each bucket and present the results in Table 3.4. The estimates suggest that repeat consumers are in fact more sensitive to list prices. This runs counter to the underlying assumptions of signaling models, suggesting that either the evolution of consumer information or the role of list prices is more complex.

Alternatively, I limit the sample to include only old consumers, and then divide the sample according to consumers who have visited the regular store in the past and those that haven't. The corresponding estimates are reported in Table 3.5. Strikingly, although full-price shoppers are much less (transactional) price sensitive than pure factory shoppers, they share almost the same sensitivity to LP_j.

An important distinction exists between *original* and *factory* goods in this market. Original goods are those that were previously sold in the firm's regular channel at their original prices. Factory goods are those that were never sold in the regular channel, but are tagged with suggested prices. Consumers in this market vary in their ability to distinguish original from factory goods. Presumably consumers who have shopped in the regular channel in the past are more able to make this distinction. Table 3.6 contains the estimated coefficient

[4]Unfortunately outside shares cannot be directly bucketed in the same way. I take the ratio of purchases of minor product categories and apply them to the outside shares for estimation purposes.

Table 3.4: New vs old consumers

	(1) First-time consumers	(2) Old consumers
p_j	-0.00689***	-0.00657***
	[0.000134]	[8.45e-05]
LP_j	0.000582***	0.000770***
	[8.21e-05]	[4.78e-05]
age	4.83e-05***	-2.06e-05***
	[1.08e-05]	[1.45e-05]
$factory$	-0.122***	-0.119***
	[0.0193]	[0.00756]
constant	-6.195***	-8.253***
	[0.761]	[0.287]
Observations	224,869	415,079
R-squared	0.555	0.477

Standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table 3.5: Pure factory vs full price shoppers

	(1) Pure factory	(2) Full-price
p_j	-0.00611***	-0.00393***
	[9.54e-05]	[0.000107]
LP_j	0.000564***	0.000541***
	[5.92e-05]	[6.14e-05]
age	-2.84e-05***	-3.08e-05***
	[1.01e-05]	[1.09e-05]
$factory$	-0.118***	-0.122***
	[0.00764]	[0.00824]
constant	-7.926***	-7.708***
	[0.176]	[0.237]
Observations	302,778	179,929
R-squared	0.501	0.595

Standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table 3.6: Interaction

VARIABLES	(1) lhs
p_j	-0.0107***
	[0.000125]
LP_j	0.00276***
	[9.58e-05]
$LP_j \times factory$	-0.000308***
	[0.000107]
age	-0.000268***
	[1.83e-05]
factory	-0.188***
	[0.0437]
constant	-6.283***
	[0.524]
Observations	429,730
R-squared	0.534

Standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

or the interaction of LP_j and $factory$, an indicator variable. As expected, list prices are a weaker signal of quality for factory goods.[5]

Table 3.7 limits the sample to repeat consumers and breaks consumers down according to their prior purchase incidences and estimates the same interaction. Both groups discount list prices on factory goods more than first-time consumers. Interestingly, both groups discount factory prices at about 40%, despite full-price consumers presumably being better able to distinguish factory goods from original goods.

These estimates imply that while LP_j may function as a signal of quality, it works in conjunction with other effects. It is also likely that the signaling mechanism is more complex

[5] A Wald test of the null that the sum of the main and interaction coefficients, i.e. the list price sensitivity of factory goods, is zero is rejected at the 1% level.

Table 3.7: Consumer sensitivity to list prices

	(1)	(2)	(3)	(4)
Shopper type	Discount	Discount	Full-price	Full-price
p_j	-0.00792***	-0.00793***	-0.00624***	-0.00635***
	[8.89e-05]	[8.25e-05]	[0.000115]	[0.000121]
LP_j	0.00173***	0.00278***	0.00158***	0.00189***
	[4.33e-05]	[9.67e-05]	[6.06e-05]	[0.000147]
$LP_j \times factory$		-0.000992***		-0.000485***
		[9.34e-05]		[0.000134]
constant	-9.004***	-9.136***	-7.432	-7.727
	[0.622]	[0.624]	[0.483]	[0.498]
Observations	185,387	185,387	92,739	92,739
R-squared	0.559	0.559	0.622	0.622

Standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

than what these simple demand models can capture. In what follows I include various reference points to the consumer's utility function in an effort to parse these effects without adding complexity to the model.

Reference dependence. The potency of price as a signal of quality and the intensity of bargain-hunting behavior are closely linked in this empirical setting. A discount is only a genuine "deal" if the original price is a dependable measure of the product's quality. One way to distinguish between these effects is by incorporating reference dependence in modeling consumer demand. The extent to which consumers respond to high original prices, or equivalently high discounts, may depend on the general level of discounting, the dispersion in discount levels, or some other reference point.

In what follows I focus on reference points that are specific to a store-week. The thinking is that consumer values are swayed by product attributes' relative distance to some reference level, which in this case is most likely determined during their store visit. Table 3.8 lists

Table 3.8: Description of variable labels in Table 3.9

Model	**Regressor**	**Definition**
1	discount	original price less transactional price
2	discount2	discount^2
3	higher disc_higher	indicator for above-median discount higher × discount
4	discz discz_disc	within-market z-score of discount discz × discount
5	posz negz disc_pos disc_neg	positive z-scores negative z-scores discount × posz discount × negz
6	avedisc sddisc disc_ave disc_sd	average discount in market st dev of discount in market discount × avedisc discount × sddisc
7	mindisc resid_disc	minimum discount in market discount less mindisc
8	resid_disc2	resid_disc^2
9	upper up_resid	indicator for above-median resid_disc resid_disc × upper
10	residdiscz residdiscz_resid_disc	within-market z-score of resid_disc resid_disc × residdiscz
11	rposz rnegz rdisc_pos rdisc_neg	positive values of residdiscz negative values of residdiscz resid_disc × rposz resid_disc × rnegz

variables that may influence the relative attractiveness of discounts in-store. Table 3.9 contains estimates for various specifications that include these variables. Most of the estimated coefficients are large and significantly different from zero, implying considerable scope for reference dependence to influence consumer choice.

The estimates support intuitive notions of reference dependence. The utility from a discount is amplified if the discount is larger than the median level of discounting. In specifications 7 through 11 of Table 3.9, the baseline minimum discount available in a store-

Table 3.9: Reference points

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
price	-0.00639***	-0.00638***	-0.00635***	-0.00638***	-0.00638***	-0.00635***	-0.00636***	-0.00636***	-0.00635***	-0.00636***	-0.00635***
	[4.03e-05]	[4.03e-05]	[4.04e-05]	[4.04e-05]	[4.04e-05]	[4.04e-05]	[4.03e-05]	[4.03e-05]	[4.04e-05]	[4.03e-05]	[4.04e-05]
age	-6.67e-05***	-6.02e-05***	-6.25e-05***	-6.19e-05***	-7.01e-05***	-6.84e-05***	-6.40e-05***	-6.01e-05***	-5.95e-05***	-6.18e-05***	-6.53e-05***
	[1.15e-05]	[1.15e-05]	[1.15e-05]	[1.15e-05]	[1.16e-05]	[1.15e-05]	[1.15e-05]	[1.15e-05]	[1.15e-05]	[1.15e-05]	[1.16e-05]
factory	-0.210***	-0.205***	-0.217***	-0.206***	-0.218***	-0.213***	-0.210***	-0.207***	-0.212***	-0.208***	-0.217***
	[0.0113]	[0.0113]	[0.0114]	[0.0114]	[0.0114]	[0.0113]	[0.0113]	[0.0113]	[0.0113]	[0.0113]	[0.0114]
discount	0.00101***	0.000306***	2.35e-05	0.000927***	0.00125***	-0.00288***					
	[2.93e-05]	[9.33e-05]	[5.95e-05]	[0.000107]	[0.000111]	[0.000318]					
discount2		1.36e-06***									
		[1.70e-07]									
higher			-0.285***								
			[0.0142]								
disc_higher			0.00137***								
			[6.70e-05]								
discz				-0.0137**							
				[0.00578]							
discz_disc				6.21e-05***							
				[1.11e-05]							
disc_pos					-5.91e-05***						
					[1.67e-05]						
disc_neg					0.000461***						
					[5.91e-05]						
posz					0.0215***						
					[0.00759]						
negz					-0.104***						
					[0.0111]						
disc_ave						2.16e-05***					
						[1.25e-06]					
disc_sd						-1.52e-05***					
						[2.22e-06]					
avedisc						-0.00283***					
						[0.000315]					
sddisc						0.00302***					
						[0.000514]					
mindisc							0.00299***	0.00291***	0.00284***	0.00257***	0.00268***
							[8.91e-05]	[9.05e-05]	[9.16e-05]	[0.000128]	[0.000130]
resid_disc							0.000996***	0.000738***	0.000467***	0.000520***	0.000753***
							[2.93e-05]	[6.32e-05]	[5.99e-05]	[0.000111]	[0.000114]
resid_disc2								7.71e-07***			
								[1.67e-07]			
up_resid									0.000730***		
									[6.90e-05]		
upper									-0.0826***		
									[0.00841]		
residdiscz										0.0170***	
										[0.00555]	
residdiscz_resid_disc										4.53e-05***	
										[1.11e-05]	
rdisc_pos											-6.75e-05***
											[1.66e-05]
rdisc_neg											0.000160**
											[6.25e-05]
rposz											0.0451***
											[0.00643]
rnegz											-0.0179***
											[0.00690]
Constant	-7.023***	-6.903***	-6.809***	-6.983***	-7.093***	-6.550***	-7.237***	-7.196***	-7.173***	-7.125***	-7.200***
	[0.741]	[0.741]	[0.741]	[0.742]	[0.742]	[0.745]	[0.741]	[0.741]	[0.741]	[0.741]	[0.741]
Observations	429,730	429,730	429,730	429,727	429,727	429,727	429,730	429,730	429,730	429,727	429,727
R-squared	0.543	0.543	0.544	0.543	0.543	0.544	0.544	0.544	0.544	0.544	0.544

Standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

week enters separately from each product's residual discount. The estimated coefficient for the baseline is about three times that for the residual, suggesting that market-wide discounting is more effective at inducing purchases than product-specific discounting. A possible reason for this is that steeper product-specific discounts may carry a negative signal about a product's popularity or earlier sales performance.

A look at the distribution of available discounts over time suggests that the firm has been decreasing the dispersion of available discounts even as it increases the average (*s*ee Figure C.1). At the same time, the firm has been decreasing the scope of product-specific discounts relative to market-specific discounts. Given the results of demand estimation, one interpretation is that the firm is taking advantage of demand-enhancing store-wide discounts, while minimizing the role of product-specific discounts that carry negative signals about product quality.

Intertemporal substitution. Consumers have been documented to time their purchases to correspond with periodic promotions (e.g. Hendel & Nevo 2011) or to take advantage of declining prices over time (e.g. Nair 2007). I argue that the empirical setting in this essay is not conducive to either of these substitution behaviors. Unlike those in grocery stores, outlet store promotions are irregularly timed and difficult to schedule visits over (see Figure C.2). Although the transactional price for each product does systematically decline over time, so does the product's inherent attractiveness as a fashion good.

I include past-period transactional price $p_{j,t-1}$ in the regression equation to assess if intertemporal substitution is in fact an important factor in purchase decisions. Controlling for the current period's price, the coefficient on the past period's price should be positive if consumers time their purchases to take advantage of lower prices. The estimated coefficient turns out to be negative and statistically significant (see Table 3.10).

Table 3.10: Past-period price effects

	(1)
$p_{j,t}$	-0.00689***
	[8.02e-05]
$p_{j,t-1}$	-0.000949***
	[6.68e-05]
LP_j	0.000889***
	[7.63e-05]
age	-0.000173***
	[1.42e-05]
$factory$	-0.265***
	[0.00851]
constant	-5.737***
	[0.584]
Observations	428,115
R-squared	0.528

Standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

3.5 Conclusion

Price comparisons, whether suggested or not, have become ubiquitous signals in retail settings. The question of how these signals affect purchase behavior is relevant to firms, regulators, and perhaps consumers themselves. Firms, in list prices, possess a potentially powerful driver of demand that is virtually costless to produce and adjust. Regulators face the challenge of assessing whether list prices inform or deceive, and ultimately whether they enhance or damage consumer welfare. Consumers may be surprised to find out how list prices are determined, and the extent to which their own decisions are reliant on them.

This chapter shows that list prices have significant effects on purchase decisions that may operate through several channels. On average, consumers may be thought of as assigning a monetary value to list prices at over 20 actual cents to a suggested dollar. This rate seems invariant to the consumer's depth of experience with a brand.

In addition, values for discounts depend on market-specific reference points. For instance, discount sensitivity is much higher at levels above the average discount in a market. Consumers are also more sensitive to discounts where the variance of discounting is higher. These suggest that optimal price-setting by the firm should incorporate reference dependence in consumer behavior.

For future work, I plan on incorporating consumer heterogeneity in measuring the impact of suggested pricing. Efforts at identifying the effect of heterogeneity in this chapter rely on strong assumptions about how past shopping experience affects consumer information and behavior. Relaxing these assumptions by allowing list price effects to vary flexibly may be provide clues as to which consumer segments are most swayed by list prices.

I also plan to study how consumer behavior provides incentives for the firm to pursue a strategy of setting suggested prices. Since this form of price-setting is costless to the firm, there must be countervailing forces that make setting ever-higher suggested original prices suboptimal. Identifying these countervailing forces is necessary to make the firm's suggested pricing optimization problem well-defined.

The existing literature on price as a signal of quality views suggested list prices only as a means of deceiving uninformed consumers. This literature relies on the strictly monotonic relationship of quality and marginal cost as providing credibility to actual selling price as a signal of quality. In the future, I plan on developing a model in which quality is generated through a stochastic process indexed by marginal cost, and exploring the role that list prices can play in reducing asymmetric information about quality between the firm and consumers. This is motivated by settings in which quality can only imperfectly be set by firms, such as in fashion and design related industries.

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Appendices

Appendix A

Appendix for Chapter 1

A.1 Estimation of taste covariance matrix

Maximization of the log-likelihood function in Equation 1.8 is performed numerically in Matlab using Knitro's interior-point direct algorithm. Efficient integration over $f(\eta_i, \nu_i; \Sigma)$ of each share $s_{zt}(j_k)$ in Equation 1.7 is achieved by quadrature on sparse grids (Heiss and Winschel, 2007). 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.

A.2 Alternative covariance specifications

Chapter 1 describes a demand model that features consumer heterogeneity in coefficients for price, distance, and product age. The covariance in coefficients for distance and product age is estimated, but covariances between coefficients for price and distance, as well as price and product age, are set to zero. Future versions of this model will allow for nonzero covariances between all random coefficients. In this section, I estimate pairwise covariances between coefficients for price, distance, and product age, and discuss possible implications on the policy simulations.

I maximize the same likelihood as in Equation 1.8 but with alternative restrictions on the joint covariance matrix of ζ_i, η_i, and ν_i—random shocks to coefficients for price, travel distance, and product age, respectively. Table A.1 presents estimates for the case in which $\eta_i \sim N(0, \sigma)$ and $[\ \zeta_i \quad \nu_i\ ]' \sim N(0, \Sigma)$, and Table A.2 presents estimates for that in which $\nu_i \sim N(0, \sigma)$ and $[\ \zeta_i \quad \eta_i\ ]' \sim N(0, \Sigma)$ While the estimated $\rho_{price,age}$ and $\rho_{price,dist}$ are significant, they are much smaller in magnitude than the estimate of $\rho_{age,dist}$. This suggests that there is less scope for the study of counterfactuals in which these correlations are made closer to zero.

Table A.1: Nonzero covariance in price and distance coefficients

	coef	se
Product level		
price	-2.199	0.690
age	-2.863	0.523
σ_{age}	0.207	0.183
Store level		
IV	0.434	0.181
distance	-1.148	0.182
chol(Σ)		
(1,1)	0.095	0.023
(2,1)	-0.077	0.012
(2,2)	0.511	0.364
Implied covariances		
σ_{price}	0.308	
σ_{dist}	0.517	
$\rho_{price,dist}$	-0.148	
N	7,566,195	
l	1,831.78	
product fixed effects	yes	
store fixed effects	yes	

Table A.2: Nonzero covariance in price and product age coefficients

	coef	se
Product level		
price	-2.468	0.722
age	-3.215	0.838
Store level		
IV	0.410	0.262
distance	-0.839	0.096
σ_{dist}	0.472	0.086
chol(Σ)		
(1,1)	0.374	0.148
(2,1)	-0.084	0.024
(2,2)	0.268	0.096
Implied covariances		
σ_{price}	0.374	
σ_{age}	0.281	
$\rho_{price,age}$	-0.299	
N	7,566,195	
l	1,830.92	
product fixed effects	yes	
store fixed effects	yes	

Future work will involve estimating the full covariance matrix, i.e. one in which each element of Σ is unconstrained, where $[\ \zeta_i \quad \eta_i \quad \nu_i\ ]' \sim N(0, \Sigma)$. Substantial variation in prices, product ages, and store locations relative to consumers, both within and across products, allows for the full identification of Σ. The computational burden of estimating two additional random coefficients, however, can be much greater given both the base size of the data and the additional (Gauss-Hermite quadrature) sample points needed to estimate a 3×3 covariance matrix for a given level of accuracy. At the accuracy in the current estimation, 53 weighted sample points are used to simulate the bivariate normal distribution. To simulate a trivariate normal at the same level of accuracy requires 165 weighted sample points, effectively tripling the number of simulated observations (Heiss and Winschel 2008).

While the pairwise correlations estimated in this section imply more limited interaction between demand coefficients for price and product characteristics than between product age and store convenience, allowing for all of these dependencies simultaneously in estimation may either temper or accentuate the estimated parameter of interest in Chapter 1: the correlation in tastes for product age and store convenience. They may also affect the magnitudes of the predicted changes in performance in Chapter 2's counterfactuals. They would not, however, alter qualitative results about how the profitability of multidimensional product differentiation depends on the correlation in consumer tastes for each quality dimension.

Appendix B

Appendix for Chapter 2

B.1 Finding optimal prices

The policy simulations in Chapter 2 involve generating optimal prices given counterfactual product characteristics. This presents a nontrivial computational task given the sheer 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 2.3,

$$\mathbf{p} = \mathbf{mc} - \boldsymbol{\Delta}^{-1}\mathbf{s}$$

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

Appendix C

Appendix for Chapter 3

Table C.1: Frequency of list prices

List price	Percent of styles	Average transacted price	Discount	Percent original styles
298	15.84	114.63	60.68	40.80
398	10.87	149.30	61.21	45.65
358	9.14	141.59	59.93	37.93
348	6.54	123.45	63.82	61.45
328	6.38	104.72	67.30	74.07
198	5.67	96.00	50.52	9.72
278	4.33	113.80	58.13	12.73
498	4.02	190.59	61.08	17.65
268	3.62	102.72	59.97	32.61
598	3.23	249.80	57.55	9.76
248	2.60	91.30	62.32	57.58
258	2.52	91.38	61.35	6.25
458	2.29	150.79	66.45	27.59
428	2.29	149.41	64.37	72.41
378	2.21	129.50	64.31	60.71

Figure C.1: Average discount percent in outlet stores

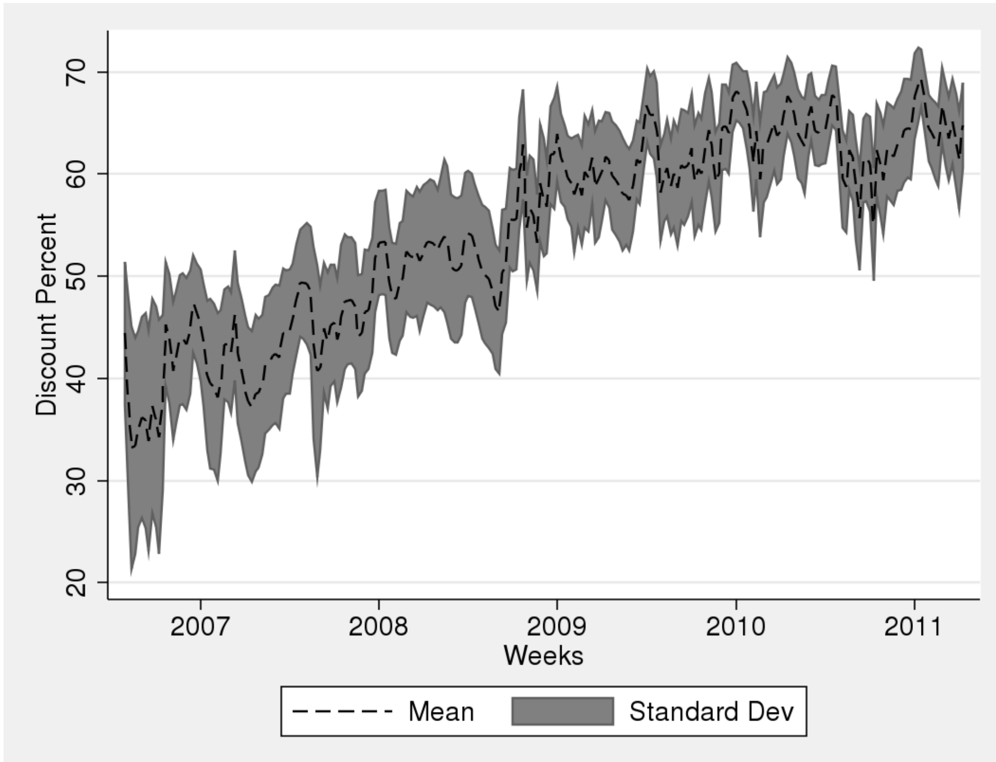

Table C.2: Traffic

Dependent variable: $foot\_traffic$	(1)	(2)
$discount\_pct_t$	69.40***	68.26***
	[1.770]	[1.806]
$discount\_pct_{t-1}$		-5.819***
		[1.800]
constant	5,486***	6,943***
	[1,699]	[2,396]
store fixed effects	yes	yes
week fixed effects	yes	yes
Observations	24,672	24,535
R-squared	0.829	0.829

Standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Figure C.2: Average discount percent in outlet stores

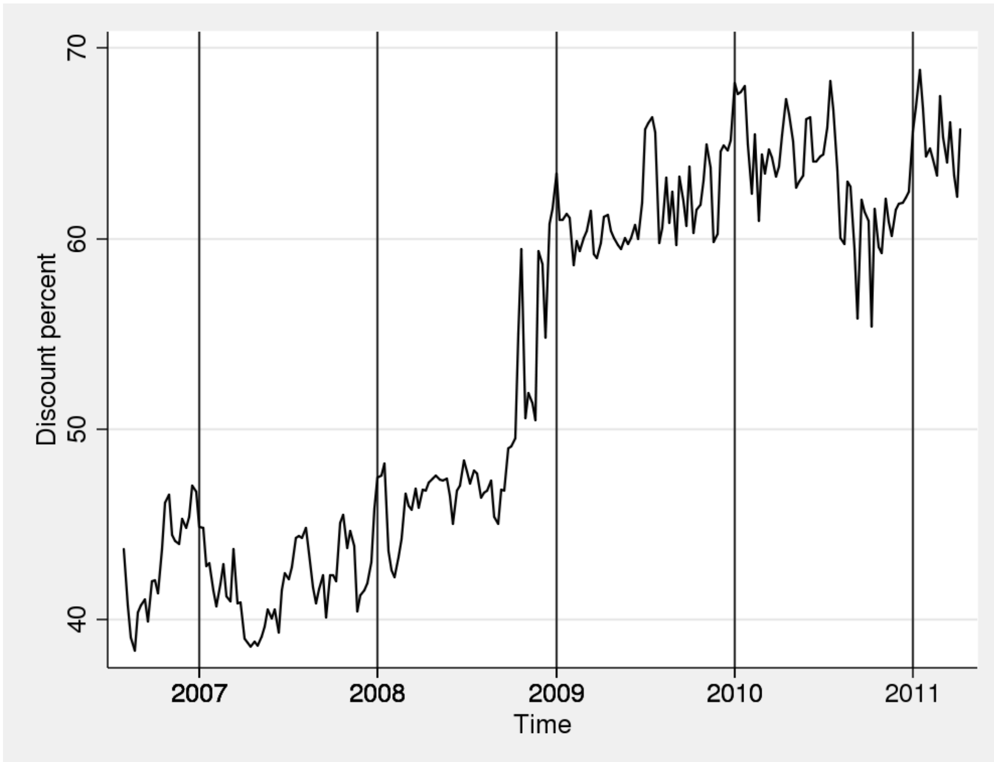

Table C.3: First stage IV regressions

VARIABLES	(1) price	(2) list price	(3) discount	(4) disc_pct
age	-0.0594***	-0.0336***	0.0258***	0.000142***
	[0.000434]	[0.000814]	[0.000597]	[8.84e-07]
factory	-28.92***	-61.51***	-32.59***	0.0232***
	[0.438]	[0.821]	[0.602]	[0.000891]
constant	545.3***	756.3***	211.0***	-0.0232
	[27.84]	[52.20]	[38.24]	[0.0567]
Observations	429,730	429,730	429,730	429,730
R-squared	0.632	0.662	0.758	0.782

Standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Figure C.3: Scatterplot of suggested prices and estimated quality

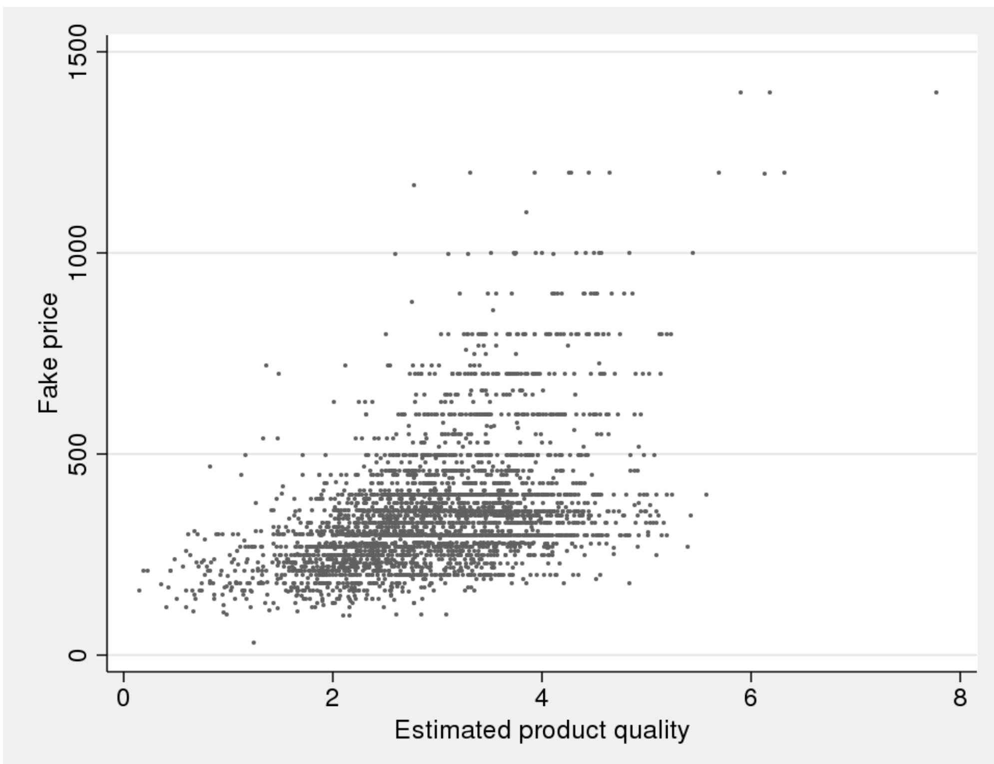

Table C.4: Shifting with store average discount percent

	(1) IV	(2) With shifter
p_j	-0.00746***	-0.00734***
	[8.63e-05]	[8.55e-05]
$suggested\_p_j$	0.000758***	-0.00546***
	[6.30e-05]	[0.000264]
$suggested\_p_j \times ave\_disc\_pct$		0.00986***
		[0.000400]
age	-0.000183***	-0.000189***
	[1.02e-05]	[1.02e-05]
$factory$	-0.287***	-0.293***
	[0.00843]	[0.00841]
constant	-6.328***	-6.375***
	[0.0541]	[0.0541]
Observations	429,730	429,730
R-squared	0.527	0.526

Standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Figure C.4: Prices over time