Fake Discounts Drive Real Revenues in Retail

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Abstract

Prices in a wide variety of contexts are often presented in three parts: an original or suggested list price, a discount off that price, and the final selling price. Limited empirical evidence is available that speaks to the relative impact of each component on purchase behavior, even as theories abound. Measuring these impacts is of critical importance to sellers, consumers, and to regulators who are keen on enforcing deceptive advertising guidelines against "fictitious pricing," or the practice of quoting list prices that do not truthfully reflect prior selling prices. This paper uses a large retail transactions data set that features wide variations in these pricing components within a relatively homogeneous product space. The data set has the unique feature of containing sales records wherein a subset of products have verifiably fictitious list prices and discounts, allowing for measurement of their impact on purchase incidence in actual retail settings. I outline the broad theories that address fictitious pricing, list their corresponding predictions, and examine their relevance empirically. I find that fake list prices have a strong influence on purchase outcomes, with a 1-dollar increase in the list price having the same positive effect on purchase likelihood as a 77-cent decrease in the actual selling price. This effect is largely invariant to consumers' experience with the brand, as inferred from their prior purchases. In addition, I find evidence for the dependence of this effect on store-level reference points such as the lowest offered discount within the store. These results have important implications for how managers should set each pricing component to maximize profits, as well as for how regulators should assess the welfare effects of allowing firms to post fake list prices.

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1 Introduction

Virtually all firms engage in some form of discount pricing. There are several reasons for which firms might drop the price of a good over time: 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. In contrast, this paper focuses on motivations for discount pricing that arise from consumers having imperfect information or possibly exhibiting irrational behavior. These are motivations that might encourage firms to post high "original" prices at which products were never actually available for purchase.

This practice, termed "fictitious pricing" by the Federal Trade Commission (FTC), occasionally results in litigation. In one recent case, a class-action lawsuit was filed against Kohl's Department Stores in California for allegedly misstating in advertising that items had been marked down (Dolan 2013). In reversing an earlier district court dismissal of the case, the US 9th Circuit Court of Appeals stated that California consumer laws permit such lawsuits if the consumer would not have made the purchase but for the perceived bargain. In December 2016, JCPenney, Sears, Macy's, and Kohl's were all hit with lawsuits over similar allegations. JCPenney and Kohl's had previously been sued over the same practice and settled respectively for \$50 million and \$6.5 million (Popken 2016).

Fictitious pricing is one area in which enforcement differences between states and the FTC loom large. Between 1950 and 1970, 30% of FTC challenges to advertising were related to "fictitious price claims" (Pitofsky et al. 2003). Since 1979, however, the FTC has not brought a single fictitious pricing case to court. Several FTC chairs have indicated that enforcement actions in this area have done more harm than good. This is because of the difficulty and arbitrariness with which a "genuine" discount might be differentiated from a deceptive one. In the current state of enforcement, state attorneys-general apply local statutes in bringing cases; however, enforcement is highly uneven, with major cases attracting widespread attention every few years but with many firms consistently ignoring fictitious pricing statutes with impunity.

The main obstacle in litigating individual cases, and therefore in policing this practice more broadly in the marketplace, stems from the difficulty in assessing private damages from fictitious pricing (Friedman 2015). Various recent cases in Illinois against large retailers such as Joseph A Bank[1], Carter's[2], and QVC[3] were found in favor of the sellers due to the plaintiffs' failure in establishing economic harm due to false price claims. The question of whether consumers are deceived by fake price claims is also a factor, with one court decision seeing no fault because consumers "see through the ruse."[4]

In this paper, I identify patterns in how consumers respond to false and genuine discount claims by the same seller. I use data from a dominant fashion goods retailer that makes heavy use of discounting in its outlet stores. This data set offers a rare and unique opportunity to study this pricing strategy because it records both list and selling prices, as well as repeat purchases. A portion of these list prices are observably genuine, while the remainder are fictitious. As with many brands and retailers, the firm implements random discounts across both time and products in-store, providing much variation in final selling prices for each product.

While a number of earlier studies have examined the question of fake prices in laboratory experiments or survey methodologies, there have been, to my knowledge, no prior studies that establish the effect of fake list prices on purchase behavior in actual retail settings. There are several benefits from using transactions data to address this question. Whereas survey methodologies must rely on a constructed notion of what constitutes the actual "market price" for a particular good, in my empirical setting such a quantity is directly observed from the data. Using sales data also sidesteps the issue of ensuring incentive compatibility in measuring changes to consumers' intent to purchase. Perhaps the most important advantage of using sales data is the ability to measure the effects across hundreds of different products, rather than relying on a few focal products in the typical survey questionnaire.

I use a parsimonious discrete choice model of demand to estimate the effect of list prices on purchase likelihood. Identification of this effect arises from variation in list prices within the same product

[1] No. 12-C-7782 (N.D. Ill. July 25, 2013).
[2] 598 F.3d 362 (7th Cir. 2010).
[3] 888 N.E.2d 1190 (Ill. App. Ct. 2008).
[4] B. Sanfield, Inc., 258 F.3d at 579.

across different styles. The large number of observations, combined with the firm's national pricing policy, permits the estimation of style and color fixed effects, without the need to use instrumental variables to control for endogeneity. I explore how responses to list prices vary according to consumer subgroups and depend on contextual reference points.

I find that consumer responses to list prices are consistent with theories that treat prices as a signal of product quality and that hypothesize reference-dependent behavior in how consumers evaluate prices. Controlling for selling prices and other product characteristics, a higher list price substantially increases a good's purchase probability. Moreover, this effect is larger for products with fake list prices than for those for which list prices are genuine. Finally, this effect seems to be invariant to the consumer's level of information.

One might expect fake list prices to have a diminishing marginal effect on purchase likelihood, such that at some point increasing the list price further would cease to be effective. Somewhat puzzlingly, I find no support for this relationship in the data, and in fact find some support for an exponentially increasing relationship. I find that reference dependence offers an explanation of this phenomenon. Consumers take the minimum offered discount in a store as the reference point, to the extent that purchase likelihood is invariant to the minimum discount and highly dependent on the distance between product-specific discounts and the benchmark.

This reference dependence is in line with the idea that firms exploit bargain-hunting behavior through false prices (Armstrong & Chen 2013). 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 list 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.

Taken together, these results confirm that fake list prices and discounts play a large role in consumer shopping decisions, but point to the need to for new thinking about this role in ways that have not been emphasized by regulators, courts, or prior literature. It is possible, for example, that fake list prices play an important role in relaying information about product quality in an environment where many consumers face high uncertainty. This may be particularly true in fashion, where a product's marginal cost may be very weakly correlated with its quality.

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

The paper proceeds as follows. Section 2 reviews the related literature on discount pricing and reference dependence. Section 3 describes the data used for the empirical analysis and provides some descriptive statistics. Section 4 outlines a demand model and presents parameter estimates. Section 5 concludes and points to directions for future work.

2 Related literature

Forms of fictitious pricing have been studied in a wide variety of circumstances. The environment I consider has the following features: a single seller that produces goods of varying quality within one category, a weak regulatory environment, consumers that have less information than the firm about product quality and past prices, and the possibility of repeat purchases. Additionally, 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 in the economics literature 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. This is related to a key empirical question of particular interest to regulators: Are consumers deceived by fake discounts?

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 the legalistic definition of fictitious pricing. The key difference between their framework and the empirical setting here 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. (See Table 1 for a summary. A similar table containing results in marketing research and a comprehensive list of references is contained in Grewal & Compeau 1992.) Complementing these theories is a robust stream of marketing research that seeks to measure the impact of reference prices on consumer perception and behavior. An early instance is Blair and Landon (1981), who present example ads to shoppers in a Houston shopping mall and elicit their understanding of the actual potential savings available given the advertised reference prices. They find that, on average, shoppers do not accept the full advertised savings at face value. The authors do not, however, establish the effects of these reference prices on purchase probabilities. Plausible and exaggerated references prices have been found in other work to have positive effects on purchase likelihoods, as well as a negative effect on the likelihood of further search (e.g. Biswas & Blair 1991, Della Bitta, Monroe & McGinnis 1981, and Urbany, Bearden & Walker 1988).

Grewal and Compeau (1992) provide a discussion of the available evidence in marketing research and explore its implications with respect to the prevailing FTC guidelines on deceptive advertising and state-level statutes on allowable price claims. They place emphasis on the latitude sellers have to make false price claims as well as the susceptibility of consumers to these claims. They conclude by advocating strict adherence to truthful claims to sellers on an ethical basis, while recommending stringent enforcement by regulators.

Prior research, beginning with the seminal work of Tversky and Kahneman (1981) and extending into a substantial amount of marketing research has examined the role of various reference points, and specifically in-store promotions, on consumer choice. Consumers have been found to consider various price signals in addition to the current selling price when making purchase decisions, including past-period promotions and other current-period prices (e.g. Lattin & Bucklin 1989, Mayhew & Winer 1992, Rajendran & Tellis 1994, Kumar et al. 1998). In addition, consumers have also been document to "discount" discounts, depending on the size of the discount (Gupta & Cooper 1992) or the frequency of promotions (Marshall & Leng 1992).

Perhaps because of the rareness of obtaining sales data that contain posted fake list prices, there has been little empirical work performed within actual retail settings. The availability of sales data from a seller that practices fictitious pricing presents a rare and unique opportunity to measure the impact of different forms and levels of reference pricing on purchase outcomes. It is also an opportunity to test and measure the relative importance of analytic results on the various forms of discount pricing.

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 the majority of its revenue from a single product category. This paper focuses on sales patterns within this product category. The firm is the market leader in this category with a market share

Table 1: Theories of fictitious pricing in economics

Notion	Papers	Critical Assumptions	Predictions
Signaling	Bagwell & Riordan (1991); Armstrong & Chen (2013)	Some consumers mistakenly believe that fake prices are original prices.	Less-informed consumers will be more likely to buy items with high "original" prices then better-informed consumers.
Bargain-hunting	Armstrong & Chen (2013)	Demand is disproportionately higher for unexpectedly low prices.	The firm finds it profitable to charge different prices to identical consumers.
Salience	Bordalo, Gennaioli & Shleifer (2013)	Consumers overweight "salient" attributes.	Demand for higher quality goods will rise more after a uniform price increase. Higher quality goods are more likely be put on sale.

A similar table containing results in marketing research and a comprehensive list of references is contained in Grewal and Compeau (1992).

of about 40%.

The firm operates two types of stores: **regular** and **outlet**. Regular stores are centrally located in cities and do not typically offer discounts on products. Outlet stores are located about an hour's drive away from city centers and offer deep discounts (both real and fake). The firm offers two 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. Table 2 shows counts of unique products sold in the data by channel and product type. The firm implements a fictitious pricing policy for its factory goods, by indicating list prices that are never actual selling prices.

Table 2: Unique product counts by channel and product type

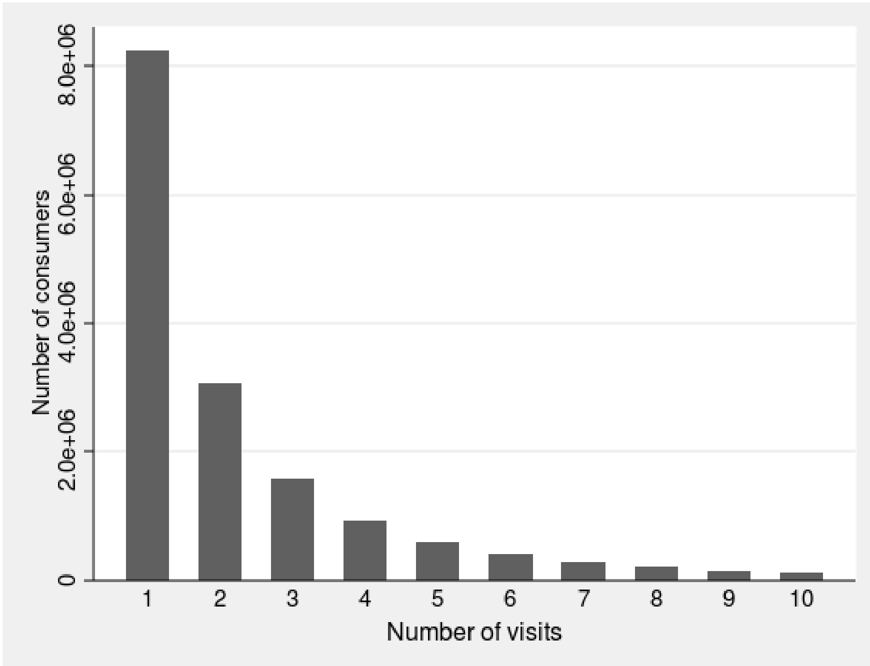
	Original products	Factory products
Regular channel	7,167	0
Outlet channel	8,479	3,696

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

Consumers. A total of 16,019,140 unique consumers are observed to make purchases within the sample. Repeat purchases by consumers are observable in the data. The proportion of purchases that are made by return consumers is significant (*see* Figure 1). In the firm's outlet channel, 24% of purchases are made by return consumers. Of this group, 38% have made purchases in the regular channel.

Products, prices, and channels. The firm produces different *styles* of its main product, and offers each style in different colors. A product is defined by its style and color. Each style-color combination has only one list price, but styles may vary in list price according to color. The list price is set at the time of product introduction and never changes. The firm's managers explain that there are several reasons why list prices may vary between colors of the same style. One reason is that some colors may be thought of as more desirable than others. Another reason is that colors may be introduced at different times, with timing being a factor in determining a product's

Figure 1: Consumers by number of within-sample purchase instances



list price. Yet another reason is that some style-color combinations are regular or outlet channel-specific. Variation in list prices within product styles provides a valuable source of identification. Overall, there are 4,610 styles observed in the data, and an average of 2.93 colors in each style for a total of 13,522 unique products sold.

Each style-color combination is either an original good or a factory good based on the channel in which the product is introduced. Table 3 describes the pricing differences between original and factory goods in outlet stores.[5] Original goods are more expensive than factory goods on average, both in terms of list prices and selling prices. However, there is much variation in these prices over time, and factory goods occasionally carry higher prices than original goods (see Figure B in the Appendix).

Figure 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.

[5]Further details are in appendix Table A.

Table 3: 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%

Standard errors are in brackets.

Figure 2: Discounting pattern in outlet channel

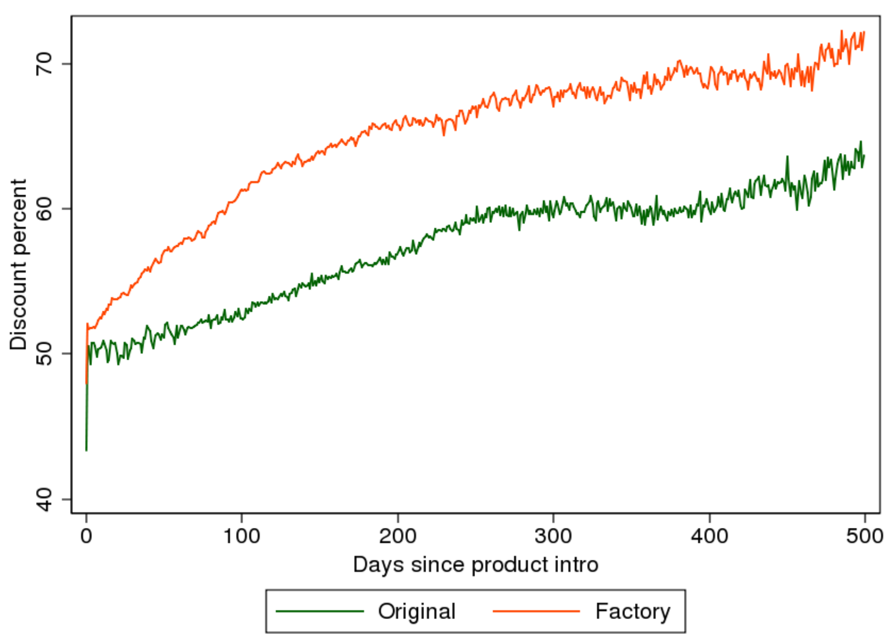
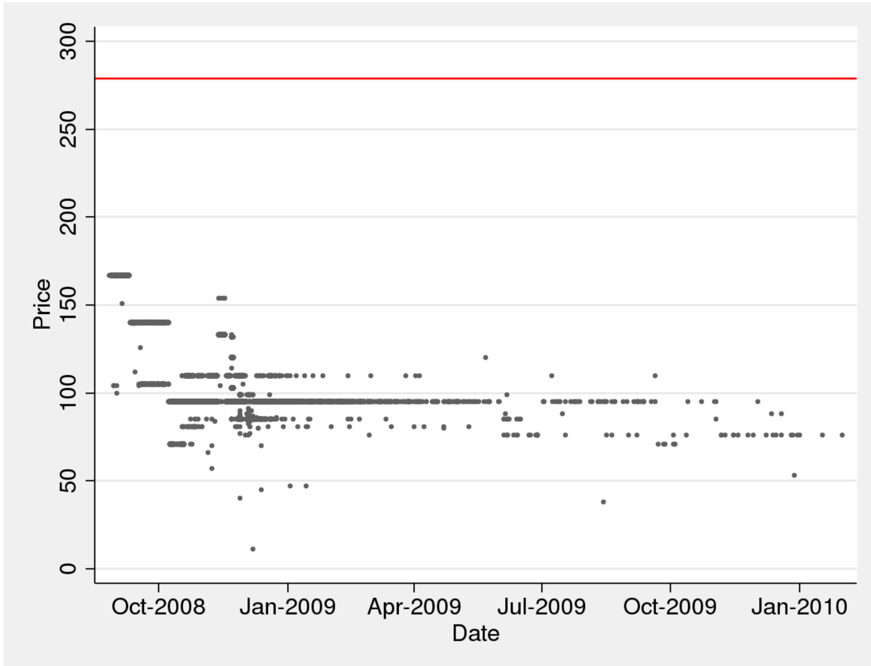


Figure 3: Observed selling prices of a typical factory good in the outlet channel



Note: The red line represents the product's list price.

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 plots the list price and observed selling prices for a representative factory good over time, displaying the resulting discount pattern for a typical product.

The red line on Figure 3 marks the product's list price. Every single purchase instance over the product's lifetime is plotted on the graph; not a single unit was sold at or even near the list price. Not 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 are consistent with statements by the firm's executives that disavow the use of discounting in order to clear inventory.

4 Demand

In this section I present a parsimonious discrete choice model of consumer purchase behavior and estimate its parameters using data from a major fashion goods retailer. The initial objective of estimation is to determine whether fake list prices affect purchase behavior keeping all other product attributes, including actual selling prices, constant. Subsequently, I measure how this effect varies between consumer types, product classes, and store conditions. I proceed to decompose consumer sensitivity into different components and ranges of discounting in order to identify the conditions under which list prices are most impactful. Finally, I test for the significance of certain reference points that may influence the effectiveness of discounting.

4.1 Baseline model

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

$$u_{ijmt} = \alpha p_{jmt} + X_{jt}\beta + \gamma LP_j + \xi_j + \epsilon_{ijmt} \tag{1}$$

where α, β, and γ, are parameters to be estimated, and ϵ_{ijmt} are idiosyncratic demand shocks. This form of utility is similar to previously considered specifications in which other price components or reference prices are included as predictors of demand (e.g. Greenleaf 1995).

Letting ϵ_{ijmt} be i.i.d. Type-I extreme value, and inverting the resulting system of market share equations (Berry 1994), mean utilities δ_{jmt} can be written as

$$\log(s_{jmt}) - \log(s_{0mt}) = \delta_{jmt} \equiv \alpha p_{jmt} + X_{jt}\beta + \gamma LP_j + \xi_j \tag{2}$$

where s_{jmt} are market shares and s_{0mt} is the share of the outside good. A consumer is counted as having chosen the outside good if she visited a store but did not make a purchase. Availability of per-period foot traffic counts for each store enables direct measurement of these outside shares.

Estimation of demand parameters is by regression of mean utility levels on observables. A market is defined as a store-month. The market size is taken to be the foot traffic recorded in each store-month. Product characteristics X_{jt} include product age and categorical variables relating to style, color, silhouette, material, and *collection*.[6] Store and month fixed effects are also included. Descriptive statistics for these variables in the estimation sample are reported in Table 4.

Table 4: Descriptive statistics for estimation data

	Mean	**St. Dev.**		**Count**
Market size	8,841.77	5,925.55	Markets (store-months)	5,704
Inside market shares	0.0011	0.0016	Stores	131
Selling price	137.58	55.26	Months	54
List price	325.24	98.74	Unique items (style-colors)	13,522
Product age (days)	231.38	508.91	Styles	4,052
Factory dummy	0.58	0.49	Colors	1,164
			Materials	48
			Silhouettes	32
			Collections	79

Table 5 contains the baseline results of demand estimation. Estimates from an OLS regression of mean utility are reported in column 1. Dummies for each categorical variable, as well as for stores and months, are included as explanatory variables. Style fixed effects are left out.[7] As anticipated, purchase probability is positively correlated with list price, negatively correlated with selling price, and negatively correlated with product age. However, these estimates are possibly biased and inconsistent due to a correlation between list price LP_j, and consequently, selling price p_{jmt}, and unobservable quality ξ_j.

The general level of p_{jmt} is determined via a national pricing strategy. Within product and time, 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, which is not influenced by the sales performance of particular products. Therefore, any systematic correlation between p_{jmt} and ξ_j must follow the same mechanism as that between LP_j and ξ_j, conditional on product age age_{jt}.

[6] A collection is a set of products that share the same general design features. 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.

[7] There is no variation in materials, silhouettes, or collections within styles.

Table 5: Demand estimates

VARIABLES	(1) OLS	(2) OLS	(3) IV	(4) OLS	(5) OLS
selling price p_{jmt}	-0.00265***	-0.00226***	-0.00428***	-0.00122***	-0.00170***
	[2.05e-05]	[1.64e-05]	[7.72e-05]	[2.48e-05]	[2.51e-05]
list price LP_j	0.000393***			0.00458***	0.00132***
	[1.29e-05]			[0.000210]	[0.000225]
discount$_{jmt}$		0.000393***	0.000340***		
		[1.29e-05]	[1.31e-05]		
product age	-0.000139***	-0.000139***	-0.000182***	-0.000193***	-0.000428***
	[2.34e-06]	[2.34e-06]	[2.85e-06]	[3.07e-06]	[3.66e-06]
factory dummy	0.520***	0.520***	0.469***	-0.0928***	-0.0807***
	[0.00269]	[0.00269]	[0.00330]	[0.00706]	[0.00796]
store dummies	yes	yes	yes	yes	yes
collection dummies	yes	yes	yes		
material dummies	yes	yes	yes		
silhouette dummies	yes	yes	yes		
color dummies	yes	yes	yes		yes
style dummies				yes	yes
constant	-7.449***	-7.449***	-6.873***	-7.626***	-6.650***
	[0.691]	[0.691]	[0.693]	[0.0690]	[0.798]
Observations	2,416,754	2,416,754	2,416,754	2,416,817	2,416,817
R-squared	0.316	0.316	0.312	0.345	0.371

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

In columns 2 and 3 of Table 5, I include

$$\text{discount}_{jmt} \equiv LP_j - p_{jmt} \tag{3}$$

as a dependent variable instead of list price LP_j (Greenleaf 1995). Assuming that discount$_{jmt}$ follows a systematic pattern across products, as the firm's managers claim, this leaves selling price p_{jmt} as the endogenous variable in the equation, instead of both p_{jmt} and LP_j. I instrument for price using each product's introduction date, coded as the number of days since a base date. While the firm's pricing benchmarks for new product introductions vary over time, there is no evidence suggesting a relationship between a product's introduction date and its quality. I present the OLS version of the regression in column 2 of Table 5, and instrument for selling price in column 3. As would be expected given the endogeneity of the price variable, the estimated price elasticity is greater in the IV model. The coefficient on list price, however, is relatively stable in both OLS and IV specifications. Table 6 contains estimates of the first stage regression for the IV model.

Columns 4 and 5 of Table 5 contain results of OLS regressions that include style fixed effects as explanatory variables. The regression in column 5 includes color fixed effects as well. Including style dummies rather than broader categorical product attributes improves goodness of fit and has interesting effects on the estimated coefficients. The coefficient on selling price is much smaller in absolute value than in earlier specifications. It is perhaps counterintuitive that estimated price sensitivity is lower when controlling for more product attributes, as the typical concern is that higher quality products are also higher priced. This is, however, consistent with the firm's policy of keeping bestselling styles on the shelf for longer at low prices, going so far as ordering additional production lines to support further sales.

The estimated coefficient for list price (or discount) is much higher by an order of magnitude in the last two specifications, which may also seem counterintuitive. We may have expected the opposite pattern, with higher estimated list price effects when controlling less finely for product attributes, given a supposed positive correlation between product quality and list price. One important factor here may be the seller's inability to precisely forecast the desirability of any particular product, which results in some products with a higher list price being less desirable than products with lower

Table 6: First stage regression

VARIABLES	(1) selling price p_{jmt}
introduction date$_j$	-0.0432***
	[0.000125]
discount$_{jmt}$	0.0608***
	[0.000546]
age$_{jt}$	-0.0620***
	[0.000146]
factory$_j$	-10.58***
	[0.109]
store dummies	yes
collection dummies	yes
color dummies	yes
constant	1,022***
	[26.39]
Observations	2,464,200
R-squared	0.322

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

list prices.

I choose the model used in column 5 of Table 5 as the preferred specification, and the baseline for all succeeding analyses. This specification enables measurement of list price effects at the most granular possible level given the context: variation in list prices between different colors of the same style. This specification also precludes the need to use instrumental variables techniques, as style and color fixed effects absorb all physical product attributes and prices are determined at the national level.

As seen when comparing estimates in columns 4 and 5, controlling for color is important; clearly, some colors are more preferable than others. Even after controlling for color, however, the measured influence of list prices on purchase probabilities is large, rivaling that of selling price. Comparing coefficients in column 5, a $1 increase in a product's list price has the same effect on purchase probabilities as a $0.77 decrease in selling price, all else held constant. Considering that a firm can increase a firm's list price at virtually no cost, this has potentially huge consequences for producer and consumer welfare.

The ideal setting for measuring the effect of list prices on purchase likelihood is one in which list prices are randomly assigned to products, or vary exogenously within products over time or location. The current setting falls short of this ideal, but arguably comes close. The key identifying assumption is that list prices are uncorrelated with unobservable product characteristics after controlling for style and color. I argue that this is a weak assumption to make given the industry. For this assumption not to hold true, it would have to be the case that: (i) there exist particular colors and styles that are particularly good "matches" such that the fixed effects do not adequately control for product desirability, and (ii) the seller is able to identify these matches and sets list prices accordingly with consistent accuracy. The second condition is highly unlikely to be the case in an industry characterized by high demand uncertainty.

I include quadratic terms for list price and discount, respectively, to the baseline model and present the estimation results in Table 7. Somewhat puzzlingly, the estimates do not suggest a diminishing marginal effect of list prices on purchase likelihood. In fact, the estimates in the second column of Table 7 seem to suggest that discounts have an exponentially increasing positive effect on purchase

Table 7: Quadratic terms for list price and discount

VARIABLES	(2) List price	(3) Discount
selling price p_{jmt}	-0.00170***	-0.000456**
	[2.51e-05]	[0.000227]
list price LP_j	0.00221***	
	[0.000663]	
LP_j^2	-1.41e-06	
	[9.84e-07]	
discount$_{jmt}$		-0.0804***
		[0.0246]
discount$^2_{jmt}$		0.00148***
		[0.000230]
factory$_j$	-0.0807***	-0.0798***
	[0.00796]	[0.00796]
age$_{jt}$	-0.000428***	-0.000427***
	[3.66e-06]	[3.67e-06]
constant	-6.753***	-6.634***
	[0.801]	[0.798]
Observations	2,416,817	2,416,817
R-squared	0.371	0.371

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

likelihood. In the following subsections, I further explore this relationship by considering real versus fake list prices separately, measuring how the effect differs by consumer experience with the brand, and exploring the relevance of reference points.

4.2 Real and fake list prices

The presence of both real and fake list prices in the data enables a comparison of their effects on purchase probabilities. A reasonable hypothesis might be that fake list prices have less of an impact on purchase than a real list price. On the supply side, fake list prices are a lower commitment for the firm than real list prices, and may thus be less anchored to product quality. On the demand side, some consumers may observe the selling prices of items over time, and hence place more weight on list prices that have been realized. From a regulatory perspective, the question is of critical importance in determining the effects of fake prices on consumer welfare.

Table 8 contains results of regressions in which the effects of real and fake list prices are parsed. In the first model, an interaction term for list price and the factory dummy is included. This provides a direct measure of the difference in effects between real and fake list prices because only factory goods carry fake list prices. Surprisingly, the coefficient estimate on the interaction term implies that list prices on factory goods are even stronger inducements to purchase than those on original goods.

In the second column of Table 8 discount_{jmt} is decomposed into real and fake components. For original goods, the entire discount is a real discount, and the fake discount is zero. For factory goods, the real discount is the difference between the current period's selling price and the maximum selling price observed in the data. The fake discount is the difference between the maximum selling price and the fake list price. Along similar lines to the specification in column 1, I find that the fake discount component has a larger impact on purchase behavior than the real discount component.

These results show that fake list prices and discounts have effects on purchase behavior that may rival those of real ones in magnitude. This raises interesting questions on the reasons behind this demand response, as well as its implications on firm decisions. In the succeeding analyses, I explore how consumer heterogeneity and reference points moderate these effects.

Table 8: Real and fake list prices

VARIABLES	(1)	(2)
price p_{jmt}	-0.00170***	-0.000644***
	[2.51e-05]	[0.000227]
list price LP_j	0.000670***	
	[0.000227]	
$LP_j * \text{factory}_j$	0.00175***	
	[8.23e-05]	
real discount$_{jmt}$		0.00103***
		[0.000226]
fake discount$_{jmt}$		0.00140***
		[0.000225]
factory$_j$	-0.628***	-0.0912***
	[0.0269]	[0.00799]
age$_{jmt}$	-0.000430***	-0.000427***
	[3.66e-06]	[3.66e-06]
constant	-6.529***	-6.623***
	[0.798]	[0.798]
Observations	2,416,817	2,416,817
R-squared	0.371	0.371

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

4.3 Fake prices and consumer heterogeneity

Consumers who lack full information on product desirability may take price as a signal of quality (Gerstner 1985). The availability of demand data that include both list and selling prices presents an opportunity to cleanly measure this signaling effect separately from price sensitivity. If less-informed consumers are more reliant on price as a signal of quality, then they should demonstrate more sensitivity to list prices than better-informed consumers (Armstrong & Chen 2013).

The current context differs from the typical environment considered in theoretical models that characterize price as a signal of quality. First, here we have a single firm selling multiple goods, whereas the usual model has two or more firms of different "quality" with one representative product each. Second, a standard assumption is for quality to be increasing in marginal cost, with the higher-quality firm having a lower cost of quality, and hence a more credible commitment to keep prices high. In the current example, higher-quality products are not necessarily more expensive to produce, as desirability is greatly influenced by aesthetic components that do not affect production costs.

While the current context has not specifically been explored in prior research, there are similar and additional reasons why one might expect price to signal quality here. Even as a monopolist, a firm may have an incentive to guide new, uninformed consumers toward better options within its own product assortment so as to increase customer lifetime value. Fake list prices may play a special role given the cost structure: because quality is not strongly related to marginal cost, the ability to post fake list prices may relieve the tension of pricing against marginal cost to maximize profits (downward pressure) while depending on price to signal quality (upward pressure).

To explore how sensitivity to list prices relates to consumer familiarity with the brand, I bucket the purchase observations according to first-time and repeat consumers.[8] The assumption is that repeat consumers are better informed about product quality owing to their greater experience with the brand. I estimate the baseline regression model for each bucket and present the results in Table 9. The estimates suggest that repeat consumers are in fact more sensitive to list prices. This runs counter to the predictions of signaling models, suggesting that either the evolution of consumer

[8] 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 9: New vs old consumers

VARIABLES	(1) New consumers	(2) Old consumers
selling price p_{jmt}	-0.00802***	-0.00815***
	[3.77e-05]	[3.62e-05]
list price LP_j	0.00588***	0.00689***
	[0.000302]	[0.000284]
product age	-2.67e-05***	-9.53e-05***
	[4.59e-06]	[4.30e-06]
factory dummy	0.0289***	-0.0366***
	[0.00972]	[0.00898]
constant	-4.435***	-4.332***
	[0.489]	[0.340]
Observations	1,166,638	1,269,551
R-squared	0.444	0.411

Standard errors are in brackets.
Style and color dummies included in regression.
*** p<0.01, ** p<0.05, * p<0.1

information or the role of list prices is more complex.

As an alternative approach, 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 who have not. The corresponding estimates are reported in Table 10, where column 1 contains estimates from a sample with customers who have only shopped at the outlet store, and column 2 contains estimates from a sample with customers who have bought a least one item from the regular store. Strikingly, although full-price shoppers are much less sensitive to selling prices than pure outlet shoppers, they share almost the same sensitivity to list price.[9]

These estimates imply that while a list price may function as a signal of quality, it works in conjunction with other factors. It is also likely that the signaling mechanism is more nuanced than what these simple demand models can capture. Perhaps most importantly, this evidence runs counter to the simple narrative that fake list prices merely deceive uninformed consumers.

[9] Table B in the appendix estimates the interaction between list prices and the factory dummy for the two groups. As with regression including the full sample of consumers, both groups place higher weight on fake list prices on factory goods, although consumers who have previously visited the full-price channel seem to place a relatively lighter emphasis.

Table 10: Pure outlet vs full-price shoppers

	(1)	(2)
VARIABLES	Pure outlet	Full-price
selling price p_{jmt}	-0.00955***	-0.00517***
	[6.39e-05]	[4.73e-05]
list price LP_j	0.00673***	0.00608***
	[0.000725]	[0.000387]
product age	-1.45e-05***	-6.31e-05***
	[2.00e-06]	[8.98e-06]
factory dummy	0.0352***	-0.0317***
	[0.00578]	[0.00733]
constant	-4.245***	-4.750***
	[0.285]	[0.486]
Observations	1,085,735	1,118,885
R-squared	0.493	0.524

Standard errors are in brackets.
Style and color dummies included in regression.
*** p<0.01, ** p<0.05, * p<0.1

Thus far, the estimation has permitted list prices to affect demand only as absolute quantities, without allowing for possible dependence of the effect on particular reference points. Prior research has established the relevance of reference points in similar settings (e.g. Mayhew & Winer 1992, Rajendran & Tellis 1994) as well as reasons for setting fake list prices that stem from reference dependence (Armstrong & Chen 2013, Bordalo et al. 2013). In the following section I allow for reference dependence and explore its implications.

4.4 Reference points

The notions of price as a signal of quality and bargain-hunting behavior among consumers are closely linked in this empirical setting. An offered discount can only be considered a genuine "deal" if the original price is a dependable measure of the product's quality. Contextual reference points may influence shoppers' judgment in this regard (Rajendran & Tellis 1994). The extent to which consumers respond to high original prices, or equivalently high discounts, may depend on the average level of discounting, the dispersion in discounts, or other reference points.

In what follows I focus on reference points that are specific to a store-month, as opposed to reference points that are specific to products or arise from prior time periods. Given the infrequency of purchase in the product category, it is highly unlikely that price levels in previous periods form relevant reference points on the product level. The hypothesis is that a consumer's valuation of a specific discount offer is influenced by its distance to a reference point related to other offers in the store during the same shopping occasion (e.g. Tversky & Kahneman 1985, Lattin & Bucklin 1989). These reference points, termed contextual (vs temporal) by Rajendran & Tellis (1994) and external (vs internal) by Mayhew & Winer (1992) have been shown in the prior literature to frequently outweigh other reference points.

I consider two reference points that a consumer may be working off in judging the value of an offered discount: the lowest available discount in the store and the average available discount in the store. These reference points correspond to those examined by Rajendran & Tellis (1994), but differ in that these focus on the distribution of discounts rather than prices.

I operationalize the estimation of these reference points differently from prior literature. I decompose each product's discount into a store-wide reference point and the product-specific distance from this reference point, where $\text{lowest\_discount}_{mt}$ is the lowest offered discount in the store[10], $\text{average\_discount}_{mt}$ is the average discount in the store, and distance1_{jmt} and distance2_{jmt} are the respective distances. A significant difference in the estimated coefficients for the reference point and the corresponding product-specific distance would provide supporting evidence for the reference point's relevance in consumer decision-making.

The results, presented in Table 11, strongly suggest that the lowest offered discount in the store serves as an important reference point. In fact, as seen in column 2 of Table 11, the entire impact of a discount on purchase likelihood comes from its distance from this reference point. Strikingly, purchase likelihood is invariant to the level of the reference point itself. The estimated coefficients for $\text{average\_discount}_{mt}$ and distance2_{jmt}, while statistically different from each other, are much closer in magnitude than those for $\text{lowest\_discount}_{mt}$ and distance1_{jmt}. This mirrors the result from Rajendran & Tellis (1994), in which the lowest in-store price is found to be more salient to consumers than the average price.

[10] The lowest offered discount is never zero in the firm's outlet stores, from which the data for this analysis has been collected.

Table 11: Reference points

VARIABLES	(1) Baseline	(2) Lowest discount	(3) Average discount
price p_{jmt}	-0.000383*	-0.000433*	-0.000378*
	[0.000226]	[0.000226]	[0.000226]
discount$_{jmt}$	0.00132***		
	[0.000225]		
distance1$_{jmt}$		0.00162***	
		[0.000225]	
lowest_discount$_{mt}$		-8.83e-05	
		[0.000229]	
distance2$_{jmt}$			0.00129***
			[0.000225]
average_discount$_{mt}$			0.00146***
			[0.000231]
factory$_j$	-0.0807***	-0.0652***	-0.0827***
	[0.00796]	[0.00797]	[0.00799]
age$_{jmt}$	-0.000428***	-0.000408***	-0.000430***
	[3.66e-06]	[3.71e-06]	[3.76e-06]
constant	-6.650***	-6.563***	-6.669***
	[0.798]	[0.798]	[0.798]
Observations	2,416,817	2,416,817	2,416,817
R-squared	0.371	0.371	0.371

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

These results resolve two puzzles from earlier estimates. The insignificant effect of a discount up to the minimum level offered in a store explains the exponentially increasing effect of list prices presented in Table 7. Given that original goods carry lower discounts on average (see Figure 2), this also demonstrates why the estimates in Table 8 imply that fake list prices have a larger effect on purchases than real ones.

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 A in the appendix). At the same time, the firm has been decreasing the scope of product-specific discounts relative to market-specific discounts. The results in this section would imply that the firm should reconsider this strategy, and instead pay closer attention to the lower end of discount magnitudes in its stores, which consumers seem to treat as a salient baseline.

These results also point to the flip side of fictitious pricing. While fake discounts may drive revenues for individual products, over time consumers may take the overall level of discounting as a given and "discount" the discounts (e.g. Gupta & Lee 1992, Marshall & Leng 2002). Indeed, the estimates show that consumers take the discount floor for granted. Even though, as the estimates in Table 8 imply, consumers may have a poor ability to distinguish real from fake discounts, the proliferation of discounts may be disciplined by reference dependence.

4.5 Intertemporal substitution

The static framework adopted in this paper is only appropriate if, as the market environment suggests, consumers do not delay their purchases in expectation of higher discounts in the future. 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). If this behavior exists in a market and is ignored in demand estimation then the estimated coefficient on price may be biased. I argue that the empirical setting considered here 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. Although the selling price for each product does systematically decline over time, so does the product's inherent attractiveness as a fashion

Table 12: Past-period price effects

	(1)
price $p_{j,t}$	-0.00132***
	[3.89e-05]
previous price $p_{j,t-1}$	-0.000782***
	[4.02e-05]
LP_j	0.00114***
	[2.49e-05]
age_{jmt}	-0.000294***
	[1.12e-05]
factory_j	-0.0861***
	[0.00947]
constant	-6.401***
	[0.142]
Observations	1,771,541
R-squared	0.375

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

good.

I include past-period selling 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 but small (see Table 12), suggesting a lack of intertemporal substitution.

5 Conclusion

Price comparisons of practically every shape and form have been heavily used by retailers in their communications from the very earliest examples of retail advertising up to the current shift to e-commerce. The question of how these signals affect purchase behavior is relevant to firms, regulators, and consumers themselves. Firms, in posting list prices different from selling 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.

The results show 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 70 "selling price cents" to a "list price dollar." This rate seems invariant to the consumer's depth of experience with a brand, with repeat customers placing as much weight on list prices as new customers.

In addition, consumer values for discounts depend on market-specific reference points. The minimum offered discount in a store is appears to be a highly influential reference point, with product-specific discounts being judged according to their distances from this minimum. In addition, the magnitude of the minimum discount itself appears have little effect on purchase likelihoods. These suggest that optimal price-setting by the firm should incorporate reference dependence in consumer behavior.

The empirical setting in this paper induces some limitations. The single-firm data source used in this paper precludes studying the competitive aspects of fake list pricing, such as possible impacts on consumers' likelihood of further search (e.g. Grewal & Compeau 1992). Although, to my knowledge, this paper is the first to exploit real transactions data to investigate fake list prices, identification of the effect of fake pricing on purchase likelihood also falls short of that which may be obtained from field experimentation.

Given the effect of list prices on purchase behavior, a potentially worthwhile area for future research lies in empirically modeling the seller's problem when setting fake list prices. The persistence of fake pricing despite frequent high-profile lawsuits against the practice suggests that it is indeed profitable for sellers to pursue. On the other hand, the practice does seem to be disciplined by natural constraints that result in its familiar patterns within industries. It would be of particular interest for regulators to identify these constraints in their efforts to curtail this practice and protect consumer interests.

Differences between industries may also merit future investigation. The existing scholarly literature on price as a signal of quality and regulatory guidelines frequently cast "fictitious" list prices 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. Some industries may be better represented by production functions in which quality is generated through a stochastic process only weakly correlated with marginal cost, with fake list prices used to reduce asymmetric information about quality between the firm and consumers. Such a viewpoint may better suit settings in which quality can only imperfectly be set by firms, such as in fashion and design related industries.

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Appendix

Table A: Frequency of list price values

List price	Percent of products	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

Table B: Consumer sensitivity to list prices by previous purchase channel

	(1)	(2)	(3)	(4)
Shopper type	Pure outlet	Pure outlet	Full-price	Full-price
p_j	-0.00955***	-0.00955***	-0.00517***	-0.00517***
	[6.39e-05]	[6.39e-05]	[4.73e-05]	[4.73e-05]
LP_j	0.00673***	0.00256***	0.00608***	0.00420***
	[0.000725]	[0.000482]	[0.000387]	[0.000167]
$LP_j \times factory$		0.00885***		0.00633***
		[0.000221]		[0.000467]
constant	-4.245***	-4.328***	-4.750***	-4.775***
	[0.285]	[0.291]	[0.486]	[0.487]
Observations	1,085,735	1,085,735	1,118,885	1,118,885
R-squared	0.493	0.493	0.524	0.524

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

Figure A: Average discount percent in outlet stores

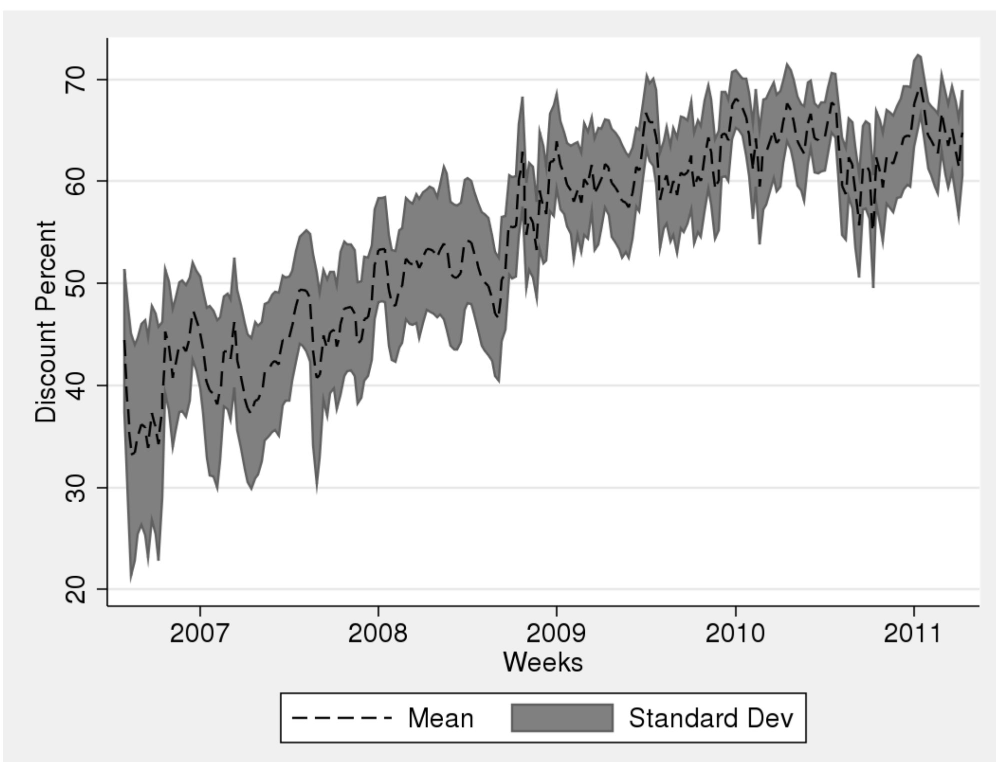

Figure B: Prices over time