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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 critically important to sellers, to consumers, and to regulators who are keen on enforcing deceptive advertising guidelines against "fictitious pricing"—the practice of quoting list prices that do not truthfully reflect prior selling prices. This paper uses a large retail transaction 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 from outlet stores 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. By measuring the impact of different pricing components on purchase likelihood, we find that list prices have a strong influence on purchase outcomes, with a $1 increase in the list price having the same positive effect on purchase likelihood on average as a $0.77 decrease in the actual selling price. This effect is larger for fake list prices, but smaller in longer-lived stores and stores closer to regular retail channels. In a

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complementary laboratory experiment, we find that fake list prices have no impact on purchase intent when consumers have full knowledge of the true original price. These results imply that fake prices enhance demand by misleading consumers about true original prices.
Keywords: retail, deceptive advertising, reference prices, discounts

1 Introduction

Virtually all firms engage in some form of discount pricing. There are several reasons that 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 resolves 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 Ninth 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 for $50 million and $6.5 million, respectively (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 state 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 (*Camasta v. Jos. A Bank Clothiers, Inc.,* 2013), Carter's (*Kim v. Carter's, Inc.,* 2010), and QVC (*Mulligan v. QVC, Inc.,* 2008) were found in favor of the defendants 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" (*B. Sanfield, Inc. v. Finlay Fine Jewelry Corp.,* 1999).

In this paper, we identify patterns in how consumers respond to false and genuine discount claims by the same seller. We use data from a dominant fashion goods retailer that makes heavy use of discounting in its outlet stores. This data set offers an unprecedented 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 a degree of randomized discounting 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 reference prices using laboratory experiments or survey methodologies, there have been, to our knowledge, no prior studies that establish the effect of fake list prices on purchase behavior in actual retail settings. There are sev-

eral benefits from using transaction 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 our empirical setting such a price 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.

We 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 style across different colors. 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. We explore how responses to list prices vary according to consumer subgroups by taking advantage of store openings and closures within the sample duration.

We 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 with genuine list prices. Importantly, this effect seems to be moderated by the consumer's level of information, with a lower estimated sensitivity to fake discounts in longer-lived stores or outlet stores closer to regular stores.

We augment our analysis with findings from a laboratory experiment. We design the experiment with the goal of measuring the effect of false original prices on purchase intent when subjects have full knowledge of a product's true original price. Our findings consistently indicate that keeping selling price constant, a higher true original price results in higher purchase intent. However, conditional on knowledge of the true original price, a higher false original price has zero effect on

purchase intent.

Taken together, evidence from our analysis of observational transaction data and our laboratory experiment suggests that fake prices provide sellers with a powerful tool to enhance demand, but one that may come at the expense of misleading consumers about products' true initial selling prices. Consumers take initial prices as signals of product quality and rate offers as being better deals the higher these initial prices are with respect to present selling prices. Accordingly, fake prices have the highest influence on purchase likelihood for less-informed consumers.

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 reports findings from a laboratory experiment. Section 6 concludes and points to directions for future work.

2 Related literature

This research relates to several literatures concerning price signals in retail settings. It takes its basic premise from research that explores the function of price as a signal of quality. Because our paper focuses on prices that are framed as discounts, it draws from research on the impact of discount cues on shopper behavior and research on reference dependence more generally. Finally, our findings relate to work on the welfare and regulatory implications of fake prices and misleading sales. In this section, we review the most closely related papers in each of these literatures with an eye toward highlighting our contributions.

There is a large body of research in marketing and economics that has studied how uninformed consumers use prices as signals of product quality. High prices can serve as credible signals of high product quality because the "consequent loss of sales volume is most damaging for lower-cost, lower-quality products" (Bagwell & Riordan 1991). Within this paradigm, the profitability of using

price to signal quality depends on the relative proportions of informed and uninformed consumer segments (Milgrom & Roberts 1986; Armstrong & Chen 2013). Our research does not rely on the disciplining force of either informed consumers or marginal costs on prices; hence, it more closely relates to research that treats high prices as strategic substitutes for advertising (e.g. Gerstner 1985; Linnemer 2002). Unlike most signals available to firms as marketing-mix variables, however, fake prices require no immediate costs to implement (Kirmani & Rao 2000). Our research thus aims to determine which aspects of the extant thinking on the relationship between prices, perceived quality, and perceived value extends to fake prices (Zeithaml 1988).

By definition, a fake price offers a fake discount—a discount that does not represent a decrease from some previous selling price but, rather, the difference between the current selling price and a fake introductory price. There is much existing literature on the impact of discounts on consumer behavior beyond what may be ascribed to quality signaling (Blattberg, Briesch & Fox 1995). Discounts have been shown to dampen further consumer search (Urbany, Bearden & Weilbaker 1988), cause consumers to weigh non-price product attributes more heavily (Bordalo, Gennaioli & Shleifer 2013), and exploit bargain-hunting tendencies (Armstrong & Chen 2013). While these effects have been explored where discounts are fake as well as where they are real, our research focuses on the common yet unexplored setting in which discounts have substantial real and fake components.

Efforts to contextualize the impact of discounts have often appealed to notions of reference dependence (Tversky & Kahneman 1981; Thaler 1985). Researchers have identified several reference points that sellers rely on: advertised prices (Biswas & Blair 1991), competitors' prices (Della Bitta, Monroe & McGinnis 1981), same-store offers (Rajendran & Tellis 1994), and fake prices (Blair & Landon 1981). Previous work has also identified upper and lower bounds beyond which discounts are less effective (Gupta & Cooper 1992). More recent work has posited a theoretical explanation of reference dependence relying on opportunity cost considerations (Kim, Joo & Allenby 2017). There has also been research that documents how certain pricing policies can have

large effects on consumer behavior due to local or cultural factors despite lacking a clear basis in established theory, such as the choice of price-endings (Stiving 2000; Anderson & Simester 2003). Our research differs from previous studies by focusing on the moderating role of what consumers know about how truthfully a discount offer reflects prior selling prices.

In addition to legalistic debates on fake prices among policymakers, marketing scholars have also conducted research on the impact of fake prices and comparative price advertising more generally on consumer welfare (Compeau & Grewal 1998). A central question is whether fake prices are deceptive, and if they are, how substantial the damage is on consumers (Grewal & Compeau 1992; Compeau, Grewal & Chandrashekaran 2002; Rhodes & Wilson 2018). Our research demonstrates the possibly large negative impacts of fake prices on consumer welfare resulting from deception.

3 Data and industry background

Data are 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 of about 40%.

Channels. The firm operates two types of stores: **regular** and **outlet**. Because fake prices are set only for products sold in outlet stores, only transaction data from outlet stores are used for estimation; however, summary statistics for both channels are provided in this section in order to provide context for the empirical setting. 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 1 shows counts of

unique products sold 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 1 about here.]

The data consist of transaction-level records over a five-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.[1]

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.

[Figure 1 about here.]

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 list price. Yet another reason is that some style-color combinations are regular or outlet channel-specific. Variation in list prices within product styles but between colors provides our primary source of identification of their effects. 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.

[1]The firm is able to construct longitudinal data through the help of a third-party provider, which uses credit card information, mailing list, and loyalty program membership, among other data sources, to link different purchases made by the same consumer over time.

Each style-color combination is either an original good or a factory good based on the channel in which the product is introduced. Table 2 describes the pricing differences between original and factory goods in outlet stores.[2] 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 selling prices over time, and factory goods occasionally carry higher prices than original goods (see Figure A2 in the Appendix).

[Table 2 about here.]

Figure 2 graphs the average percent discount over time for original goods and factory goods in the firm's outlet channel. (Average overall discounts over time are presented in Figure A1 in the appendix.) 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.

[Figure 2 about here.]

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.

[Figure 3 about here.]

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.

[2] Further details are in appendix Table A1.

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 we present a parsimonious discrete choice model of consumer purchase behavior and estimate its parameters using the data set described above. The objective of estimation is to determine whether fake discounts affect purchase behavior, keeping all other product attributes, including actual selling prices and real discounts, constant. We are particularly interested in how the impact of fake discounts compares to that of real discounts. In addition, we seek to measure how this effect varies according to proxies for consumer familiarity with the brand. We find that fake prices and their implied fake discounts have a large positive effect on purchase likelihood, and we find evidence that this effect is smaller for better-informed consumers.

4.1 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 list price may be "true" in the sense that $LP_j = \max_{m,t} p_{jmt}$ or "fake" if $LP_j > \max_{m,t} p_{jmt}$. In general, the difference between the list price and the selling price is composed of a real and a fake discount, i.e.

$$LP_j - p_{jmt} \equiv (LP_j - \max_{m,t} p_{jmt}) + (\max_{m,t} p_{jmt} - p_{jmt}) \equiv \text{fake\_disc}_j + \text{real\_disc}_{jmt} \qquad (1)$$

The indirect utility of consumer i from purchasing product j in store m at time t is denoted as

$$u_{ijmt} = \alpha_{mt} p_{jmt} + X_{jt}\beta + \gamma_{mt}^{fd} \text{fake\_disc}_j + \gamma_{mt}^{rd} \text{real\_disc}_{jmt} + \xi_j + \epsilon_{ijmt} \quad (2)$$

where α_{mt}, β, γ_{mt}^{fd}, and γ_{mt}^{rd} are taste parameters, and ϵ_{ijmt} are idiosyncratic demand shocks. We incorporate consumer heterogeneity by allowing parameters to vary by store and period in order to streamline estimation and exposition. 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

$$\log(s_{jmt}) - \log(s_{0mt}) = \alpha_{mt} p_{jmt} + X_{jt}\beta + \gamma_{mt}^{fd} \text{fake\_disc}_j LP_j + \gamma_{mt}^{rd} \text{real\_disc}_{jmt} + \xi_j \quad (3)$$

where s_{jmt} are market shares (the number of units of product j sold divided by the market size for store m and time t) and s_{0mt} is the share of the outside good. A consumer is considered to have chosen the outside good if she visited a store but did not make a purchase. In the estimation of this model, availability of per-period foot traffic counts for each store enables direct measurement of these outside shares.

4.2 Identification

In this subsection, we describe how variation in list prices, discounts, and the assignment of real and fake discounts allows us to estimate demand parameters. In general, using transaction data can raise possible issues of selection relating to both products and consumers. On the product side, if certain kinds of products are systematically more likely to be assigned fake prices, or if they have higher fake prices, then this may influence the estimated effects of fake prices on purchase outcomes. The estimates may also be skewed if specific types of consumers are more attracted to

the outlet channel and the fake pricing policy accounts for this market composition.

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 in which list prices 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. We argue that this is a weak assumption to make given the industry. For this assumption not to hold true, two conditions need to be met: (i) there are particular colors and styles that are particularly good "matches" such that style and color 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. While the first condition may be true, the second condition is highly unlikely to be the case in an industry characterized by high demand uncertainty.

[Table 3 about here.]

Style fixed effects address much of the selection issue where products are concerned, as their inclusion results in fake price effects being identified from within-style variation in list prices. This within-style variation arises from between-color variation in fake prices. Table 3 illustrates the source of variation in list prices by style and color. The frequency of specific list prices is listed in Table A1 in the appendix. Color fixed effects are included to account for the relative attractiveness of each color.

Factory products, which all feature fake prices, are only sold in the outlet channel—which is the only channel for which data is used in the analysis. Hence, a factory product indicator adequately controls for selection in which products are assigned fake prices; the coefficient on this indicator reflects demand variation for styles that are found in both channels. In a general retail environment there may be selection in the relative magnitudes of fake and real discounts assigned to products. For instance, products that have been found to sell poorly may be assigned higher real discounts, thus biasing the effect of real discounts toward zero. As discussed in Section 3, however, the

firm implements a national pricing scheme that does not allow for discounting based on the sales performance of individual products.

It is not possible to exactly verify the absence of a systematic relationship between products' sales performance and their selling prices, as in practice prices can be influenced by a combination of a large number of non-product-specific factors, e.g. outlet mall-wide sales and national promotions. In order to gain some measure of the likelihood of such a systematic relationship, we look to the most important distinction between products in the firm's portfolio: that between factory and original goods.

We run a series of hedonic regressions in order to examine systematic differences in list and selling prices between factory and original goods. The results from these regressions are reported in Table 4. Each observation in these regressions is a unique product (style-color pair). The estimates in column 1 show that on average, a factory product has a list price that is \$43.38 less than an original product. Column 2 includes style fixed effects, and shows that, for styles that the firm sells in both channels, factory versions do not have systematically lower or higher list prices. Columns 3–5 contain results from regressions of average selling prices in the outlet channel. Factory products sell for \$42.46 less than original products on average. While there is a statistically significant difference in selling prices between factory and original products of the same style, this difference is minimal at \$7.15. When controlling for the duration in which each product was available for sale, we find no evidence of a difference in pricing strategies for factory and original goods on average. These results suggest that including style fixed effects and product age in our estimation of demand coefficients can adequately control for selection in pricing strategies between factory and original goods.

[Table 4 about here.]

4.3 Estimation and Results

We estimate demand parameters by regressing mean utility levels as defined in Equation 3 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 and color. Store and month fixed effects are also included. Descriptive statistics for these variables in the estimation sample are reported in Table 5.

[Table 5 about here.]

Table 6 contains the baseline results of demand estimation. Estimates from an OLS regression of mean utility are reported in the first column. Dummies for product color and style, as well as for stores and months, are included as explanatory variables. As anticipated, purchase probability is positively correlated with both real and fake components of discounts, negatively correlated with selling price, and negatively correlated with product age.

[Table 6 about here.]

The second column in Table 6 includes an interaction between real discount and a factory dummy. We include this interaction to control for possible discrepancies in how real discounts for original products (where the real discount is always the whole discount) and real discounts for factory products (for which the discount always includes real and fake parts) impact purchase likelihood. We find that real discounts have a stronger effect for factory products than original products, while the effect of fake discounts dominates that of real discounts.

The third column in Table 6 contains results from an alternative specification in which the list price is included as a regressor instead of discount variables. Comparing coefficients, we see that 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 fourth column presents estimates from a model with an interaction term between list price and the factory dummy. Recall that all factory products have fake prices while no original products have fake prices; hence the factory dummy is equivalent to a fake price dummy. The estimates show that fake list prices have an effect size on purchase probabilities that is almost twice that of real list prices. This comparison needs to be interpreted with caution, however, since there may be unobservable differences between original and factory products that influence the relative importance of list prices.

These results show that fake list prices and discounts have effects on purchase behavior that rival those of real ones in magnitude. These findings raise interesting questions on the reasons behind this demand response, as well as its implications on firm decisions. In the succeeding analyses, we explore how consumer familiarity with the brand moderates these effects.

4.4 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 scenario 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 scenario 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 fake discounts relates to consumer familiarity with the brand, we estimate interactions between discount variables and proxies for consumers' experience with the brand. The first proxy is the length of time, in months, that the store has been operating. This presumes that the average consumer in a store is better-informed about the store's pricing policies, and the existence of fake prices, the longer the store has been open. The second proxy is the distance between a focal store and the brand's nearest regular retail store. (Recall that each store in the estimation data set is an outlet store.) The operating assumption for this variable is that the closer a regular retail store, the greater the awareness of the average consumer in identifying differences in product assortment between the two channels and, consequently, the presence of fake prices in the outlet channel. Given that store fixed effects are included in all regressions, these interactions are identified from store openings and closures in the data.

[Table 7 about here.]

Table 7 contains the estimation results including store-level interactions. The first column includes results from the model accounting for store age. Precise store ages are available only for stores that opened during the five-year sample duration; the variable *In sample* is an indicator for these stores. The estimates indicate that consumers in stores that have been operating for a longer period are less sensitive to fake discounts. There is also some evidence that consumers in older stores are more sensitive to real discounts, although this difference is statistically insignificant between stores that opened within the sample duration.

The second column of results in Table 7 accounts for the distance of each store from the nearest regular retail store. This distance changes over time due to the opening or closing of regular stores by the brand. The average distance between an outlet store and the nearest regular store, taken over all observations in the data, is 39 miles. There are 53 cases in which an outlet store's closest regular store changes as a result of a store opening, and seven cases where the change is the result of a store closure. For these cases, the average change in the distance variable is -23 miles when a regular store opens and 12 miles when a regular store closes. The estimates imply that the farther the nearest regular store is, the more sensitive consumers are to both real discounts and fake discounts. Both proxies are included in the model for which estimates are presented in the third column.

These estimates provide suggestive evidence that the more experience consumers have with the brand, either through a store's age or its proximity from a second channel, the less sensitive they are to fake discounts. We motivate the laboratory experiment in the following section by observing that any proxy of consumer information would be an imperfect indicator of consumer beliefs about the firm's pricing practices. Indeed, our proxies are possibly correlated with other factors that may also influence sensitivity to fake prices. We complement our findings from observational data with those from experimental data in which subjects are provided with specific information about true and displayed original prices.

5 Laboratory experiment

This section contains results from a laboratory experiment designed to measure the effect of fake prices on purchase intent. This study serves as a useful complement to the preceding analysis of observational data as it allows for direct manipulation and verification of subjects' understanding of the fakeness or realness of list prices. The findings strongly reject the hypothesis that fake prices influence purchase intent when subjects understand that they are false.

As discussed in our review of the literature, several authors have previously established a positive

relationship between reference prices and purchase intention. In multiple studies, the plausibility of reference prices—manipulated by comparing the effects for unfamiliar versus familiar brands—has been found to moderate this relationship (e.g. Biswas & Blair 1991). However, to our knowledge, there is no prior work published that tests for this effect when consumers have full information about the truthfulness of posted list prices. Existing research on uninformative anchors provides reason to expect a positive relationship on purchase intent even under these conditions (e.g. Wilson, et al. 1996).

Participants (N = 1,085: 53% female, M_{age} = 35 years, participants from MTurk) were presented with the image of a bag together with price information. The bag was chosen to roughly correspond with the relevant product category in the preceding analysis of observational data. All participants were told that the bag had a sale price of $40. Each participant was also presented with a potentially fake displayed original price, as well as information about the true original price. Figure 4 is one instance of the stimulus.

[Figure 4 about here.]

Participants were randomly assigned to conditions with varying levels of true and displayed original prices, ranging from $40 to $90 in $10 intervals (where the true original price is at most as high as the displayed original price). Table 8 shows the number of subjects that were assigned to each treatment group. To ensure that participants understood the scenario correctly, they were asked to type in what they understood to be the product's true original price. We drop observations in which participants enter an incorrect price. This shrinks the number of observations from 1,085 to 877.[3] Each participant was asked to rate their purchase likelihood on a seven-point scale.

[Table 8 about here.]

To measure the impact of each piece of price information on purchase likelihood, we run the following model on the data:

[3]Results from analysis using all 1,085 observations are nearly identical to those using the smaller set of 877 observations.

$$Purchase\_intent_i = \beta_0 + \beta_1 Displayed\_price_i + \beta_2 True\_original\_price_i + \epsilon \quad (4)$$

Table 9 contains the results of this regression. Strikingly, although the true original price has a significantly positive effect on purchase intent, the displayed original price does not have a statistically significant effect. These results are particularly remarkable when considering that, in the survey design, the true original price was provided only in the initial prompt, whereas only the displayed original price was presented when asking for purchase intent (and subsequent questions about sentiment).

[Table 9 about here.]

These results lend support to the contention that fake prices increase purchase likelihoods by deception. To further investigate how consumer inferences derive from price signals, subjects were asked to rate the offer on specific dimensions after they are asked about purchase intent. These dimensions, all rated on a seven-point scale, include: (i) the subject's own rating of product quality, (ii) the subject's prediction of other people's rating of product quality, (iii) whether the subject thinks the offer is a good deal, (iv) whether the subject thinks the product is being offered at a fair price, and lastly (v) whether the subject feels that the seller is being dishonest.

[Table 10 about here.]

Table 10 summarizes the results of this survey by regressing each rating on the pricing components. We find that high true original prices lead subjects to rate the product as higher quality, as well as to infer other subjects' higher quality ratings. We also find that they perceive the offer to be a better deal, and the price to be fairer the higher the true original price. Ratings of deal attractiveness are roughly three times more sensitive to the true original price than those of product quality. Strikingly, the displayed original price has no influence on these ratings. We do find, however, that consumers consider sellers more dishonest the farther the displayed original price is from the true original price.

[Table 11 about here.]

We complete a mediation analysis by regressing purchase intent on price signals and sentiment ratings jointly. Results are presented in Table 11. We find that sentiment ratings completely mediate the effect of price signals on purchase intent, with the subject's own quality rating being slightly more important than their ratings for deal attractiveness. Subject's perceptions of others' quality ratings do not seem to impact their own purchase intent. Interestingly, ratings for whether the seller is dishonest also do not correlate with purchase intent. Analysis of these different dimensions of consumer sentiment are remarkably consistent in that they verify previously theorized or established relationships between reference prices and consumer beliefs (e.g. Dodds, Kent & Grewal 1991).

These results imply that positive demand effects from fake prices detected from observational data arise largely from the false understanding by consumers that fake prices represent past selling prices. The higher the product's previous selling price, the higher subjects rate product quality and the attractiveness of the offer, and the higher subjects rate their likelihood of purchase. Given knowledge of the true original price, however, a higher reference price in the form of a displayed original price has no effect on demand or consumer sentiment apart from the inference that the seller is dishonest.

6 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 by the extent to which their own decisions are reliant on them.

The results show that list prices have significant effects on purchase decisions. 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 is moderated by the length of time at which stores have been in operation, as well as their distance from alternative channels under the same brand. This implies that better-informed customers may place less stock on list prices than newer customers do.

Findings from a laboratory experiment confirm that knowledge of a product's true original price attenuates the effect on purchase intent of a displayed original price. Strikingly, when subjects are informed of a product's true original price, their purchase intent is found to be completely invariant to displayed original prices. We find that subjects rely on products' prior selling prices in making inferences of product quality and that they regard sellers that display original prices higher than true original prices as dishonest.

The empirical settings in this paper introduce 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 our 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 familiar patterns within industries (e.g. Anderson & Simester 1998). 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 for advertised prices 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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Figure 1: Consumers by number of within-sample purchase instances

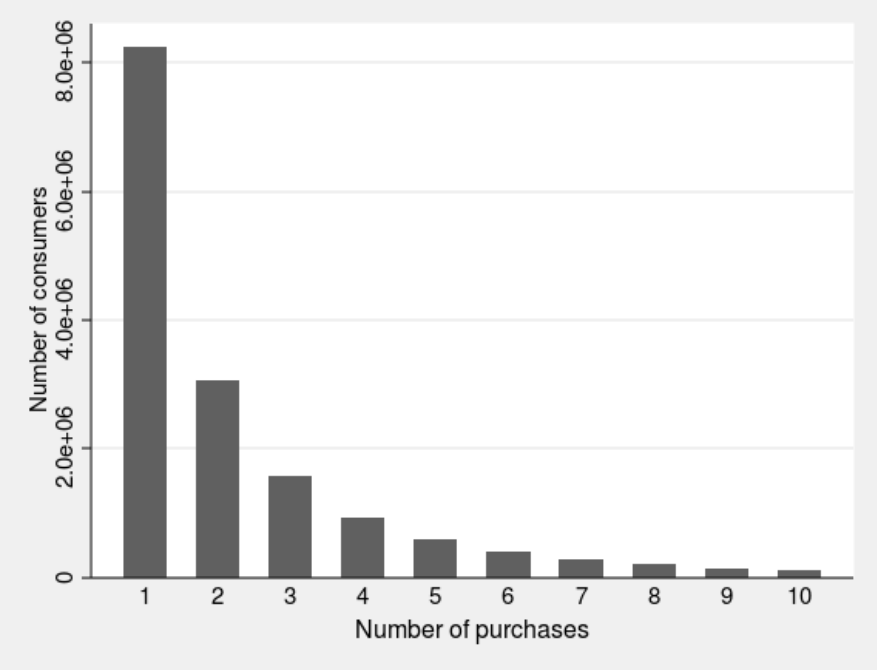


Figure 2: Discounting pattern in outlet channel

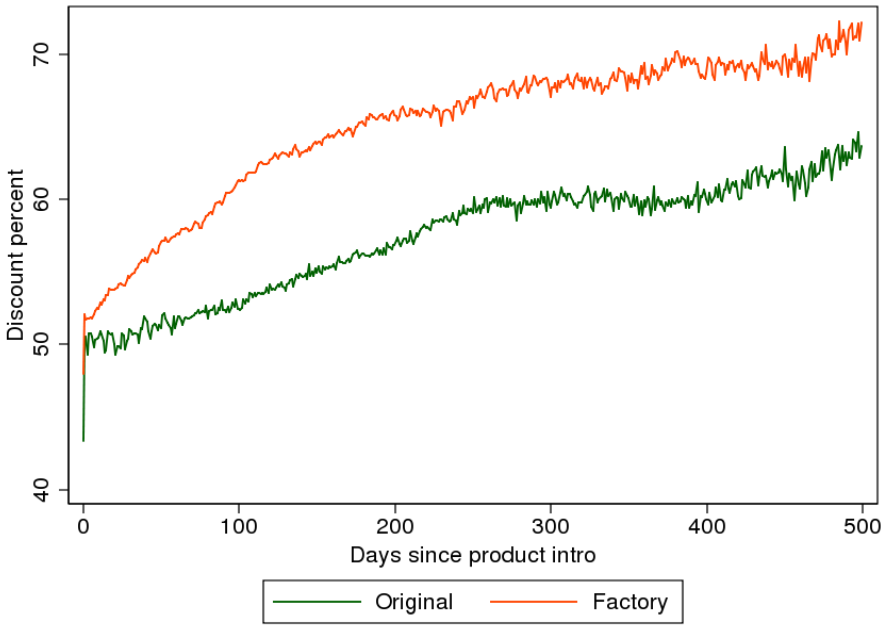
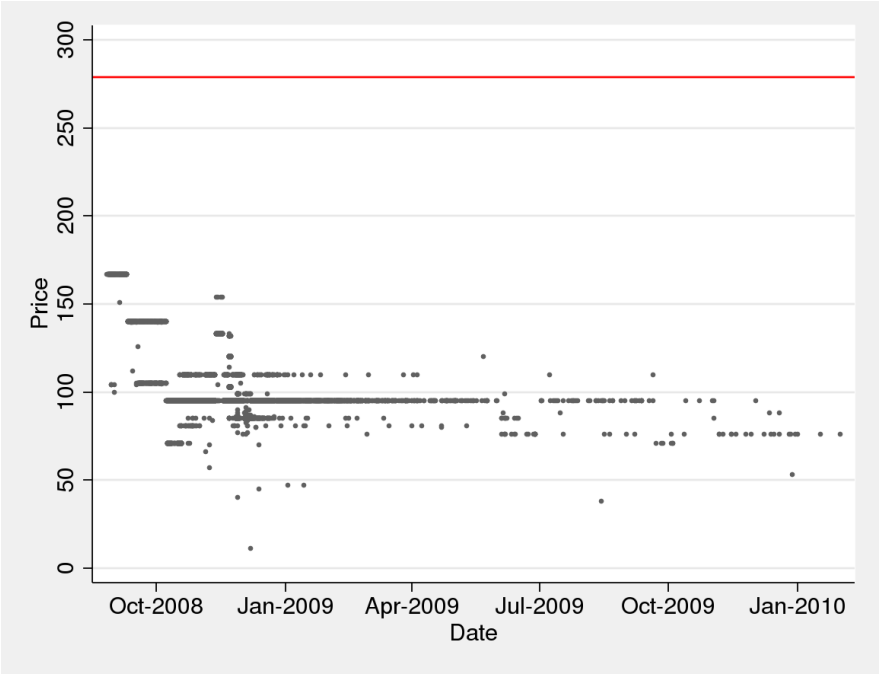
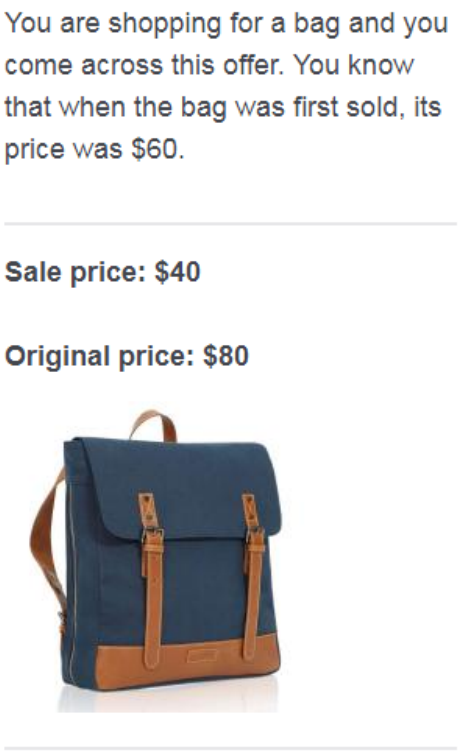


Figure 3: Observed selling prices of a typical factory good in the outlet channel



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

Figure 4: Lab study stimulus



Note: In this instance, the “true original price” is $60 and the “displayed original price” is $80.

Table 1: Unique product counts by channel and product type

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

Table 2: 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]
Selling price	165.76	123.20
	[85.82]	[38.03]
On-shelf composition (units)	69.64%	30.36%
Revenue composition	30.90%	69.10%

Standard errors are in brackets.

Table 3: Illustration of variation in list prices

	Style 1	Style 2	Style 3	Style 4
Color 1	298	148	-	328
Color 2	298	178	198	328
Color 3	328	148	198	368
Color 4	298	148	198	368

Table 4: Hedonic regressions

	List price		Average selling price		
Variables	1	2	3	4	5
Factory dummy	-43.38***	0.771	-42.46***	-7.151***	-0.907
	[3.101]	[1.219]	[1.470]	[1.837]	[2.051]
Style fixed effects	-	+	-	+	+
Days available					-0.564***
					[0.0905]
Constant	351.0***	337.6***	165.5***	154.8***	158.6***
	[1.708]	[0.398]	[0.810]	[0.599]	[0.839]
Observations	13,522	13,522	13,522	13,522	13,522
R-squared	0.016	0.993	0.064	0.935	0.936

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

Table 5: Descriptive statistics for estimation data

Variable	**Mean**	**SE**	*Variable*	**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

Table 6: Baseline demand estimates

	Main model		List price	
Variables	1	2	3	4
Fake discount	0.00165***	0.00218***		
	[0.000225]	[0.000226]		
Real discount	0.000846***	0.000495***		
	[0.000226]	[0.000226]		
Real discount × Factory		0.00104***		
		[4.47e-05]		
List price			0.00132***	0.000670***
			[0.000225]	[0.000227]
List price × Factory				0.00175***
				[8.23e-05]
Selling price	-0.000826***	-0.000764***	-0.00170***	-0.00170***
	[0.000227]	[0.000227]	[2.51e-05]	[2.51e-05]
Product age	-0.000427***	-0.000431***	-0.000428***	-0.000430***
	[3.66e-06]	[3.66e-06]	[3.66e-06]	[3.66e-06]
Factory dummy	-0.136***	-0.297***	-0.0807***	-0.628***
	[0.00832]	[0.0108]	[0.00796]	[0.0269]
Store fixed effects	+	+	+	+
Color fixed effects	+	+	+	+
Style fixed effects	+	+	+	+
Constant	-6.558***	-6.546***	-6.650***	-6.529***
	[0.798]	[0.798]	[0.798]	[0.798]
Observations	2,416,817	2,416,817	2,416,817	2,416,817
R-squared	0.371	0.371	0.371	0.371

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

Table 7: Heterogeneity

Variables	(1)	(2)	(3)
Real discount	0.00109***	0.000521**	0.000590***
	[0.000226]	[0.000226]	[0.000226]
Real discount × In sample	-0.000391***		-0.000159***
	[5.35e-05]		[5.36e-05]
Real discount × In sample × Store age	2.58e-06		-2.97e-06
	[2.61e-06]		[2.61e-06]
Real discount × Distance		1.26e-05***	1.24e-05***
		[2.86e-07]	[2.87e-07]
Fake discount	0.00137***	0.00123***	0.00121***
	[0.000225]	[0.000225]	[0.000225]
Fake discount × In sample	0.000667***		0.000754***
	[4.89e-05]		[4.90e-05]
Fake discount × In sample × Store age	-3.42e-05***		-3.65e-05***
	[2.23e-06]		[2.23e-06]
Fake discount × Distance		3.39e-06***	3.83e-06***
		[2.45e-07]	[2.46e-07]
Selling price	-0.000635***	-0.000685***	-0.000650***
	[0.000227]	[0.000227]	[0.000227]
Product age	-0.000429***	-0.000422***	-0.000425***
	[3.66e-06]	[3.66e-06]	[3.66e-06]
Factory dummy	-0.0931***	-0.0876***	-0.0900***
	[0.00799]	[0.00799]	[0.00799]
In sample	-1.393***		-1.191***
	[0.0206]		[0.0211]
In sample × Store age	0.00686***		0.00908***
	[0.000456]		[0.000457]
Distance		0.00118***	0.00151***
		[6.86e-05]	[6.94e-05]
Store fixed effects	+	+	+
Color fixed effects	+	+	+
Style fixed effects	+	+	+
Constant	-6.620***	-6.828***	-6.865***
	[0.798]	[0.797]	[0.797]
Observations	2,416,817	2,416,817	2,416,817
R-squared	0.371	0.372	0.373

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

Table 8: Subject counts by treatment group

		Displayed original price			
		60	70	80	90
True original price	90				61
	80			63	59
	70		61	63	61
	60	60	58	59	62
	50	60	61	56	61
	40	60	61	58	61

Table 9: Main results from lab study

Variables	Dependent variable: Purchase intent
Displayed original price	-0.00402
	[0.00508]
True original price	0.0193***
	[0.00371]
Constant	2.486***
	[0.379]
Observations	877
R-squared	0.032

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

Table 10: Sentiment ratings

Variables	Own quality rating	Others' quality rating	Good deal	Fair price	Dishonest seller
Displayed original price	-0.00498	-0.00186	-0.00320	-0.00368	0.0266***
	[0.00335]	[0.00314]	[0.00421]	[0.00492]	[0.00612]
True original price	0.00976***	0.0103***	0.0296***	0.0304***	-0.0449***
	[0.00245]	[0.00229]	[0.00308]	[0.00360]	[0.00447]
Constant	4.277***	4.163***	2.631***	3.048***	4.720***
	[0.250]	[0.234]	[0.314]	[0.368]	[0.457]
Observations	877	877	877	877	877
R-squared	0.018	0.024	0.104	0.082	0.104

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

Table 11: Mediation

Variables	Dependent variable: Purchase intent
Displayed original price	-0.000292
	[0.00379]
True original price	-0.00179
	[0.00298]
Own quality rating	0.447***
	[0.0601]
Others' quality rating	-0.0767
	[0.0581]
Good deal	0.331***
	[0.0445]
Fair price	0.279***
	[0.0366]
Dishonest seller	0.0168
	[0.0219]
Constant	-0.907**
	[0.357]
Observations	877
R-squared	0.477

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

Appendix

[Table A1 about here.]

[Figure A1 about here.]

[Figure A2 about here.]

Figure A1: Average discount percent in outlet stores

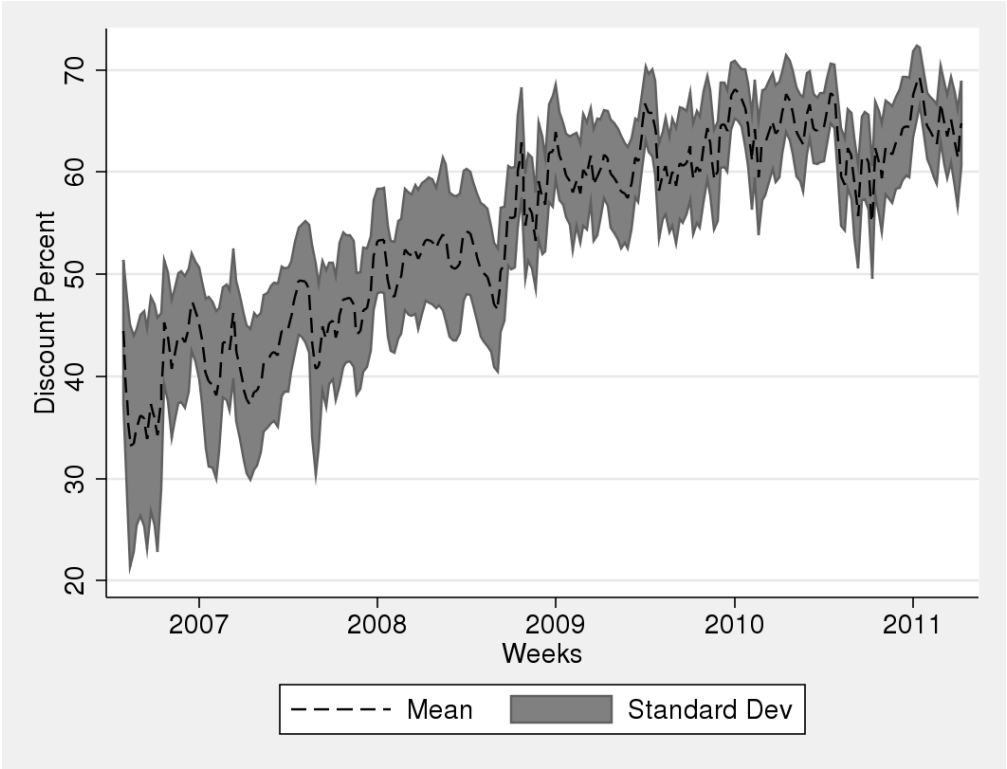


Figure A2: Prices over time

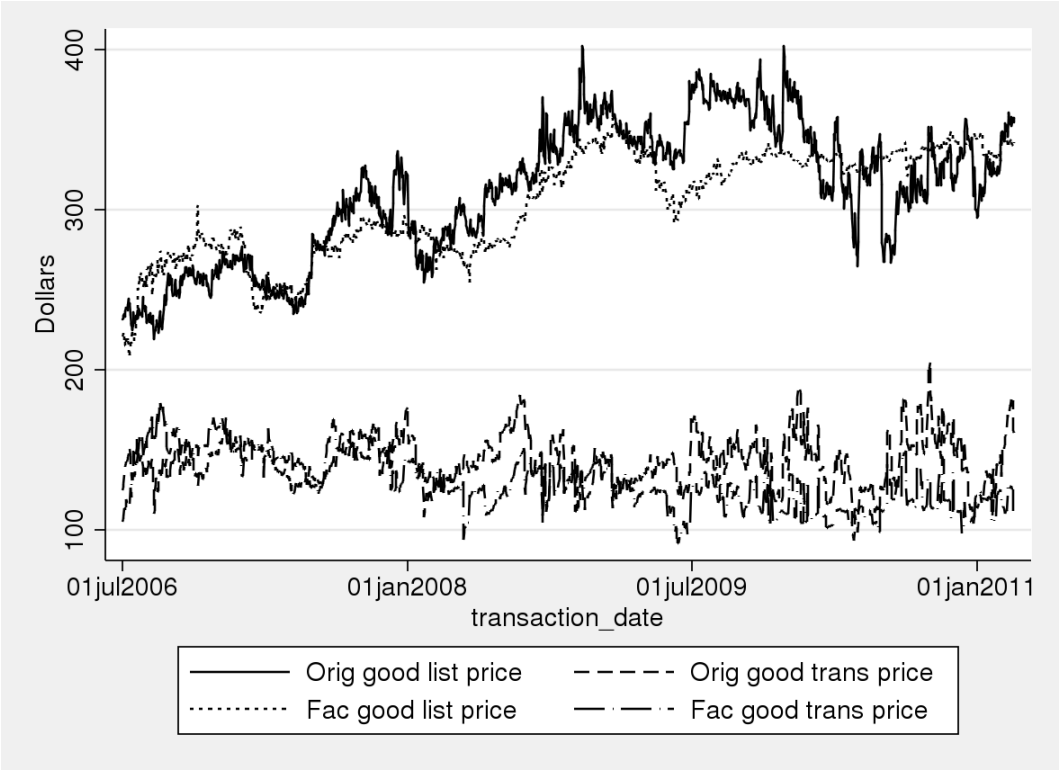


Table A1: Frequency of list price values

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