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INSIDE THE PRICE DISPERSION BOX: EVIDENCE FROM US SCANNER DATA

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Abstract

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INSIDE THE PRICE DISPERSION BOX: EVIDENCE FROM US SCANNER DATA*

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September, 2016

Abstract

To characterize the cross sectional price distribution of supermarket prices, we divide the stores in each good-week combination (UPC-week cell) into bins according to their price. For example, in the 3 bins division case we have a high price bin, a medium price bin and a low price bin. Our main findings are: (a) The variations over weeks in the (cross sectional) average price and quantity sold is lower for higher price bins; (b) Temporary sales contribute substantially to variations over weeks in the average price of the typical good; (c) The elasticity of the quantity sold by stores in the high price bin with respect to the quantity sold by stores in a low price bin (the quantity elasticity) is less than unity; (d) The elasticity of the quantity sold by stores in the high price bin with respect to the price in a low price bin (the cross price elasticity) is positive but less than the absolute value of the own price elasticity. More generally, we provide results about elasticities within UPC-week cells, variations over weeks within UPC and the role of temporary sales.

Key Words: Price Dispersion, Sequential Trade, Temporary Sales
JEL Code: D40

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1. INTRODUCTION

Models of price dispersion use various assumptions. Among these are monopolistic competition, menu costs, search frictions and uncertainty about aggregate demand. Different assumptions may lead to drastically different policy implications and therefore attempting to differentiate between various models is important. Here we study some implications of monopolistic competition models that assume a CES utility function and versions of the Prescott (1975) model.

The paper complements Eden (2016) who focuses on variations in the cross sectional price dispersion across goods. Here we focus on the within good behavior of prices and quantities. We divide stores that sell a given product in a given week into bins according to their posted price. For example, we look at stores with price above the median and below the median. Stores may be above the median in one week and below the median in another week. In the same week a store may have goods that are priced above the median and below the median. We therefore define the bins for each good-week combination (UPC-week cell).

Our main findings are: (a) The variations over weeks in the average price and quantity sold is lower for higher price bins; (b) Temporary sales contribute substantially to variations over weeks in the (cross sectional) average price of the typical good[1]; (c) The elasticity of the quantity sold by stores in the high price bin with respect to the quantity sold by stores in a low price bin (the quantity elasticity) is less than unity; (d) The elasticity of the quantity sold by stores in the high price bin with respect to the price

[1] The focus here is on the behavior of posted prices. Glandon (2015) study the behavior of transaction prices, obtained by dividing aggregate revenues across stores in each UPC-week cell by the aggregate quantity sold in the cell. He finds that temporary sales have a large impact on the price actually paid by consumers. Coibion et.al (2015) find that effective (transaction) prices are procyclical while posted prices are acyclical. They explain this difference by changes in shopping activities: In recessions consumers spend more time shopping and tend to reallocate expenditures towards lower price retailers. This is consistent with Kaplan and Menzio (2015) who found a significant effect of the employment status of the head of the household on the average price paid.

in a low price bin (the cross price elasticity) is positive but less than the absolute value of the own price elasticity.

We attempt to explain the above findings with a model in which price dispersion arises as a result of uncertainty about aggregate demand. We start with a simple monopolistic competition model in which there are many buyers who belong to a single household. Each buyer visits one store only and is instructed by the head of the household to buy a quantity that depends on the price. We derive the prediction of this model about the elasticities within UPC-week cell under the assumption that the head of the household maximizes a CES utility function. We then explore a flexible price version of the Prescott model, the Uncertain and Sequential Trade (UST) model, where buyers can costlessly move across stores and buy at the cheapest available price. The "simple versions" of the two models do not explain the main empirical findings. Observation (a) is a challenge to Prescott type models that assume a tradeoff between the probability of making a sale and the price. Observations (c) and (d) are a challenge to versions of monopolistic competition models that imply a quantity elasticity of unity and a cross price elasticity that is equal to the absolute value of the own price elasticity. We attempt to explain the main findings with a model in which some buyers shop around (as in the UST model) and some buyers do not shop around (as in our monopolistic competition model).

Previous empirical studies of price dispersion focused on the implications of search models. See for example, Sorensen (2000), Lach (2002) and Kaplan and Menzio (2015). There is also an empirical literature that focus on sticky price models of price dispersion. See for example, Reinsdorf (1994), Eden (2001a), Baharad and Eden (2004) and Ahlin and Shintani (2007). And there is a literature that focus on price dispersion in the airline industry. See for example, Escobari (2012), Gerardi and Shapiro (2009) and Cornia, Gerardi and Shapiro (2012). Here we use the UST model to discuss the empirical findings. One reason for our focus on the UST model is the finding that demand uncertainty is important in explaining differences in price dispersion across goods (Eden

[2016]). Another rather obvious reason is that we are more familiar with this model. We hope however that the facts recovered in this paper will be of interest also to readers who are not familiar with the UST model and who wish to regard the UST framework as an organizational device.

Section 2 is about the monopolistic competition model. Section 3 is about a flexible price version of the Prescott model: the Uncertain and Sequential Trade (UST) model. Section 4 describes the data and variations in the (cross sectional) average price over weeks. Section 5 is about elasticities. Section 6 repeats the calculations after controlling for store effects and section 7 repeats the calculations after controlling for UPC specific store effects. Section 8 assesses the importance of temporary sales in the variation of the (cross sectional) average price over weeks. Section 9 computes the probabilities of attracting shoppers by lower price stores. Section 10 provides concluding remarks.

2. MONOPOLISTIC COMPETITION

We start with a model in which the household uses a CES utility function to allocate expenditure over stores as in Dixit and Stiglitz (1977).[2]

There is a single household with $2N$ members: N workers (sellers) and N buyers. Members live in N neighborhoods. There are two members per neighborhood: A buyer and a seller. Each seller produces a good and offers it for sale in his neighborhood. There are thus N goods that are differentiated by location but have identical physical characteristics. In week t, the head of the household decides how much to buy from each of the N goods and instructs the buyer who lives in neighborhood i to buy x_{it} units from the seller in his neighborhood.

[2] This model is an important component of the New Keynesian literature. See for example, Christiano et.al (1997) and Coibion et. al (2015).

The head of the household chooses to spend a total of I_t dollars on the N goods. He faces the prices $(p_{1t},...,p_{Nt})$ and chooses the quantities $(x_{1t},...,x_{Nt})$ to maximize a CES utility function. In week t, the head of the household solves the following problem:

$$\max_{x_{jt}} \left(\sum_{j=1}^{N} (x_{jt})^{\gamma} \right)^{1/\gamma} \quad \text{s.t.} \quad \sum_{j=1}^{N} p_{jt} x_{jt} = I_t \tag{1}$$

where $0 < \gamma < 1$.

The first order conditions to this problem requires:

$$x_{jt} = x_{1t} \left(\frac{p_{jt}}{p_{1t}} \right)^{\theta} \quad \text{for all } j \tag{2}$$

where $\theta = \frac{1}{\gamma - 1} < 0$. We take logs and add a classical measurement error to obtain:

$$\ln(x_{jt}) = \ln(x_{1t}) + \theta \ln(p_{jt}) - \theta \ln(p_{1t}) + e_t \tag{3}$$

This regression imposes strong restrictions on the coefficients. It says that the quantity elasticity (the coefficient of $\ln(x_{1t})$) is unity and the absolute value of the own price elasticity is equal to the cross price elasticity.

In the above model each buyer visits one store. We now turn to the other extreme in which buyers can costlessly move between stores and buy at the cheapest available price.

3. SEQUENTIAL TRADE

The original Prescott (1975) model assumes that prices are set in advance and cheaper goods are sold first. Eden (1990) relaxes the price rigidity assumption and describes a sequential trade process in which cheaper goods are sold first.[3] In his Uncertain and Sequential Trade (UST) model, buyers arrive at the market place sequentially. Each buyer sees all available offers, buys at the cheapest available price and disappears. Sellers

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[3] For other extensions of the Prescott model, see Dana (1998, 1999,2001) and Deneckere and Peck (2012).

must make irreversible selling decisions before they know the aggregate state of demand. In equilibrium they are indifferent between prices that are in the equilibrium range because the selling probability is lower for higher prices. Sellers in the model make time consistent plans and do not have an incentive to change prices during the trading process. Prices are thus completely flexible.

We start with a simple version and then augment it to account for various features of the data.

3.1 A simple version

There are many goods and many sellers who can produce the goods at a constant unit cost. Here we focus on one good with a unit cost of λ. Production occurs at the beginning of the period before the arrival of buyers. Storage is not possible. The number of buyers $\tilde{N}$ is an iid random variable that can take two possible realizations: N with probability $1-q$ and $N+\Delta$ with probability q. Buyers arrive sequentially in batches. The first batch of N buyers buys in the first market at the price P_1. The second market opens only if the second batch of Δ buyers arrives. If this second batch arrives the second market opens at the price P_2.

The demand of each of the active buyer at the price P is given by: $D(P)$. In equilibrium sellers supply x_1 units to the first market and x_2 units to the second market.

Equilibrium is a vector (P_1, P_2, x_1, x_2) such that the expected profits for each unit is zero:

(4) $$P_1 = qP_2 = \lambda$$

And markets that open are cleared:

(5) $$x_1 = ND(P_1) \text{ and } x_2 = \Delta D(P_2)$$

Figure 1 illustrates the equilibrium solution. The demand in market 1 at the price λ, $ND(\lambda)$ is equal to the supply to the first market (x_1). When market 2 opens at the price λ / q, the demand in this market, $\Delta D(\lambda / q)$, is equal to the supply (x_2).

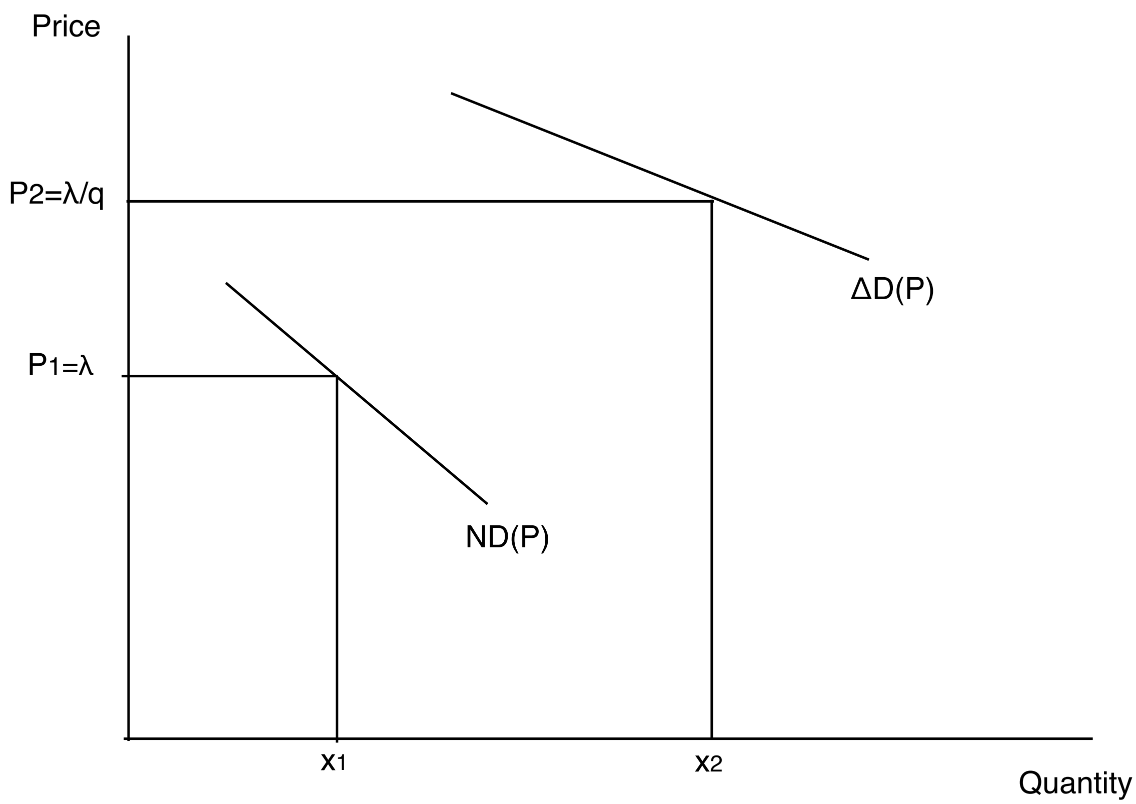


Figure 1: Prices and quantities in the simple version

Note that in this simple version posted prices do not change over time. The quantity sold at the low price does not change over time but the quantity sold at the high price fluctuates over time.

3.2 Storage

Bental and Eden (BE, 1993) studied a UST model with storage and in their model both quantities and prices fluctuate with the beginning of period level of inventories. The BE model can be easily extended to allow for supply shocks. In Eden (2001), the amount available for sale fluctuates as a result of both *iid* demand and supply shocks. In this model, an increase in the amount of inventories carried from the previous period reduces all prices. A temporary reduction in the cost of production will have a similar effect.

Prices will in general depend on the amount available for sale (inventories + current production) and when this amount is high, prices will remain low until inventories are back to "normal". Thus, "temporary sales" may be the result of both demand and supply shocks. Eden (2001) uses aggregate NIPA data and VAR analysis to test the implications of the model. The model is also consistent with the findings of Aguirregabiria (1999) who used a unique data set from a chain of supermarket stores in Spain and found a very significant and robust effect of inventories at the beginning of the month on current price.[4]

The BE model assumes a convex cost function and exponential depreciation. Here we assume a constant per unit cost and one-hoss-shay depreciation. The one-hoss-shay depreciation is realistic because most supermarket items have an expiration date. It also serves as a tiebreaker and yields predictions about temporary sales that are an important feature of the data.

To simplify, we assume that the good can be stored for one period only. Thus, if a good is not sold in the first period of its life, it can still be sold in the second period but it has no value if it is not sold within the two period limit.

As before, the number of buyers $\tilde{N}_t$ is iid and can take two possible realizations: $\tilde{N}_t = N$ with probability $1-q$ and $\tilde{N}_t = N+\Delta$ with probability q.

[4] Aguirregabiria (1999) provides a description of the negotiation between the firm (chain's headquarter) and its suppliers. The toughest part of the negotiation with suppliers is about the number of weeks during the year that the brand will be under promotion, and about the percentage of the cost of sales promotions that will be paid by the wholesaler (e.g. cost of posters, mailing, price labels). A similar description is in Anderson et.al (2013) who present institutional evidence that sales (accompanied by advertising and other demand generating activities) are complex contingent contracts that are determined substantially in advance. There is also some flexibility. For many promotions manufacturers allow for a "trade deal window" of several weeks where the seller can execute the promotion. These descriptions are consistent with the hypothesis that temporary sales are used to respond to high inventories. Sometimes the delivery schedule allows the firm to predict the level of inventories and as a result temporary sales are set in advance. The flexibility in the timing of sales reflects the need to respond to inventories that were accumulated as a result of demand shocks. The observation that temporary sales do not respond to cost shocks (Anderson et.al [2013]) and are largely acyclical (Coibion et.al [2015]) is also consistent with the hypothesis that temporary sales are used to respond to transitory changes in the level of inventories that last for a relatively short time and not to changes that last for relatively long time (like changes in cost and the level of unemployment). This is different from the view that temporary sales are not used to respond to changes in fundamentals and are merely a discrimination device.

At the beginning of period t the economy can be at two states. In state I (I for inventories) the demand in the previous period was low ($\tilde{N}_{t-1} = N$) and the second market did not open. As a result inventories were carried from the previous period. In state NI (NI for no inventories) demand was high ($\tilde{N}_{t-1} = N + \Delta$) and there are no inventories. The price in the first market is $P(1,I)$ in state I (with inventories) and $P(1,NI)$ in state NI (with no inventories). The quantity offered for sales in market 1 is $x(1,I)$ in state I and $x(1,NI)$ in state NI. The price in the second market (P_2) and the supply (x_2) do not depend on the level of inventories. The quantity sold in the first market is equal to the quantity offered for sale. The quantity sold in the second market is zero if demand is low and x_2 if demand is high. Table A describes the total amount sold (over the two markets) as a function of last period's demand and this period's demand.

Table A: Total amount sold in period t

	$\tilde{N}_t = N + \Delta$	$\tilde{N}_t = N$
$\tilde{N}_{t-1} = N + \Delta$	$x(1,NI) + x_2$	$x(1,NI)$
$\tilde{N}_{t-1} = N$	$x(1,I) + x_2$	$x(1,I)$

A formal analysis and the equilibrium definition is in Eden (2016, Appendix C). To make this paper self-contained we repeat here the description of the model.

The main idea is that in allocating the available amount of goods (from new production and inventories) across the two markets, the older units get a "priority" in the first market (and the younger units get a "priority" in the second market). Given prices the allocation rule is as follows. If the amount of old units that come from inventories is less than the demand in the first market then all old units are supplied to the first market. If the amount of old units is greater than the demand in the first market then only old units are supplied to the first market. This allocation rule can be justified on efficiency grounds. Suppose for example, that a chain has two stores: Store O with old units and store Y with young units. Suppose further that store Y posts the first market low price and store O posts the second market high price. In this case if aggregate demand is low and store O does not sell, the units supplied by store O expire. Alternatively, if store O posts the first market price and store Y posts the second market price, the unsold units supplied by store Y do not expire and can be sold next period. Thus the chain's profits will be higher if the store with the young units supplies to the second market.

The value of a young unit that is not sold in the current period (the value of inventories) is $\beta P(1,I)$, where $0<\beta<1$ is a constant that captures discounting, storage costs and depreciation. The value of an old unit that is not sold is zero. Given the above allocation rule and given that production is strictly positive in each period, newly produced units are supplied to the second market and in equilibrium the following arbitrage condition must hold.[5]

(6) $$qP_2+(1-q)\beta P(1,I)=\lambda$$

The left hand side of (6) is the expected present value of revenues from a newly produced unit allocated to the second market. If the second market opens (with probability q) the seller gets P_2. Otherwise he will get the unit value of inventories, $\beta P(1,I)$. The right hand side of (6) is the unit cost of production. Thus, (6) says that the marginal cost is equal to expected revenues.

We now distinguish between two cases. In the first case, illustrated by Figure 2A, inventories in state I are relatively low and newly produced goods are supplied in state I to the first market. The price in the first market is the marginal cost: $P(1,I)=P(1,NI)=\lambda$. Substituting this into (6) yields:

(7) $$P_2=\frac{\lambda\left(1-(1-q)\beta\right)}{q}$$

In the second case, illustrated by Figure 2B, newly produced goods are supplied to the first market only in state NI. In state I the entire supply to the first market is out of inventories and the supply to the second market is of both newly produced units and

[5] Production must be positive because the entire supply in the first market is always sold.

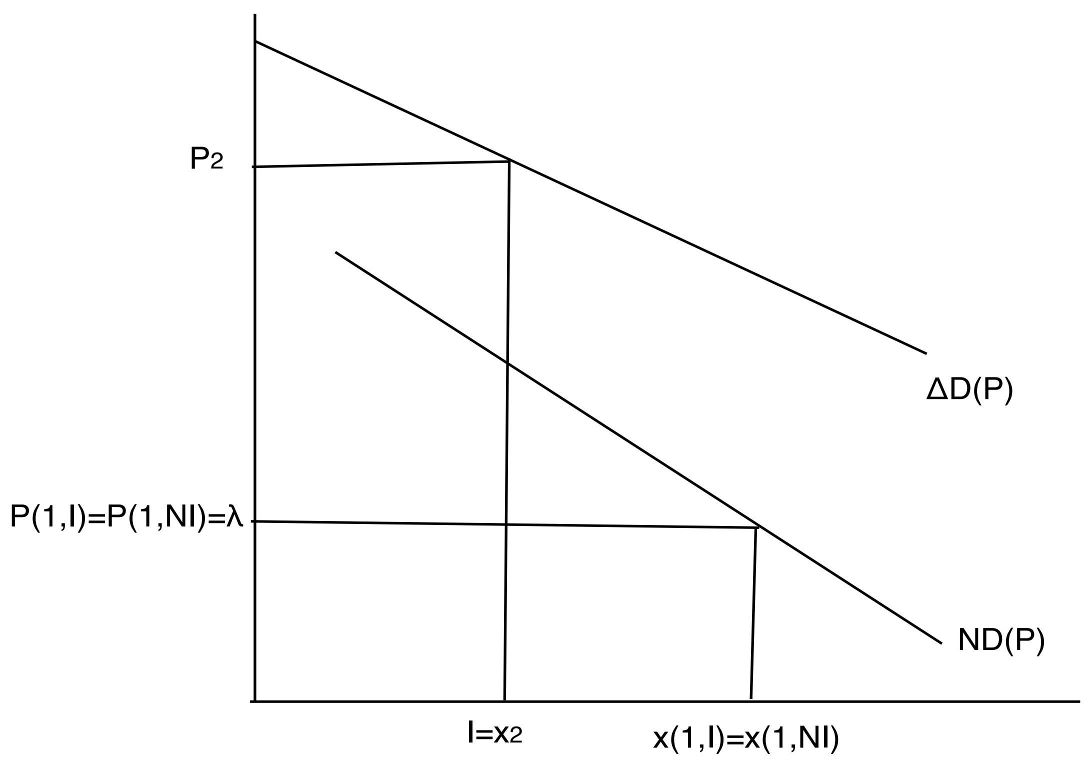
old units. The following arbitrage condition must hold when some old units are supplied to the second market.

(8) $$qP_2 = P(1,I)$$

This says that the expected revenue of supplying an old unit to the second market is the same as the revenue from supplying it to the first market. The solution to (6) and (8) is:

(9) $$P(1,I) = \frac{\lambda}{1+(1-q)\beta} < \lambda \text{ and } P_2 = \frac{\lambda}{q\left(1+(1-q)\beta\right)}$$

Note that the first market price in state I is below cost as in the loss-leaders model of Lal and Matutes (1994).[6]



A. In state I, $I = x_2$ "old units" and $x(1,I) - I$ newly produced units are supplied to the first market. The supply to the first market does not depend on the amount of inventories in this case.

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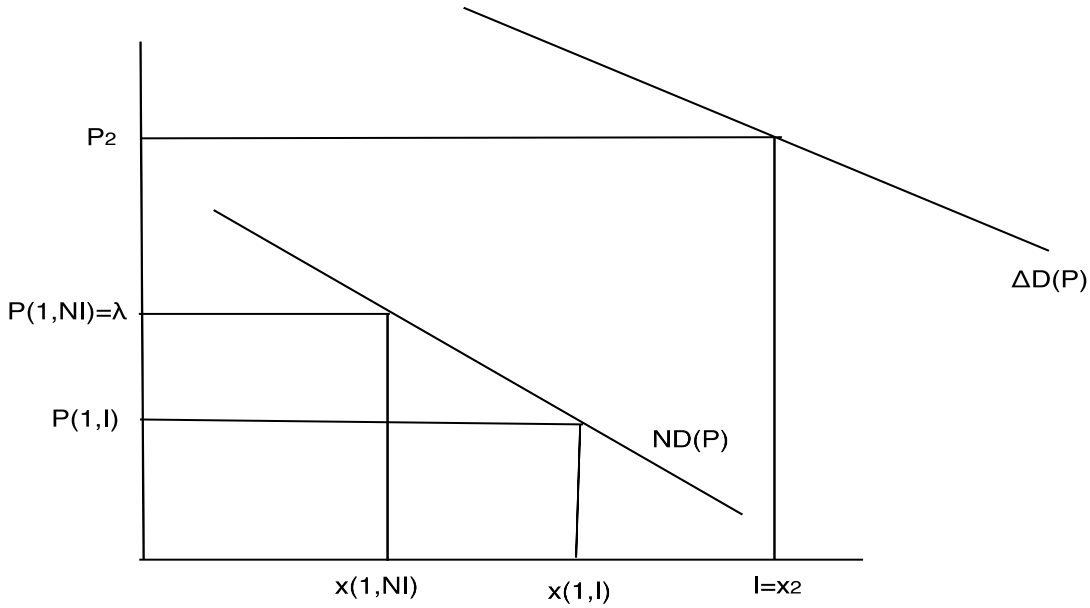
6 It is also possible that all the old units are allocated to the first market and all the new units are allocated to the second market. Also in this case the first market price can be below cost: $P(1,I) \leq \lambda$. See, Eden (2016).



B. In state I, $x(1,I)$ "old units" are supplied to the first market and $I - x(1,I)$ "old units" are supplied to the second market. No new units are supplied to the first market.

Figure 2: Possible Equilibria

The model described by Figure 2 may account for temporary sales. Some stores offer their newly produced good at the high ("regular") price of market 2. Then if demand is low they accumulate inventories and offer the good for sale at the low price of market 1. We also note that the price and quantity in the first market may change over time.

3.3 Using sales by low price stores to predict sales by high price stores.

In section 3.1 and 3.2, the amount sold in the second market does not depend on the amount sold in the first market. This result is special to the assumption that $\tilde{N}$ can take only two possible realizations.

In the more general case in which $\tilde{N}$ may take many possible realizations the quantity sold in market $k < i$ may be correlated with the quantity sold in market i, because strictly positive sales in market k imply $\tilde{N} \geq N_k$ and leads to an upward revision in the probability that $\tilde{N} \geq N_i$ and market i will open.

We now establish this correlation under the assumption that the amount supplied to market s (x_s) does not change over time. This assumption holds if inventories are not too large as in Figure 2A.

We start with the case in which the number of buyers $\tilde{N}$ can take 3 possible realizations: (N_0,N_1,N_2) with probabilities (π_0,π_1,π_2), where $N_0=0<N_1<N_2$. There are two hypothetical markets. The first market opens with probability $1-\pi_0$ and if it opens it serves N_1 buyers. The second market opens with probability π_2 and if it opens it serves $\Delta=N_2-N_1$ buyers. The unconditional expected quantity sold in market 2 is: $E(x_2)=\pi_2\Delta D(P_2)$. The expected quantity sold in market 2 conditional on sale in market 1 is:[7]

(10) $$E(x_2\,|\,x_1>0)=\frac{\pi_2\Delta D(P_2)}{1-\pi_0}$$

And the expected quantity sold in market 2 conditional on no sales in market 1 is:

(11) $$E(x_2\,|\,x_1=0)=0$$

There is thus a positive relationship between the quantity sold in market 1 and the quantity sold in market 2.

We now consider the more general case. We assume that the number of buyers $\tilde{N}$ can take $m+1$ possible realizations: $(N_0,N_1,...,N_m)$, where $(0=N_0<N_1<N_2...<N_m)$. The probability that the number of buyers is N_s is denoted by: $\pi_s=\Pr ob(\tilde{N}=N_s)$. The probability that the number of buyers is greater than N_s is denoted by:

(12) $$q_s=\Pr ob(\tilde{N}\geq N_s)=\sum_{i=s}^{m}\pi_i$$

The demand in market m if it opens is: $\Delta_m D(P_m)$, where $\Delta_m=N_m-N_{m-1}$. The expected quantity sold in market m given x_i is:

(13) $$E(x_m\,|\,x_i>0)=\frac{\pi_m\Delta_m D(P_m)}{q_i}\,,\;E(x_m\,|\,x_i=0)=0$$

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[7] Applying Bayes' rule leads to: $\Pr ob(\tilde{N}=N_2\,|\,\tilde{N}\geq N_1)=\dfrac{\Pr ob(\tilde{N}=N_2\cap\tilde{N}\geq N_1)}{\Pr ob(\tilde{N}\geq N_1)}=\dfrac{\pi_2}{1-\pi_0}$.

There is thus a positive relationship between the quantity sold in market i and the quantity sold in market m. We now make the following additional observation.

Claim 1: The expected sales in market m conditional on $x_i > 0$ is increasing in the index i.

To see this claim, note that the probability of making a sale in market i is q_i and (12) implies: $q_1 > q_2 > \ldots > q_m = \pi_m$.

The intuition for Claim 1 is in the observation that $\Pr ob(\tilde{N} = N_m \mid \tilde{N} \geq N_i)$ is increasing in i. Therefore, from the point of view of the highest price stores, positive sales by medium price stores are more encouraging news than positive sales by low price stores.

Equations (13) may be tested by running the quantity sold by the highest price store (store m) on a dummy that is equal to 1 if sales in a lower price store was positive and zero otherwise. We did not pursue this route because we cannot distinguish in the data between the case in which the good was on the shelf and was not sold to the case in which the good was not on the shelf. For this reason we used only good-store combinations with positive sales in all weeks. To account for the observations that sales are always positive, we follow Salop and Stiglitz (1977), Shilony (1977) and Varian (1980) and add non-shoppers to the model.

3.4 Non-shoppers

We abstract from storage and extend the model in section 3.1 to include two types of buyers: shoppers and non-shoppers. The monopolistic competition model in section 2 and the UST model in section 3.1 may be obtained as special cases. The monopolistic competition model may be obtained if we eliminate shoppers from the model. The UST model may be obtained if we eliminate non-shoppers from the model.

We focus here on predicting the quantity sold by the highest price stores on the basis of the quantity sold by medium and low price stores. To simplify, we assume that shoppers' activity is not important for the highest price stores and focus on the quantity elasticity: The elasticity of the quantity sold by the highest price stores with respect to the quantity sold by lower price stores.

In the absence of shoppers we get the monopolistic competition result of unit elasticity. In the presence of shoppers we get an elasticity that is less than unity because of the following signal extraction problem. For predicting the quantity sold by the highest price stores only the demand of non-shoppers is relevant and therefore shoppers' activity introduces noise that leads to an elasticity that is less than unity.

Sales by medium price stores provide relatively more information about the demand of non-shoppers because they are less influenced by shoppers' activity. And therefore as in section 3.3, we find that for predicting sales by the highest price stores, sales by medium price stores are more relevant than sales by low price stores.

To model this idea, we assume n sellers and $nk+m$ buyers, where $n>m$. Some sellers advertise their price and some do not. There are $m>0$ advertisers and $n-m>0$ non-advertisers. Similarly there are some buyers who shop around and some who do not. There are $m>0$ shoppers and $nk>0$ non-shoppers.

At the beginning of week t, sellers (advertisers and non-advertisers) produce the good at the cost of λ_t, where λ_t is the realization of an iid random variable $\tilde{\lambda}$.

The demand of an active buyer at the price P is $a_t P^\theta$ where $\theta<0$ and a_t is the realization of an iid random variable $\tilde{a}$. The demand of the individual buyer is similar to the demand of the individual buyer in the monopolistic competition model (3) where the price of the numeraire good is unity and the level of consumption from the numeraire good is the realization of $\tilde{a}$.

Sellers and non-shoppers are distributed over n locations. In each location there is one store (seller) and k non-shoppers that always buy in the local store.

The number of active shoppers is an iid random variable $\tilde{s}$ that can take $m+1$ possible realizations: $s=0,\ldots,m$, where realization s occurs with probability π_s. Thus, in state s there are s active shoppers and $m-s$ shoppers who are not active.

We may imagine that active shoppers use the internet. The web site of each advertiser includes information about the price and about availability. When an advertiser is stocked out this information is immediately on the web site.[8]

Each of the $n-m\geq 0$ non-advertisers sells only to the k non-shoppers in his location. Each of the m advertisers may attract some shoppers in addition to the non-shoppers in his location. To simplify, we assume that each advertiser chooses capacity (production) to satisfy the demand of $1+k$ buyers. We thus assume that a store satisfies the demand of its k regular clients and has an additional capacity to serve one shopper if he arrives. Unlike New Keynesian models, here stores may be stocked out. Unlike some search models, here capacity depends on the price.

We also simplify by assuming that non-shoppers buy first. After non-shoppers have completed their trade there is still available capacity in m stores. At this point the shoppers form a hypothetical line. There may be no shoppers (if $\tilde{s}=0$) and in this case there is no more trade. Otherwise, the first shopper buys at the cheapest advertised price. The second in line has less choice because one store is already stocked out. In general, the active shoppers who are "last" in line have less choice than those who are at the head of the line. Figure 3, describes the sequence of events within the week.

[8] This is different from Burdett, Shi and Wright (2001) who assume that buyers can see all prices but cannot see availability.

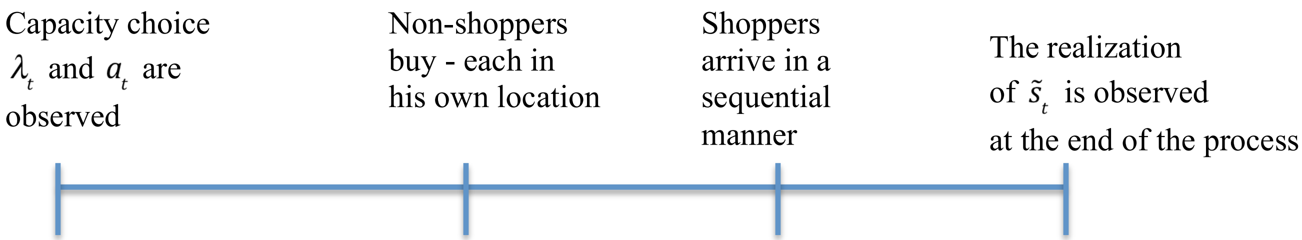


Figure 3: Sequence of Events within the week

The price posted by an advertiser in location i in week t is P_{it}. We choose indices such that the price posted by advertisers increases with the location index: $P_{1t} < \dots < P_{mt}$. The price posted by non-advertisers (indexed $i > m$) is the monopoly price P_t^m.

As was said above, shoppers buy at the cheapest available price. The first shopper chooses store 1 with the price P_1. The second shopper chooses store 2 with the price P_2 and so on. The probability of attracting a shopper by a store that advertise the price P_i $(i \leq m)$ is:

(14)
$$q_i = \Pr ob(\tilde{s} \geq i) = \sum_{s=i}^{m} \pi_s$$

In equilibrium all advertisers make the same expected profits, Π:

(15)
$$(k+q_i)P_{it}a_t P_{it}^{\theta} - (k+1)\lambda_t a_t P_{it}^{\theta} = \Pi_t$$

This leads to:

(16)
$$P_{it} = \frac{(k+1)\lambda_t}{k+q_i} + \frac{\Pi_t}{(k+q_i)a_t P_{it}^{\theta}}$$

In the simple version of the UST model in section 3.1, $k = \Pi = 0$ and the expected revenue per unit $q_i P_{it} = \lambda_t$ is the same across prices. Here the first term is the unit cost divided by the average capacity utilization $(k+q_i)/(k+1)$. The second term is the expected profit per unit sold. For the definition and existence of equilibrium, see Appendix A.

We now turn to study the relationship between the quantity sold by a non-advertiser and the quantity sold by an advertiser. The quantity sold by the non-advertisers is:

(17) $$\ln(x_t^m) = \ln(k) + \ln(a_t) + \theta \ln(P_t^m)$$

The quantity sold by an advertiser is:

(18) $$\ln(x_{it}) = \ln(\tilde{\omega}_i) + \ln(a_t) + \theta \ln(P_{it})$$

where $\tilde{\omega}_i = \{1+k$ with probability q_i and k otherwise$\}$ is the number of buyers that shop in the advertiser's store.

Subtracting (18) from (17) leads to:

(19) $$\begin{aligned}\ln(x_t^m) &= \ln(k) + \theta \ln(P_t^m) + \ln(x_{it}) - \ln(\tilde{\omega}_i) - \theta \ln(P_{it}) \\ &= \ln(x_{it}) + \theta \ln(P_t^m) - \theta \ln(P_{it}) + D_{it}\end{aligned}$$

where D_{it} is the difference in the number of buyers between the non-advertiser and the advertiser:

(20) $$D_i = \ln(k) - \ln(\tilde{\omega}_i) = \{\ln(k) - \ln(1+k) \text{ if } s \geq i \text{ and zero otherwise}\}$$

This difference is negative if a shopper arrives at the advertiser's store and zero if he does not arrive. Since $\frac{x_{it}}{aP_{it}^{\theta}} = 1+k$ if $s \geq i$, we can write (20) as:

(21) $$D_{it} = \{\ln(k) - \ln\left(\frac{x_{it}}{a_t P_{it}^{\theta}}\right) \text{ if } s \geq i \text{ and zero otherwise}\}$$

Since $\Pr ob(s \geq i) = q_i$, (21) implies

$$E(D_{ij} \mid \tilde{a} = a) = q_i\left(\ln(k) - \ln\left(\frac{x_i}{aP_i^{\theta}}\right)\right) = q_i\left(\ln(k) - \ln(x_i) - \theta \ln(P_i) - \ln(a)\right).$$ The unconditional expectations are:

(22) $$E(D_{it}) = q_i \ln(k) - q_i \ln(x_{it}) + q_i \theta \ln(P_{it}) + q_i E \ln(\tilde{a})$$

We write:

(23) $$D_{it} = E(D_{it}) + \varepsilon_{it}$$

By construction ε_{it} has zero mean and is iid.

Substituting (22) and (23) in (19) leads to:

(24) $$\ln(x_t^m) = \psi_i + (1-q_i)\ln(x_{it}) + \theta\ln(P_t^m) - (1-q_i)\theta\ln(P_{it}) + \varepsilon_{it}$$

where $\psi_i = q_i\left(\ln(k) + E\ln(\tilde{a})\right)$.

We can use (24) to interpret a regression of the average quantity sold by stores in the high price bin on the average price in the high price bin and the average price and quantity in the low price bin. Equation (24) has the following strong predictions.

Claim 2: (a) the quantity elasticity (the coefficient of $\ln x_{it}$) is between zero and unity and the own price elasticity (the coefficient of $\ln P_t^m$) is greater in absolute value than the cross price elasticity (the coefficient of $\ln P_{it}$); (b) the quantity elasticity and the cross price elasticity are decreasing in the index of the bin.

The quantity elasticity is less than unity because an increase in the quantity sold by the advertiser may be due to the arrival of a shopper rather than an increase in a. It is due to the arrival of a shopper with probability q and therefore the elasticity is only $1-q$. Since the quantity elasticity is decreasing in q it decreases with the index of the bin. In Appendix B we generalize the results in Claim 2 to the case in which the dependent variable is the quantity sold by an advertiser.

4. DATA

We use a rich set of scanner data from Information Resources Inc. (IRI).[9] The complete data set covers 48 markets across the United States, where a market is sometimes a city (Chicago, Los Angeles, New York) and sometimes states (Mississippi). There are 31 diverse categories of products found in grocery and drug stores, such as carbonated beverages, paper towels, and hot dogs. We define goods by the Universal Product Code

[9] A complete description of the entire data set can be found in Bronnenberg, Bart J., Michael W. Kruger, Carl F. Mela. 2008. Database paper: The IRI marketing data set. Marketing Science, 27(4) 745-748.

(UPC). The data provide information about the total number of units and total revenue for each UPC-store-week cell. We obtain the posted price for each cell by dividing revenue by the number of units sold. We use data from grocery stores in Chicago during the years 2004 and 2005. We use 3 samples. The 52 weeks in the year 2004, the 52 weeks in the year 2005 and the 104 weeks in the combined sample of 2004-2005.[10]

We apply the following filtering (in a sequential manner):

(a) We drop all UPC-Store cells that do not have positive revenues in all of the sample's weeks.[11]

(b) We drop all UPCs that were sold by less than 11 stores.

(c) We drop all categories with less than 10 UPCs.

(d) We drop UPC-Week observations with no price dispersion.

The first exclusion is applied because we cannot distinguish between zero-revenue observations that occur when the item is not on the shelf and zero-revenue observations that occur when the item is on the shelf but was not sold. It is also required for identifying "temporary sale" prices. The second exclusion is aimed at reliable measures of cross sectional price dispersion. The third economizes on the number of category dummies. After applying (a)-(c) we get "semi balanced" samples in which the number of stores varies across UPCs but stores that are in the sample sold their products in all of the sample's weeks.

The requirement that the product be sold continuously by more than 11 stores leads to a sample of fairly popular brands.[12] The focus on fairly popular items is likely to reduce the problem of close substitutes that have different UPCs. In addition, the

[10] We also replicated the results for other cities (New York, Los Angeles, Philadelphia, Raleigh/Durham and Washington, D.C.). We find strong agreement with the Chicago data presented here.

[11] We also dropped observations in which the quantity sold was zero but revenues were positive.

[12] This bias is not unique to this paper. Sorenson (2000) has collected data on 152 top selling drugs. Lach (2002) excluded products that were sold by a small number of stores. Kaplan and Menzio (2015) exclude UPCs with less than 25 reported transactions during a quarter in a given market.

exclusion of items sold by less than 11 stores significantly reduce the number of items with very high price dispersion that may arise as a result of measurement errors.[13]

Temporary Sales.

We assume that a temporary sale occurs when a drop in the price of at least 10% is followed by a price equal to or above the pre-sale price within four weeks. To study the effects of temporary sales we use samples of regular prices obtained from the original samples after deleting all observations in which the price was a "sale" price. After eliminating "sale prices" we used an additional filter that dropped all UPC-week cells that had less than 11 stores or had no price dispersion. Note that the original filter required that each UPC- store cell have strictly positive revenues in all weeks. This allowed for the implementation of our definitions of sales. We drop this requirement in the second round of filtering and as a result the number of stores that sell a given UPC (at a "regular" price) may vary across weeks.

Bins.

We split the stores in each UPC-Week cell into bins of approximately equal size. For example, the 2 bins division split the stores in each UPC-Week cell into two categories: High and low price stores, where the price of the stores in the high price bin (bin 1) is greater than or equal to the median. For example, if there are 3 stores and the prices are: 5 in store 1, 6 in store 2 and 7 in store 3 then stores 2 and 3 are in bin 1. If the prices are 6 by stores 1 and 2 and 7 by store 3, then only store 3 will be in bin 1.

[13] To get a sense of the effect of the sample exclusion on the result, Eden (2013) studies one week in detail. Indeed there is a difference between the sample of 8602 UPCs that were sold by more than 1 store during that week and the sample of 4537 UPCs that were sold by more than 10 stores. Relative to the larger sample, price dispersion in the smaller sample is lower. The highest price dispersion was found in an item that was sold by 2 stores and for this item the ratio of the highest to lowest price was 15.

The price of a UPC in a given store can be above the median in one week and below the median in another week. Indeed most UPC-Store combinations are sometimes above the median and sometimes below the median. Only about 4% of the UPC-Store combinations are above the median in more than 95% of the weeks.

Summary statistics are in Table 1. The first rows are the number of UPCs and the number of observations for individual categories based on the 2 bins samples. In the 2004 sample there were 32 UPCs in the beer category. The number of observations (UPC-Week cells) is (32)(52)=1664. In 2005 there were 56 UPCs in the beer category. The number of observations is not equal to (56)(52) because in 3 cells there was no price dispersion. The total number of observations for each sample is in the bottom of the Table. The combined 04-05 sample has fewer UPCs because criterion (a) in our filtering procedure is harder to satisfy when there are 104 weeks. As a result the combined sample includes relatively more popular brands. The total number of observations varies with the number of bins because of insufficient price dispersion. For example if there are 20 stores in a UPC-week cell with 10 stores posting the price 1 and 10 posting the price 2, the stores can be easily divided into 2 bins but not into 3 or 5 bins. For the same reason, the number of observations in the samples of regular prices is lower than the number of observations in the samples of all prices. The number of observations reported here is for the original dollar prices. Later, when we use residuals instead of the original prices, almost all cells have price dispersion and as a result the number of observations is closer to the number of UPCs times weeks.

Table 1*: Summary statistics for the three samples

	2004		2005		2004-2005	
Category	# UPCs	Obs.	# UPCs	Obs.	#UPCs	Obs.
Beer	32	1,664	56	2,909	20	2,080
Carbonated Beverages	86	4,472	144	7,471	58	6,032
Cold Cereal	93	4,836	133	6,900	53	5,512
Facial Tissue	12	624	18	893	-	-
Frozen Dinner Entrees	36	1,871	75	3,765	-	-
Frozen Pizza	25	1,300	53	2,744	12	1,248
Hot Dogs	14	728	21	1,091	-	-
Margarine & Butter	25	1,300	40	2,060	18	1,872
Mayonnaise	17	884	19	988	-	-
Milk	32	1,664	64	3,294	23	2,392
Mustard & Ketchup	14	728	21	1,092	-	-
Paper Towels	-	-	19	901	-	-
Peanut Butter	18	936	24	1,245	11	1,144
Salty Snacks	94	4,887	120	6,226	42	4,368
Soup	49	2,548	74	3,826	22	2,288
Spaghetti Sauce	13	676	32	1,660	-	-
Toilet Tissue	13	676	19	958	-	-
Yogurt	92	4,783	152	7,870	65	6,760
Totals						
1 Bin, All Prices	665	34,580	1084	56,368	324	33,696
2 Bin, All Prices	665	34,577	1084	55,893	324	33,696
3 Bin, All Prices	665	34,273	1084	54,650	324	33,624
5 Bin, All Prices	665	29,533	1084	45,923	324	29,234
1 Bin, Regular Prices	80	4,160	215	11,180	18	1,872
2 Bin, Regular Prices	80	4,158	215	10,860	18	1,872
3 Bin, Regular Prices	80	3,286	215	10,060	18	1,640
5 Bin, Regular Prices	72	2,424	212	7,770	18	1,160

* An observation is a UPC - Week cell. The first column is the category name. The two columns that follow are about the 2004 sample. The first is the number of UPCs in each category and the second is the number of UPC-Weeks in that category. The next two columns are for the 2005 sample and the last two columns are for the combined 2004-05 sample. Totals are in the last rows.

Table 2 is about bin size. As was said before, the bins are only approximately the same size because of the discrete nature of the data. In the 2 bins division, 60% of the stores are in bin 1 and 40% in bin 2. Later, when we control for store effects, the size of the bins are much more similar.

Table 2a is about the frequency of temporary sales. The last column labeled as "frequency of sales" is the number of "sale prices" divided by the number of prices in the sample. Since our sample size varies with the number of bins, the frequency of sales varies slightly between samples. It is 0.20 when dividing the stores in the 2005 sample into 2 or 3 bins and 0.22 when dividing the stores into 5 bins.

The first 5 columns in Table 2a are the frequency of sales by bin. This is calculated by dividing the number of "sale prices" in the bin (aggregating over all UPCs and weeks) by the number of prices in the bin. When using the 2005 sample and the 2 bins division, 10% of the prices in bin 1 are "sale prices". The number for bin 2 is 34%. Using the 2005 sample and the 5 bins division, 42% of the prices in the lowest price bin (bin 5) are sale prices. The number for the highest price bin (bin 1) is 5%. This says that the fact that an item is on sale does not guarantee that it is cheap relative to the prices offered in the same week. The fraction of prices on sale is increasing with the index of the bin suggesting that the probability that an item is cheap relative to other stores given that it is on "sale" is higher than the unconditional probability.

Table 2b estimates the conditional probabilities: The probability that a price is in bin i given that it is a "sale price". For example, when using the 2005 sample and a 2 bins division, the probability that a "sale price" is in bin 1 is 0.3. This conditional probability is calculated as follows. Using Table 2, the unconditional probability that a price is in bin 1 is: $\Pr ob(bin1) = 0.6$. Using the last column in Table 2a, the unconditional probability that a price is a "sale price" is: $\Pr ob(sale) = 0.2$. The probability that a price in bin 1 is a "sale price" is in the first column of Table 2a. It is: $\Pr ob(Sale \mid bin = 1) = 0.1$. The probability that a price is in bin 1 and it is a "sale price" is: $\Pr ob(bin1 \cap Sale) = \Pr ob(bin1) \Pr ob(Sale \mid bin = 1) = (0.6)(0.1) = 0.06$. The probability that a price is in bin 1 given that it is a sale price is: $\Pr ob(bin1 \mid price = "sale") = \frac{\Pr ob(bin1 \cap Sale)}{\Pr ob(Sale)} = \frac{0.06}{0.2} = 0.3$. There is a remarkable agreement about the estimates of the conditional probabilities across samples.

The observation that a "sale price" can be in the highest price bin is surprising. It is possible that some stores are more expensive than others and they are in the highest price bin even when they have a "sale". It is also possible that the timing of "sales" is correlated across stores. We will try to distinguish between these two explanations later when we remove store effects.

Table 2*: Bin size

	bin 1	bin 2	bin 3	bin 4	bin 5
2 bins					
2004	0.60	0.40			
2005	0.60	0.40			
2004-2005	0.60	0.40			
3 bins					
2004	0.47	0.25	0.28		
2005	0.47	0.24	0.29		
2004-2005	0.46	0.25	0.29		
5 bins					
2004	0.34	0.16	0.16	0.15	0.19
2005	0.34	0.16	0.15	0.15	0.20
2004-2005	0.33	0.16	0.16	0.15	0.20

* The average fraction of stores in each bin. Averages are over weeks and UPCs.

Table 2a: Frequency of temporary sales by bins

	bin 1	bin 2	bin 3	bin 4	bin 5	Freq. Sale
2 bins						
2004	0.09	0.35				0.19
2005	0.10	0.34				0.20
2004-2005	0.10	0.37				0.21
3 bins						
2004	0.06	0.22	0.38			0.19
2005	0.07	0.24	0.37			0.20
2004-2005	0.07	0.25	0.41			0.21
5 bins						
2004	0.04	0.16	0.24	0.33	0.43	0.21
2005	0.05	0.18	0.27	0.32	0.42	0.22
2004-05	0.05	0.18	0.27	0.35	0.45	0.23

* The first 5 columns are the frequency of "temporary sales" by bins. These frequencies are obtained by dividing the number of "temporary sale prices" in the bin (aggregating over UPCs and weeks) by the total number of prices in the bin. The last column is obtained by dividing the number of "temporary sale prices" in the sample (aggregating over bins, weeks and UPCs) by the total number of prices.

Table 2b: The probability that the price is in bin i given that it is a "sale price"

	bin 1	bin 2	bin 3	bin 4	bin 5
2 bins					
2004	0.28	0.72			
2005	0.30	0.70			
2004-2005	0.28	0.72			
3 bins					
2004	0.15	0.29	0.56		
2005	0.16	0.30	0.54		
2004-2005	0.15	0.30	0.56		
5 bins					
2004	0.07	0.12	0.18	0.24	0.39
2005	0.07	0.13	0.18	0.23	0.39
2004-2005	0.07	0.12	0.18	0.23	0.39

Table 3 provides the averages of the main variables using the 2 bins division. The difference in average log price between the high price stores and the low price stores (P1-P2) is about 20%. (It is 21% for the 2004 sample, 18% for the 2005 sample and 21% for the combined 04-05 sample). The difference in the average log quantity sold (X2-X1) is 58% for the 2004 sample, 37% for the 2005 sample and 49% for the 04-05 sample. These differences are smaller when using the sample of regular prices. For regular prices, the average price is about 15% higher in the high price bin and the average quantity is about 25% higher in the low price bin. Thus temporary sales contribute to both price dispersion and unit dispersion.

Table 3*: Means

All prices	P1	P2	X1	X2	# stores
2004	0.81	0.59	2.76	3.35	15.43
2005	0.86	0.68	2.63	2.99	21.05
2004-05	0.76	0.55	3.07	3.56	14.56
Reg. Prices					
2004	0.9	0.76	2.97	3.27	15.89
2005	1.08	0.93	2.7	2.93	22.54
2004-05	1.17	1.03	3.01	3.33	15.7

* The Table uses the 2 bins division to provide the mean of the variables. P1 is the average log price for high price stores, P2 is the average log price for low price stores, X1 is the average log of the quantity sold for the high price stores and X2 is the average for the low price stores. The first rows use the sample of all prices and the last rows use the sample of regular prices obtained by deleting observations that are labeled as "sale prices". The last column is the average number of stores (average across UPCs).

Table 3a computes the standard deviation of the average price and the average quantity over weeks. We first calculate the average (over stores) price and units for each UPC-week-bin cell. We then calculate the standard deviation of these averages for each UPC-bin across weeks. Table 3a reports the average of these standard deviations across UPCs. In the two bins case, the standard deviation of P2 (the average weekly price in the low price bin) is more than 30% larger than the standard deviation of P1. It is larger by 54% for the 2004 sample, by 30% for the 2005 sample and by 40% for the 04-05 sample. The standard deviations of the quantities are also larger for the low price bin. The quantity standard deviation is larger by 47% for the 2004 sample, by 35% for the 2005 sample and by 39% for the 04-05 sample.

The following 3 rows in Table 3a describe the standard deviations when dividing each UPC-Week cell into three bins: High, medium and low. Also here the standard deviation of the price in the low price bin is higher than the standard deviation of the price in the high price bin. The last rows in Table 3a are the standard deviations when dividing each UPC-Week cell into 5 bins. The standard deviations in bin 5 (the lowest price bin) are higher than the standard deviations in bin 1 (the highest price bin). The ratio of the standard deviations of the average price in bin 5 to the standard deviation in bin 1 is 1.8 on average (2 for 2004, 1.6 for 2005 and 1.76 for 2004-05). For quantities the average ratio is 1.6 (1.76 for 2004, 1.46 for 2005 and 1.61 for 2004-05). When using the samples of regular prices (Table 3b) these ratios are smaller. For prices the average ratio is 1.62 (1.64, 1.46 and 1.77). And for quantities the average ratio is 1.36 (1.42, 1.23 and 1.44).

Table 3a: Standard deviations over weeks

	2004	2005	2004-2005
One bin			
P	0.0765	0.0908	0.0837
X	0.3132	0.3166	0.3049
Two bins			
P1	0.0690	0.0862	0.0784
P2	0.1066	0.1119	0.1106
X1	0.3276	0.3401	0.3289
X2	0.4824	0.4586	0.4562
Three bins			
P1	0.0633	0.0758	0.0728
P2	0.0936	0.1065	0.1008
P3	0.1172	0.1129	0.1174
X1	0.3422	0.3543	0.3494
X2	0.4856	0.5001	0.4970
X3	0.5951	0.5138	0.5544
Five bins			
P1	0.0612	0.0721	0.0712
P2	0.0822	0.0967	0.0941
P3	0.0953	0.1060	0.1029
P4	0.1140	0.1109	0.1148
P5	0.1248	0.1148	0.1253
X1	0.3865	0.3914	0.3972
X2	0.5317	0.5295	0.5533
X3	0.5751	0.5632	0.5902
X4	0.6520	0.5921	0.6359
X5	0.6806	0.5726	0.6394

* The Table reports standard deviations over weeks. We first calculate the average price and units for each UPC-week-bin cell. We then calculate the standard deviation of these averages for each UPC-bin across weeks. The first rows report the standard deviation for the 2 bins case. The next rows report the standard deviation for the 3 bins case and the rows in the bottom report the standard deviation for the 5 bins case.

Table 3b: The Samples of regular prices.

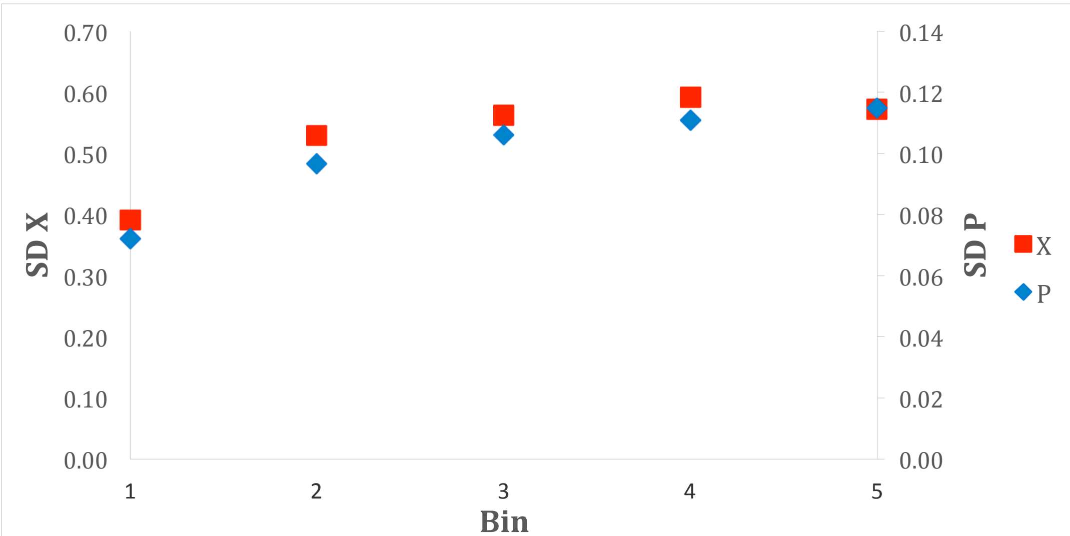
	2004	2005	2004-2005
One bin			
P	0.0219	0.0392	0.0318
X	0.1943	0.2068	0.2104
Two Bins			
P1	0.0244	0.0392	0.0309
P2	0.0363	0.0544	0.0424
X1	0.2300	0.2595	0.2334
X2	0.3019	0.3288	0.3536
Three Bins			
P1	0.0251	0.0386	0.0287
P2	0.0435	0.0548	0.0539
P3	0.0420	0.0554	0.0460
X1	0.2576	0.2963	0.2668
X2	0.4094	0.4206	0.4603
X3	0.3473	0.3586	0.3998
Five Bin			
P1	0.0270	0.0393	0.0282
P2	0.0416	0.0547	0.0535
P3	0.0430	0.0566	0.0529
P4	0.0460	0.0585	0.0548
P5	0.0443	0.0573	0.0499
X1	0.2975	0.3412	0.2977
X2	0.4732	0.4980	0.5247
X3	0.4752	0.4916	0.5318
X4	0.4974	0.4961	0.5255
X5	0.4211	0.4202	0.4296

* This Table repeats the calculations in Table 3a after eliminating all "temporary sale" observations.

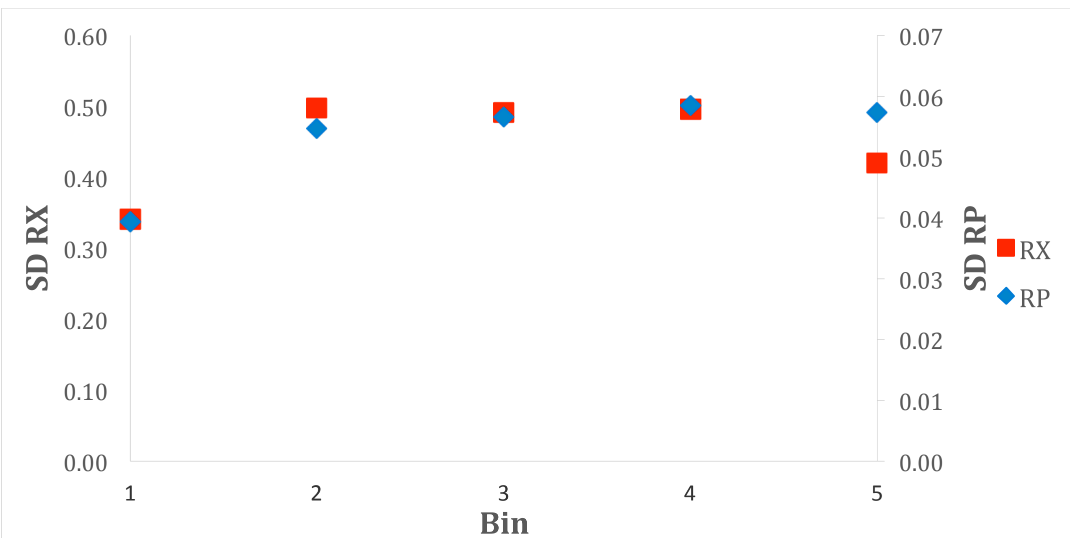
Figure 4A plots the standard deviations in the last rows of Table 3a (5 bins division) and the 2005 sample. The standard deviations are increasing with the index of the bin and there is a good fit between the quantity standard deviation and the price standard deviation. The quantity standard deviation is about 5.7 times the price standard deviation.[14] Figure 4B uses the sample of regular prices (Table 3b). The standard deviation of the regular price (SD RP) in the highest price bin (bin 1) is lower than the standard deviations in lower price bins. The standard deviation of the "regular" quantity (SD RX) is relatively low both for the highest price bin and the lowest price bin. Figure

[14] The coefficient varies across bins and samples from 5 to 6.5. For the 2004 sample the average coefficient is 6 and for the 2005 sample it is 5.3.

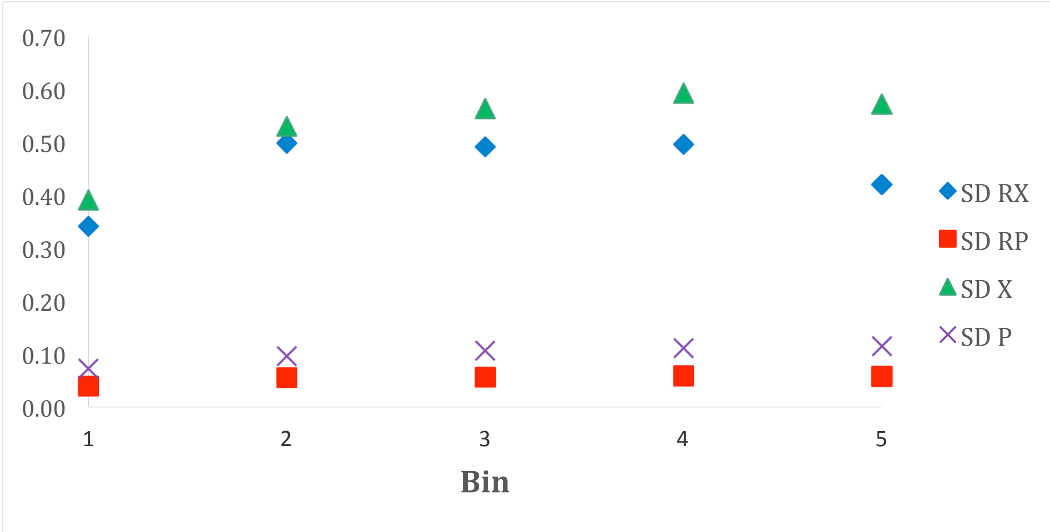
4C compares the standard deviations. The standard deviations are higher in the all prices sample. The standard deviations of quantities are increasing in the all price sample but are more like a "hump shape" in the sample of regular prices.



A. The sample of all prices: SD X is the standard deviation of the quantity and SD P is the standard deviation of the price



B. The sample of regular prices: SD RX is the standard deviation of the quantity and SD RP is the standard deviation of the price



C. The sample of all prices (SD X and SD P) and the sample of regular prices (SD RX and SD RP)

Figure 4: The standard deviations across bins. Using the 2005 sample.

The observation that variations over weeks in posted price are lower for higher price bins is roughly consistent with the model in section 3.2. In this model there are no variations in the high price but the low price may depend on the amount of inventories. It seems that we need non-shoppers to account for the observation that variations over weeks in the quantity sold are lower for higher price bins. In section 3.4 high price stores specialize in servicing non-shoppers and the quantity sold by the high price stores do not fluctuate with the number of shoppers. The observation that the standard deviations are lower for the sample of regular prices and the difference in the standard deviations is especially large for the cheapest price bin is consistent with the model in section 3.2 because eliminating temporary sales observations reduces the variations over weeks in the first market price and quantity.

5. ELASTICITIES

We now turn to examine the relationship (24) between the quantity sold by the highest price stores and the quantity sold by lower price stores. We start by splitting the stores in each UPC-week cell into two groups (below and above the median price) and run in Table 4 the average log quantity in the high price bin (X1) on the average log quantity and price in the low price bin (X2 and P2) and the average log price in the high price bin (P1). Averages are across the stores in the UPC-week-bin cell. The elasticity with respect to the average quantity sold per store in the low price group (X2) is about 0.6 in all the three samples. The own price elasticity is about -2 and the cross price elasticity is about 1.8. The rows in the bottom of the Table report the results when using the samples of regular prices. Part (a) of Claim 2 works. The quantity elasticity is less than unity and the cross price elasticity is less than the absolute value of the own price elasticity.

To examine Part (b) which says that the quantity elasticity and the cross price elasticity decline with the price distance, we need the 3 and 5 bins divisions. Table 5 describes the results when using the 3 bins division. The first 2 columns use the 2004 sample: The first uses the averages from the medium price stores as explanatory variables and the second uses the variables from the low price stores as explanatory variables. The quantity sold by the high price stores is more sensitive to the variables in the medium price stores. The elasticity with respect to the quantity sold in the medium price stores (the coefficient of X2) is 0.6 while the elasticity with respect to the quantity sold in the low price stores (the coefficient of X3) is 0.5. The elasticity with respect to the price in the medium price group is 1.7 while the elasticity with respect to the price in the low price group is 1.5. This pattern occurs also in the other two samples and is consistent with Claim 2. The rows that follow use samples of regular prices. The coefficients of X2 are slightly lower than the coefficients of X3. The coefficients of P2 are much higher than the coefficients of P3. Also here part (a) of Claim 2 works. Part (b) works for the sample of all prices but the results for the sample of regular prices are mixed.

Table 4*: Two bins regression.

Dependent Variable	X1	X1	X1
	2004	2005	2004-2005
X2	0.6240***	0.6390***	0.6487***
	(0.0030)	(0.0024)	(0.0031)
P1	-1.9794***	-1.8803***	-2.0269***
	(0.0208)	(0.0157)	(0.0225)
P2	1.7941***	1.6484***	1.8618***
	(0.0209)	(0.0157)	(0.0218)
R^2	0.6846	0.6950	0.6977
Regular prices			
X2	0.5919***	0.6759***	0.6593***
	(0.0085)	(0.0058)	(0.0121)
P1	-1.7665***	-1.2157***	-0.7332***
	(0.1138)	(0.0556)	(0.1938)
P2	1.5475***	1.0903***	0.6356***
	(0.1115)	(0.0537)	(0.1874)
R^2	0.8205	0.7063	0.7563

*Standard errors in parentheses. One star (*) denotes p-value of 10%, two stars (**) denote p-value of 5% and three stars (***) denote p-value of 1%. Category dummies are included in all the regressions. X1 is the average log of the quantity sold across stores in the high price bin, X2 is the average across stores in the low price bin, P1 is the average log price across stores in the high price bin and P2 is the average across stores in the low price bin.

Table 5*: 3 bins regressions

	2004		2005		04-05	
Dep. Var.	X1	X1	X1	X1	X1	X1
X2	0.6125***		0.6019***		0.6062***	
	(0.0034)		(0.0028)		(0.0035)	
P2	1.7259***		1.7131***		1.8254***	
	(0.0271)		(0.0208)		(0.0280)	
X3		0.5026***		0.5466***		0.5418***
		(0.0032)		(0.0027)		(0.0033)
P3		1.5115***		1.4728***		1.6487***
		(0.0193)		(0.0152)		(0.0205)
P1	-1.89***	-1.76***	-1.92***	-1.75***	-1.95***	-1.84***
	(0.0274)	(0.0196)	(0.0208)	(0.0153)	(0.0289)	(0.0214)
R^2	0.6241	0.5838	0.6248	0.6057	0.6261	0.6081
N	34,273	34,273	54,650	54,650	33,624	33,624
Regular Prices						
X2	0.5048***		0.6308***		0.6160***	
	(0.0118)		(0.0072)		(0.0151)	
P2	2.3644***		1.0252***		2.4977***	
	(0.1712)		(0.0811)		(0.2223)	
X3		0.5146***		0.6518***		0.6423***
		(0.0105)		(0.0066)		(0.0127)
P3		1.5361***		0.7428***		0.6728***
		(0.1098)		(0.0557)		(0.1797)
P1	-2.6050***	-1.7701***	-1.1542***	-0.8342***	-2.6847***	-0.7556***
	(0.1751)	(0.1138)	(0.0835)	(0.0583)	(0.2257)	(0.1856)
R^2	0.5532	0.5925	0.5943	0.6435	0.6607	0.7255
N	3,286	3,286	10,060	10,060	1,640	1,640

* Each UPC-week cell is divided into three bins. Xj = the average log units in bin j. Pj = the average log price in bin j. Category dummies are included in all the regressions.

Table 6 uses the 5 bins division and the largest 2005 sample. It describes the results when running the average quantity in the high price stores (bin 1) on the average quantity and price in the other 4 bins. In the first 4 columns the explanatory variables are from a single bin: From bin 2 in the first column, from bin 3 in the second and so on. In the last column we report the regression results when using all the explanatory variables. The first rows use the sample of all prices. The last rows use the sample of regular prices.

Part (a) of Claim 2 works. The quantity elasticity is less than unity and the cross price elasticity is less than the absolute value of the own price elasticity. Part (b) works for the sample of all prices. In the first four columns the elasticities decline with the distance from the high price group. The elasticity of the quantity sold with respect to the quantity sold by stores in bin 2 is 0.57 while the elasticity with respect to the quantity sold by stores in bin 5 (the lowest price stores) is 0.48. The elasticity with respect to the price posted by bin 2 stores is 1.75 while the elasticity with respect to the price posted by bin 5 stores is 1.3. Part (a) works also for the sample of regular prices but for these samples the results with respect to part (b) are mixed.

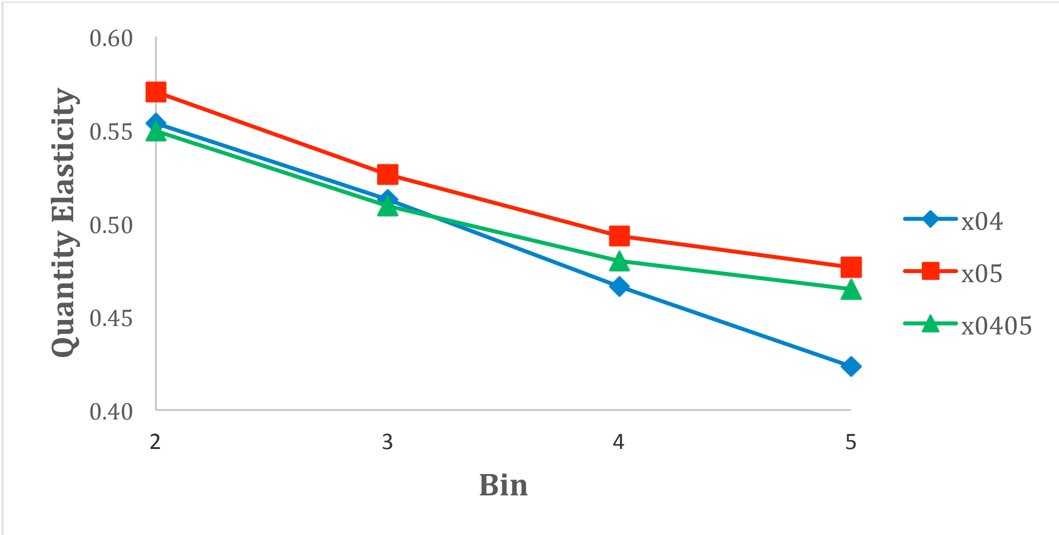
Figure 5 describes the results for the 3 samples of "all prices" when using three explanatory variables as in the first four columns of Table 6. Figure 5A is the elasticity with respect to the quantity sold (the quantity elasticity = the coefficient of Xj), Figure 5B is the cross price elasticities (the coefficient of Pj). As can be seen there is a strong agreement among the three samples. The quantity and cross price elasticities are both decreasing in the bin index. Figure 6 uses the samples of all prices to plot the coefficients of the regressions that use 9 explanatory variables as in the last column in Table 6. Also here there is a strong agreement among the three samples and the qualitative results do not change.

The results obtained when using the samples of all prices support the hypothesis that the quantity elasticities and the cross price elasticities decrease in the index of the bin. The results when using the samples of regular prices are mixed, possibly due to the fact that shoppers play a critical role in obtaining the results in Claim 2 and removing temporary sales prices may have reduced the role of shoppers who are looking for bargains.

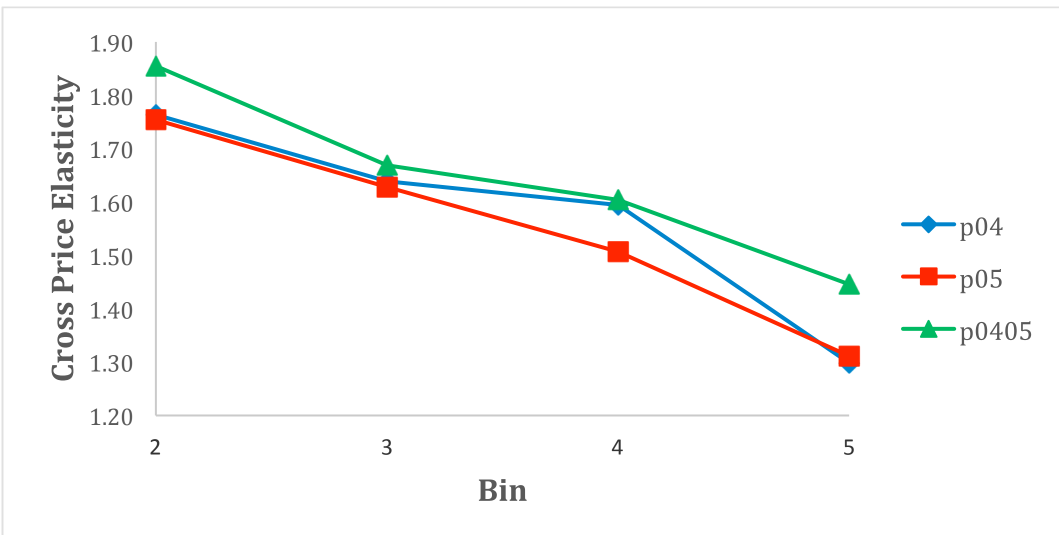
Table 6*: 5 bins regression using the 2005 sample

Dep. Variable	X1	X1	X1	X1	X1
X2	0.5703***				0.2868***
X3		0.5259***			0.1718***
X4			0.4933***		0.1456***
X5				0.4764***	0.1468***
P1	-1.9572***	-1.8640***	-1.7809***	-1.6082***	-2.591***
P2	1.7537***				1.3498***
P3		1.6279***			0.6461***
P4			1.5063***		0.2972***
P5				1.3114***	0.1389***
R^2	0.582	0.5483	0.5399	0.5382	0.6684
N	45,923	45,923	45,923	45,923	45,923
Regular prices					
X2	0.5534***				0.2384***
X3		0.5556***			0.1927***
X4			0.5424***		0.1784***
X5				0.5696***	0.1986***
P1	-1.3523***	-1.4064***	-1.2412***	-1.0328***	-1.8160***
P2	1.2258***				1.0234***
P3		1.2685***			0.5513***
P4			1.0965***		0.1396
P5				0.9089***	0.0331
R^2	0.5692	0.5511	0.5534	0.5748	0.6799
N	7,770	7,770	7,770	7,770	7,770

* The first four columns report the results when using 3 explanatory variables. The last column is the results when using 9 explanatory variables. The first rows use the sample of all prices. The rows that follow use the sample of regular prices. Category dummies are included in all the regressions.

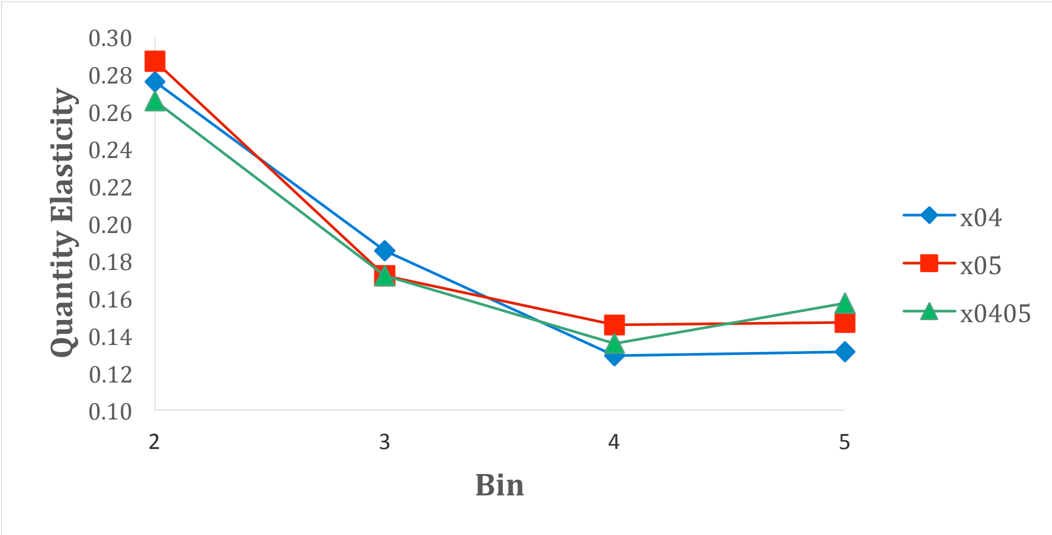


A. Elasticity with respect to the quantity sold

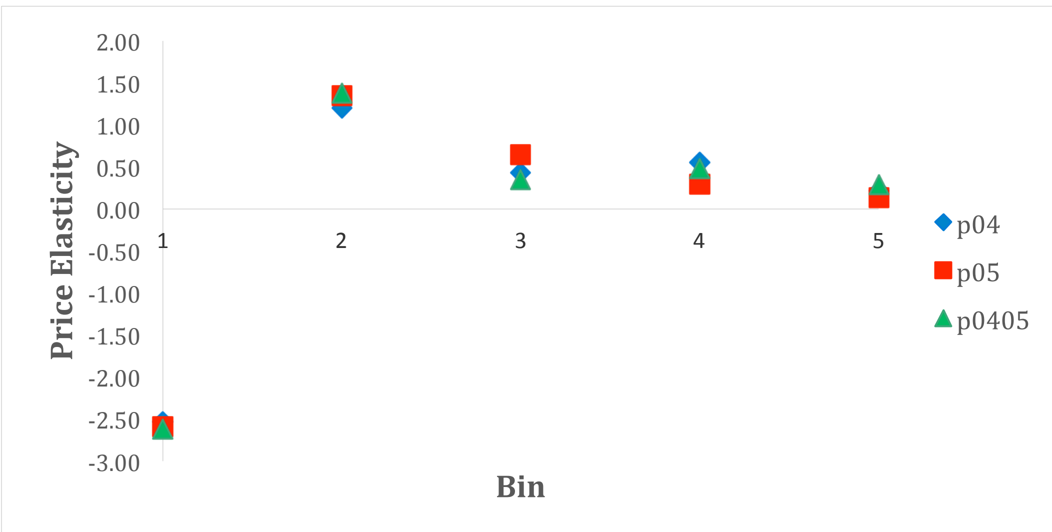


B. Cross Price Elasticities

Figure 5: Elasticities based on a 3 explanatory variables regressions (First four columns in Table 6, sample of all prices).



A. Quantity Elasticities



B. Price Elasticities

Figure 6: Elasticities based on a 9 explanatory variables regression in the last column of Table 6.

6. STORE EFFECT

Stores that are similar in price may be similar in other ways. For example, stores in rich neighborhoods may charge on average a price that is higher than the price charged by stores in poor neighborhoods. If shoppers shop with higher intensity in their own neighborhood, the quantity sold by a group of stores maybe more sensitive to the variables in a group of stores that is close in price because the two groups are also closer in locations.

In an attempt to address this problem we remove the store effect by running the following regressions.

$$\ln(P_{ijt}) = a_i + b_j(store - dummy) + e^P_{ijt} \quad (25)$$

$$\ln(x_{ijt}) = a_i + b_j(store - dummy) + e^x_{ijt} \quad (26)$$

where P is price, x is quantity sold, i index the UPC, j index the store and t index the week. We then repeat the above Tables after replacing ln(P) with the residuals e^P_{ijt} and ln(x) with the residuals e^X_{ijt}.

Tables 2' are comparable Tables 2. The bins are much more equal in sizes because the residuals are different across stores and the problem of lack of price dispersion is less common. The conditional probability in Table 2b' are not very different from the conditional probabilities in Table 2b.

Table 2': Bin size

	bin 1	bin 2	bin 3	bin 4	bin 5
2 bins					
2004	0.52	0.48			
2005	0.51	0.49			
2004-2005	0.52	0.48			
3 bins					
2004	0.35	0.31	0.34		
2005	0.35	0.32	0.33		
2004-2005	0.36	0.31	0.34		
5 bins					
2004	0.23	0.19	0.19	0.19	0.21
2005	0.22	0.19	0.19	0.19	0.21
2004-2005	0.23	0.19	0.18	0.19	0.22

Table 2a': Frequency of temporary sales by bins

	bin 1	bin 2	bin 3	bin 4	bin 5	Freq. Sale
2 bins						
2004	0.08	0.31				0.19
2005	0.11	0.29				0.19
2004-2005	0.10	0.34				0.21
3 bins						
	Bin1	Bin2	Bin 3			0.19
2004	0.06	0.16	0.35			0.19
2005	0.08	0.19	0.32			0.21
2004-2005	0.07	0.19	0.38			
5 bins						
2004	0.05	0.09	0.16	0.27	0.39	0.19
2005	0.07	0.12	0.18	0.26	0.35	0.19
2004-2005	0.06	0.11	0.18	0.30	0.42	0.21

Table 2b': The probability that the price is in bin i given that it is a "sale price"

	bin 1	bin 2	bin 3	bin 4	bin 5
2 bins					
2004	0.23	0.77			
2005	0.28	0.72			
2004-2005	0.24	0.76			
3 bins					
2004	0.11	0.27	0.62		
2005	0.15	0.30	0.55		
2004-2005	0.12	0.27	0.61		
5 bins					
2004	0.06	0.09	0.16	0.26	0.43
2005	0.08	0.11	0.18	0.25	0.37
2004-2005	0.06	0.10	0.16	0.26	0.43

Table 3a' and 3b' are comparable to Tables 3a and 3b. The results are qualitatively the same suggesting that store effects do not drive our findings about the standard deviations by bins.

Table 3a': Standard deviations of the quantity sold for the average UPC by bin (all prices)

	2004	2005	2004-2005
One bin			
P	0.0765	0.0908	0.0836
X	0.3132	0.3166	0.3049
Two bins			
P1	0.0641	0.0801	0.0722
P2	0.1036	0.1125	0.1108
X1	0.3131	0.3284	0.3184
X2	0.4396	0.3985	0.4099
Three bins			
P1	0.0612	0.0750	0.0692
P2	0.0926	0.1036	0.0911
P3	0.1157	0.1166	0.1218
X1	0.3428	0.3460	0.3473
X2	0.3902	0.4077	0.4003
X3	0.5127	0.4273	0.4647
Five bins			
P1	0.0597	0.0718	0.0679
P2	0.0708	0.0879	0.0786
P3	0.0844	0.1054	0.0931
P4	0.1025	0.1170	0.1140
P5	0.1275	0.1209	0.1303
X1	0.3902	0.3794	0.3865
X2	0.4228	0.4255	0.4321
X3	0.4480	0.4531	0.4626
X4	0.5024	0.4798	0.4994
X5	0.6049	0.4708	0.5270

Table 3b': The samples of regular prices.

	2004	2005	2004-2005
One bin			
P	0.0241	0.0391	0.0320
X	0.1922	0.2054	0.2094
Two Bins			
P1	0.0237	0.0367	0.0298
P2	0.0290	0.0462	0.0389
X1	0.2168	0.2409	0.2352
X2	0.2359	0.2391	0.2378
Three Bins			
P1	0.0236	0.0358	0.0302
P2	0.0284	0.0437	0.0323
P3	0.0316	0.0481	0.0429
X1	0.2413	0.2639	0.2505
X2	0.2541	0.2719	0.2765
X3	0.2645	0.2600	0.2626
Five Bin			
P1	0.0246	0.0356	0.0300
P2	0.0251	0.0395	0.0326
P3	0.0287	0.0443	0.0324
P4	0.0337	0.0483	0.0407
P5	0.0345	0.0500	0.0454
X1	0.2854	0.3070	0.2854
X2	0.3213	0.3216	0.3343
X3	0.3036	0.3172	0.3179
X4	0.3136	0.3198	0.3342
X5	0.3167	0.3009	0.2996

Table 4' uses the residuals from (25) and (26) to estimate the two bins regression. The quantity elasticity is about 0.75 and is higher than the elasticity in Table 4. As in Table 4 and consistent with Claims 2 the absolute value of the own price elasticity is higher than the cross price elasticity.

Table 4'*: Two bins regression.

Dependent Variable	X1	X1	X1
	2004	2005	2004-2005
X2	0.7305***	0.7546***	0.7697***
	(0.0028)	(0.0021)	(0.0028)
P1	-2.3756***	-2.0344***	-2.1366***
	(0.0204)	(0.0152)	(0.0212)
P2	2.1127***	1.7960***	1.9594***
	(0.0205)	(0.0152)	(0.0206)
R^2	0.7701	0.7963	0.7879
N	34,580	56,368	33,696
Regular prices			
X2	0.7081***	0.8580***	0.8967***
	(0.0081)	(0.0044)	(0.0101)
P1	-1.4920***	-1.6860***	-0.7566***
	(0.1010)	(0.0541)	(0.1556)
P2	1.2213***	1.6050***	0.6351***
	(0.1018)	(0.0533)	(0.1576)
R^2	0.8806	0.8639	0.8838
N	4,160	11,180	1,872

*Standard errors in parentheses. Category dummies are included in all the regressions.

Table 5' uses 3 bins division: high, medium and low price. The estimated elasticities are higher than in Table 5 but as in Table 5, the quantity elasticity is less than unity and the own price elasticity is higher in absolute value than the cross price elasticity. As in Table 5, in the sample of all prices, the quantity sold by the high price stores is more strongly related to the quantity and price in the medium price stores.

Table 5': 3 bins regressions

	2004		2005		04-05	
Dep. Var.	X1	X1	X1	X1	X1	X1
X2	0.7439***		0.7696***		0.7616***	
	(0.0031)		(0.0024)		(0.0032)	
P2	1.9836***		2.0645***		2.1473***	
	(0.0301)		(0.0205)		(0.0310)	
X3		0.6302***		0.6712***		0.6791***
		(0.0031)		(0.0024)		(0.0032)
P3		1.8253***		1.5818***		1.7519***
		(0.0194)		(0.0146)		(0.0197)
P1	-2.214***	-2.159***	-2.248***	-1.884***	-2.31***	-1.99***
	(0.0301)	(0.0193)	(0.0205)	(0.0147)	(0.0316)	(0.0205)
R^2	0.7411	0.6776	0.7668	0.7118	0.7432	0.6987
N	34,580	34,580	56,368	56,368	33,696	33,696
Regular Prices						
X2	0.7387***		0.8075***		0.8653***	
	(0.0089)		(0.0048)		(0.0125)	
P2	1.1600***		1.6713***		0.6341**	
	(0.1531)		(0.0735)		(0.3219)	
X3		0.6122***		0.8027***		0.8210***
		(0.0094)		(0.0052)		(0.0123)
P3		1.3228***		1.4705***		0.6226***
		(0.0887)		(0.0502)		(0.1522)
P1	-1.4607***	-1.6792***	-1.7698***	-1.5768***	-0.8800***	-0.8171***
	(0.1534)	(0.0873)	(0.0743)	(0.0513)	(0.3203)	(0.1498)
R^2	0.8734	0.8357	0.8230	0.8049	0.8427	0.8330
N	4,160	4,160	11,180	11,180	1,872	1,872

Table 6' reports the regression estimates when using 5 bins. The quantity elasticities are higher but still less than unity and decreasing with the distance from the highest price bin. The cross price elasticity also decreases with the distance and the absolute value of the own price elasticity is greater than the cross price elasticity.

Table 6'*: 5 bins regression using the 2005 sample

Dep. Variable	X1	X1	X1	X1	X1
X2	0.7102***				0.3752***
X3		0.6699***			0.2068***
X4			0.6199***		0.1095***
X5				0.5791***	0.1235***
P1	-2.0454***	-2.0671***	-1.8820***	-1.6689***	-2.4396***
P2	1.8549***				0.9778***
P3		1.8247***			0.9138***
P4			1.5756***		0.1376***
P5				1.3139***	0.2245***
R^2	0.6946	0.6617	0.6349	0.6179	0.7468
N	56,368	56,368	56,368	56,368	56,368
Regular prices					
X2	0.7700***				0.2952***
X3		0.7483***			0.2208***
X4			0.7342***		0.2223***
X5				0.7227***	0.1538***
P1	-1.9860***	-1.9842***	-1.8659***	-1.4147***	-2.2054***
P2	1.8611***				0.5169***
P3		1.8453***			0.5732***
P4			1.6952***		0.7013***
P5				1.2750***	0.3115***
R^2	0.7512	0.7404	0.7351	0.7098	0.8119
N	11,180	11,180	11,180	11,180	11,180

* The first four columns report the results when using 3 explanatory variables. The last column is the results when using 9 explanatory variables. The first rows use the sample of all prices. The rows that follow use the sample of regular prices. Category dummies are included in all the regressions.

7. UPC SPECIFIC STORE EFFECT

A store may promote a specific UPC by placing it in a visible and easy to reach place. Therefore we allow for the store effect to vary across UPCs and run for each UPC the following regression.

(25') $$\ln(P_{ijt}) = a_i + b_{ij}(store - dummy) + e^{P}_{ijt}$$

(26') $$\ln(x_{ijt}) = a_i + b_{ij}(store - dummy) + e^{x}_{ijt}$$

As before, we repeat the Tables after replacing ln(P) with the residuals e_{ijt}^{P} and ln(x) with the residuals e_{ijt}^{X}. It turns out that the results are qualitatively similar to the case in which we control for non-UPC specific store effects, but there are some large differences in the magnitudes of the estimated elasticities. It thus makes a difference whether one controls for store effects or for UPC specific store effects.

Tables 2'' are comparable to Tables 2 and Table 2'. The bin sizes are the same as in Table 2' and so are the unconditional frequency of sales (the last column of Table 2a'). Instead of reporting the unconditional frequency of sales, we report now in the last column of Table 2a'', the percentage of weeks in which an average UPC is not on sale in any store. For example, in 2005 the average UPC was not on sale in 43% of the weeks. To appreciate this number we consider the case in which each store uses a mixed strategy to determine whether the item is on sale or not. In the 2005 sample there are on average 21 stores per UPC and the frequency of sale is 0.19. If stores use a mixed strategy as in Varian (1980), the probability that there are no sales is: $(1-0.19)^{21}=0.01$. This suggests no sales in only 1% of the weeks. Since no sales occur in 43% of the weeks, temporary sales are correlated across stores.

In the 2005 sample, the fraction of stores that has the item on sale fluctuates between 0 and 0.7. The average (over UPCs) standard deviation of this fraction is 0.2. There are thus substantial variations (over weeks) in the percentage of stores that has the item on sale. This may explain the conditional probabilities in Table 2b''. In the absence of variations over weeks we will have the item on sale in 19% of the stores in every week and the probability that a price is in bin 5 given that it is a "sale price" should be close to one. Instead we find that the conditional probabilities in Table 2b'' are less than 0.5.

Table 2a": Frequency of temporary sales by bins*

	bin 1	bin 2	bin 3	bin 4	bin 5	No sales
2 bins						
2004	0.07	0.32				0.40
2005	0.09	0.31				0.43
2004-2005	0.08	0.35				0.38
3 bins						
2004	0.05	0.15	0.38			0.40
2005	0.06	0.18	0.35			0.43
2004-2005	0.05	0.18	0.41			0.38
5 bins						
2004	0.03	0.08	0.15	0.27	0.42	0.40
2005	0.05	0.10	0.17	0.27	0.39	0.43
2004-2005	0.04	0.09	0.17	0.31	0.44	0.38

*The frequency of temporary sales are the same as in Table 2a'. The last column is the percentage of weeks in which the average UPC is not on "sale" in any store.

Table 2b": The probability that a price is in bin i given that it is a "sale price"

	bin 1	bin 2	bin 3	bin 4	bin 5
2 bins					
2004	0.18	0.82			
2005	0.23	0.77			
2004-2005	0.20	0.80			
3 bins					
2004	0.08	0.25	0.67		
2005	0.11	0.29	0.60		
2004-2005	0.09	0.26	0.64		
5 bins					
2004	0.04	0.07	0.15	0.27	0.47
2005	0.05	0.10	0.17	0.27	0.42
2004-2005	0.05	0.08	0.15	0.27	0.45

Table 3" is comparable to Tables 3 and 3'. It shows the same pattern: The standard deviation across weeks is increasing with the index of the bin. This is not the case in the sample of regular prices.

Table 3a": Standard deviations of the quantity sold for the average UPC by bin

	2004	2005	2004-2005
One bin			
P	0.0765	0.0908	0.0836
X	0.3132	0.3166	0.3049
Two bins			
P1	0.0600	0.0912	0.0713
P2	0.1069	0.1122	0.1126
X1	0.2931	0.3211	0.2964
X2	0.4282	0.3868	0.4005
Three bins			
P1	0.0582	0.0762	0.0692
P2	0.0787	0.1036	0.0906
P3	0.1214	0.1172	0.1250
X1	0.3095	0.3287	0.3117
X2	0.3713	0.3919	0.3707
X3	0.4908	0.4099	0.4487
Five bins			
P1	0.0573	0.0724	0.0672
P2	0.0659	0.0904	0.0789
P3	0.0904	0.1056	0.0926
P4	0.1041	0.1161	0.1135
P5	0.1345	0.1227	0.1336
X1	0.3415	0.3490	0.3384
X2	0.3757	0.3952	0.3718
X3	0.4104	0.4262	0.4085
X4	0.4672	0.4467	0.4517
X5	0.5709	0.4467	0.4965

Table 3b": Standard deviations of the quantity sold for the average UPC by bin. The Samples of regular prices.

	2004	2005	2004-2005
One bin			
P	0.0211	0.0380	0.0312
X	0.1861	0.2017	0.2081
Two Bins			
P1	0.0189	0.0385	0.0320
P2	0.0266	0.0430	0.0359
X1	0.2111	0.2232	0.2350
X2	0.2190	0.2328	0.2317
Three Bins			
P1	0.0204	0.0403	0.0343
P2	0.0174	0.0370	0.0286
P3	0.0315	0.0472	0.0410
X1	0.2335	0.2418	0.2547
X2	0.2329	0.2468	0.2492
X3	0.2451	0.2548	0.2539
Five Bin			
P1	0.0228	0.0425	0.0369
P2	0.0173	0.0387	0.0317
P3	0.0174	0.0372	0.0286
P4	0.0225	0.0410	0.0337
P5	0.0367	0.0522	0.0457
X1	0.2635	0.2682	0.2766
X2	0.2776	0.2812	0.3002
X3	0.2709	0.2772	0.2817
X4	0.2806	0.2826	0.2961
X5	0.2806	0.2880	0.2833

Table 4" is comparable to Tables 4 and 4'. There are large differences between the Tables. The quantity elasticities and the cross price elasticities are much lower. The quantity elasticity is about 38 to 55 percent of the quantity elasticities in Table 4 and 32 to 47 percent of the quantity elasticities in Table 4'. But still the quantity elasticities are between zero and unity as predicted by the theory. The cross price elasticities are 38-51 percent of the cross price elasticities in Table 4 and 32-37 percent of the cross price elasticities in Table 4'. The own price elasticities are higher. They are 140-149 percent of the own price elasticities in Table 4 and 124-130 percent of the own price elasticities in Table 4'.

Note that in Table 4" the quantity elasticity is close to the cross price elasticity divided by the absolute value of the own price elasticity as implied by (24).

Table 4"*: Two bins regression.

Dependent Variable	X1	X1	X1
	2004	2005	2004-2005
X2	0.2359***	0.3544***	0.3040***
	(0.0041)	(0.0035)	(0.0045)
P1	-2.9514***	-2.6542***	-2.6505***
	(0.0185)	(0.0123)	(0.0182)
P2	0.6822***	0.8430***	0.7886***
	(0.0168)	(0.0129)	(0.0170)
R^2	0.5216	0.6025	0.518
N	34,580	56,368	33,696
Regular prices			
X2	0.4753***	0.5612***	0.6208***
	(0.0133)	(0.0079)	(0.0191)
P1	-2.4648***	-1.9469***	-2.3481***
	(0.1309)	(0.0448)	(0.1644)
P2	0.8285***	0.9728***	1.2196***
	(0.1013)	(0.0447)	(0.1363)
R^2	0.3141	0.4426	0.4292
N	4,160	11,180	1,872

*Standard errors in parentheses. Category dummies are included in all the regressions.

Table 5" is comparable to Tables 5 and 5'. Also here the quantity elasticities and the cross price elasticities are much lower than in Tables 5 and 5' and the own price elasticity is higher in absolute value. Here, with UPC specific residuals, the distance matters more than with non-specific residuals.

Table 5'': 3 bins regressions

	2004		2005		04-05	
Dep. Var.	X1	X1	X1	X1	X1	X1
X2	0.3317***		0.4177***		0.3956***	
	(0.0050)		(0.0038)		(0.0051)	
P2	0.9280***		1.0959***		1.0987***	
	(0.0254)		(0.0168)		(0.0238)	
X3		0.1254***		0.2259***		0.1728***
		(0.0040)		(0.0036)		(0.0045)
P3		0.3594***		0.5044***		0.4481***
		(0.0160)		(0.0128)		(0.0166)
P1	-2.815***	-2.876***	-2.661***	-2.66***	-2.598***	-2.608***
	(0.0227)	(0.0191)	(0.0163)	(0.0128)	(0.0220)	(0.0188)
R^2	0.4928	0.4441	0.5662	0.5057	0.4919	0.4275
N	34,580	34,580	56,368	56,368	33,696	33,696
Regular Prices						
X2	0.4535***		0.5425***		0.6062***	
	(0.0142)		(0.0083)		(0.0202)	
P2	-0.0394		0.8814***		0.8299***	
	(0.1869)		(0.0666)		(0.2093)	
X3		0.3533***		0.43556***		0.5160***
		(0.0140)		(0.0086)		(0.0206)
P3		0.5490***		0.6682***		0.8143***
		(0.0928)		(0.0437)		(0.1242)
P1	-1.5125***	-2.2996***	-1.7748***	-1.8736***	-1.7624***	-2.1259***
	(0.1717)	(0.1304)	(0.0582)	(0.0447)	(0.2094)	(0.1583)
R^2	0.2726	0.2079	0.3963	0.3206	0.3897	0.3219
N	4,160	4,160	11,180	11,180	1,872	1,872

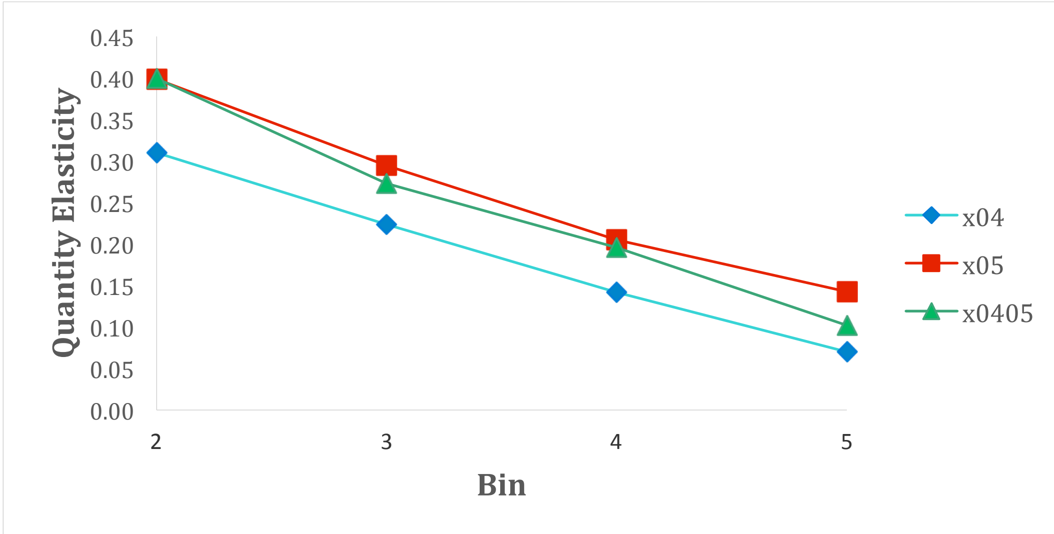
Table 6'' is comparable to Table 6 and Table 6'. Relative to Table 6', the quantity elasticity and the cross price elasticities are considerably lower, suggesting that it makes a difference if we control for UPC specific store effects or just for store effects.

Table 6"*: 5 bins regression using the 2005 sample

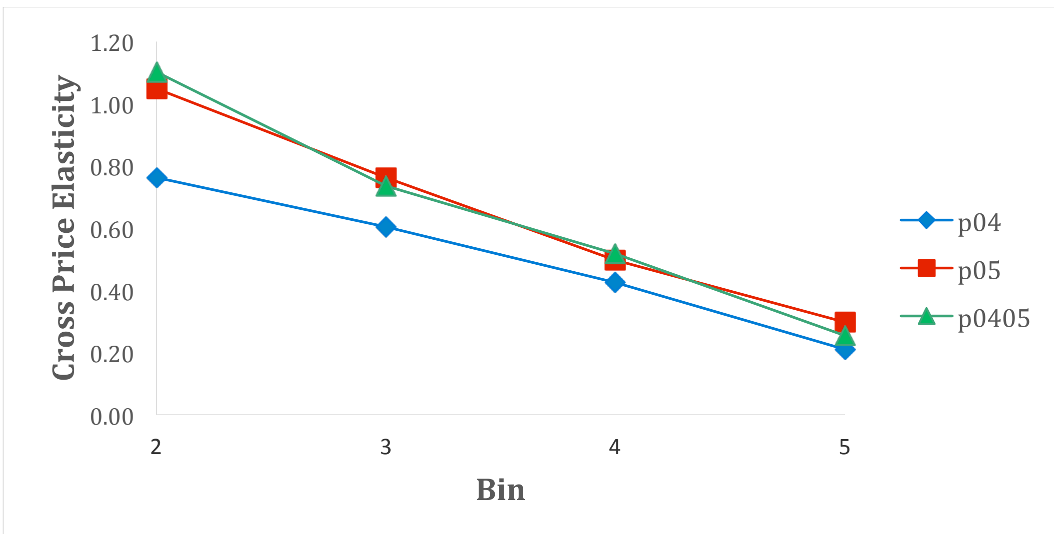
Dep. Variable	X1	X1	X1	X1	X1
X2	0.3982***				0.3235***
X3		0.2946***			0.1425***
X4			0.2053***		0.0517***
X5				0.1423***	0.0212***
P1	-2.6320***	-2.6298***	-2.6328***	-2.6397***	-2.6640***
P2	1.0487***				0.8685***
P3		0.7621***			0.4185***
P4			0.4971***		0.1064***
P5				0.2977***	0.0425**
R^2	0.5009	0.4565	0.4312	0.4189	0.5182
N	56,368	56,368	56,368	56,368	56,368
Regular prices					
X2	0.4442***				0.2991***
X3		0.3948***			0.1752***
X4			0.3544***		0.1308***
X5				0.2949***	0.0733***
P1	-1.3769***	-1.6784***	-1.7796***	-1.8096***	-1.4170***
P2	0.2386***				-0.2194
P3		0.5126***			0.6979***
P4			0.5233***		0.3604***
P5				0.3685***	0.0328
R^2	0.3202	0.2699	0.2471	0.2184	0.3784
N	11,908	11,908	11,908	11,908	11,908

* The first four columns report the results when using 3 explanatory variables. The last column is the results when using 9 explanatory variables. The first rows use the sample of all prices. The rows that follow use the sample of regular prices. Category dummies are included in all the regressions.

We calculated Table 6" for the other two samples (2004 and 04-05). Figures 5" and 6" are comparable to Figures 5 and 6 and describe the estimate of all three samples. As can be seen there is a considerable degree of consensus about the elasticities across the three samples, especially if we use the 9 variables regression that is reported in the last column of Table 6".

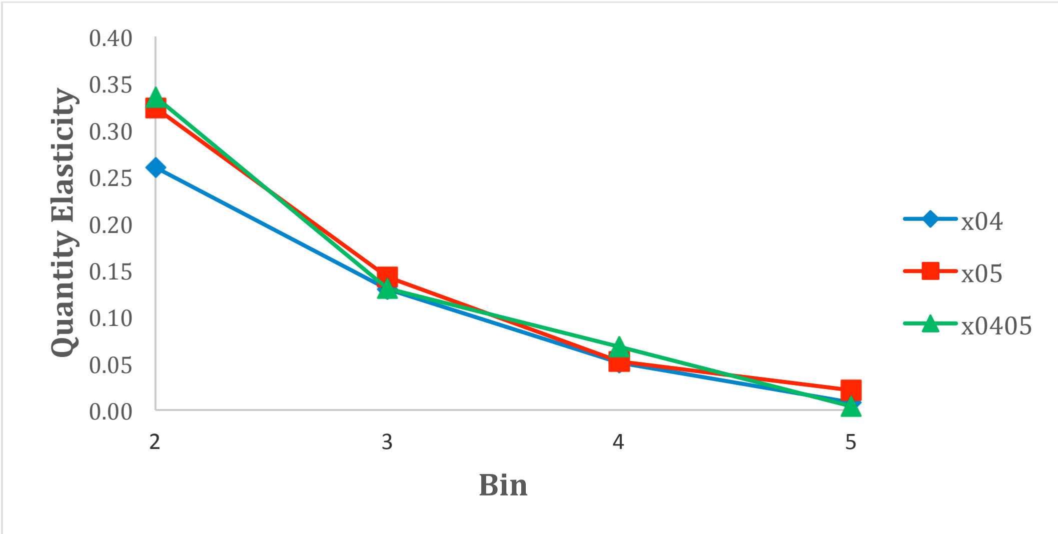


A. Quantity Elasticities.

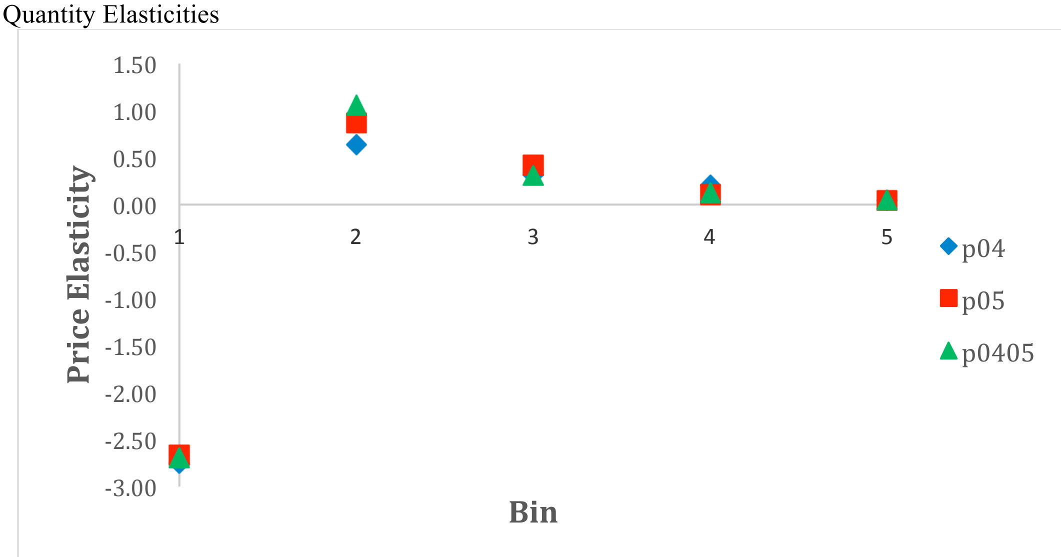


B. Cross Price Elasticities

Figure 5": Elasticities based on a 3 explanatory variables regressions (using the samples of "all prices").



A. Quantity Elasticities



B. Price Elasticities

Figure 6": Elasticities based on a 9 explanatory variables regression (using the samples of "all prices").

8. THE CONTRIBUTION OF TEMPORARY SALES TO PRICE FLEXIBILITY

In Bental and Eden (1993) demand shocks are *iid* but nevertheless they have a lasting effect on output. A high realization of demand is associated with high consumption and possibly high output in the current period. In the following period, inventories are low and the prices in all the hypothetical markets are relatively high. Production that is determined by equating the marginal cost to the first market price is relatively high but the increase in production is not enough to bring inventories back to "normal" in the current period. It takes time until inventories are back to normal and during this time production is relatively high. Thus a positive demand shock leads to an effect on output that may last for a long time. For money to have a lasting effect on output, it is essential that prices react to changes in inventories. See Bental and Eden (1996). Since in the model, the prices in all markets react to changes in inventories, the cross sectional average price must fluctuate over time.

In the Bental-Eden model the behavior of the price at the individual store level is not important and so is the distinction between regular and sale prices. What is important is the behavior of the cross sectional price distribution which we will proxy by the cross sectional average price.[15] This is different from the approach taken by the sticky price literature. Sticky price models may be rejected if prices move too much. The Bental-Eden model may be rejected if prices move too little.

A first look at the data through the lens of sticky price models, suggests that prices move too much. But this is not the case once a distinction between regular and sale prices is introduced. For example, Kehoe and Midrigan (2015) use a Calvo type model and assume that sometimes the store is allowed to make a regular price change and sometimes it is allowed to make a temporary price change that lasts for one period only. In this framework, the effect of money will depend primarily on the probability of making a regular price change and not on the probability of making a temporary price change.[16] An extreme view of this approach is that "temporary sale prices" are not important for macro.

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[15] As was noted by Eden (1994) and Head et.al. (2012), looking at the behavior of the average price is different from looking at the behavior of the price in an "average store". It is possible for example that in each period x% of the stores put the item "on sale" and discount its price by y%. In this case, if the regular price does not change over time, the cross sectional average posted price will not change but the price in the "average store" will fluctuate.

[16] See also Nakamura and Steinsson (2008) and Eichenbaum et. al. (2011).

Looking at the data through the lens of the Bental-Eden model, "temporary sale prices" are important if they move the cross sectional price distribution. Here we examine the contribution of temporary sales to the variations in the cross sectional average price over weeks.

Table 7 calculates the ratio of the variations over weeks in the samples of regular prices to variations over weeks in the samples of all prices. The columns 3b/3a use Tables 3a and 3b to compute the ratio of the standard deviation in the sample of regular prices to the standard deviation in the sample of all prices. Similarly, the columns 3b'/3a' use Tables 3a' and 3b' that control for store effects and the columns 3b''/3a'' use Tables 3a'' and 3b'' that control for UPC specific store effects. Average prices and quantities vary less overs weeks in the samples of regular prices. The effect of temporary sales on the variations in prices is larger than the effect on the variations in quantities. When looking at the entire sample (one bin) the standard deviation of the average price in the sample of regular prices is on average 37% of the standard deviation of the average price in the sample of all prices. The standard deviation of quantities in the sample of regular prices is 65% of the standard deviation in the sample of all prices. The effect of temporary sales is relatively large on the cheapest price bin. The standard deviation of the average regular price in the high price bin is on average 40% of the standard deviation in the sample of all prices. The percentage for the low price bin is 36. What may be somewhat of a surprise is that temporary sales affect the standard deviation in the high price bin. We find that this is also the case when using the 3 and 5 bins divisions (not reported in Table 7). One possible explanation relies on the observation that temporary sales are synchronized across stores (see the last column in Table 2a''). Sometimes an item is on sale in most stores and the average price in all bins goes down. This is consistent with Bental and Eden (1993, 1996) that assume increasing marginal cost. As was said above, in their model an increase in inventories leads to a decrease in all prices until inventories are back to "normal". It is therefore possible that all stores will have a "sale" at the same time.

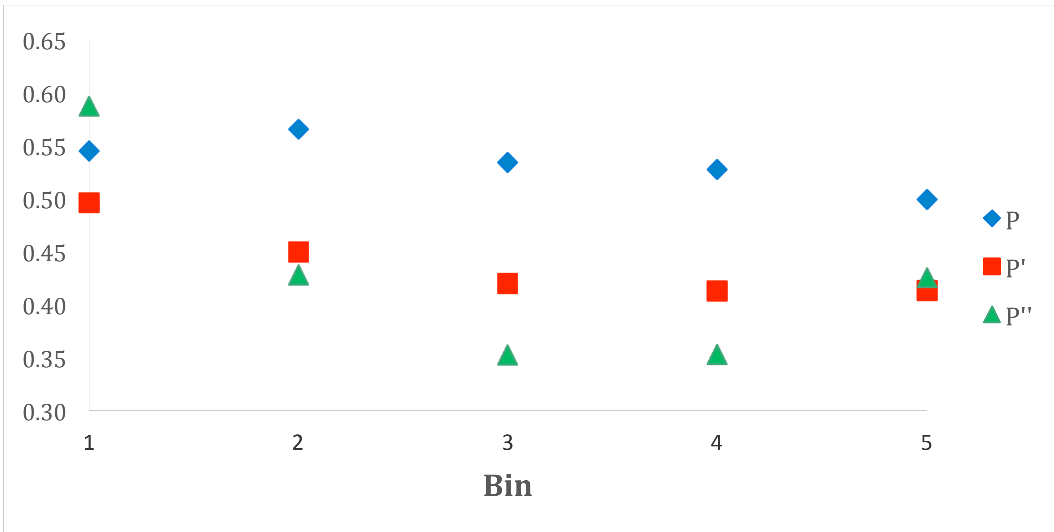
Table 7*: The ratio of the standard deviation in the sample of regular prices to the standard deviation in the sample of all prices.

	Orginal Prices (3b/3a)			Store effect (3b'/3a')			UPC specific (3b''/3a'')			
	2004	2005	04-05	2004	2005	04-05	2004	2005	04-05	Average
One bin										
P	0.29	0.43	0.38	0.31	0.43	0.38	0.28	0.42	0.37	0.37
X	0.62	0.65	0.69	0.61	0.65	0.69	0.59	0.64	0.68	0.65
Two bins										
P1	0.35	0.45	0.40	0.37	0.46	0.41	0.32	0.42	0.45	0.40
P2	0.34	0.49	0.38	0.28	0.41	0.35	0.25	0.38	0.32	0.36
X1	0.70	0.76	0.71	0.69	0.73	0.74	0.72	0.70	0.79	0.73
X2	0.63	0.72	0.78	0.54	0.60	0.58	0.51	0.60	0.58	0.61

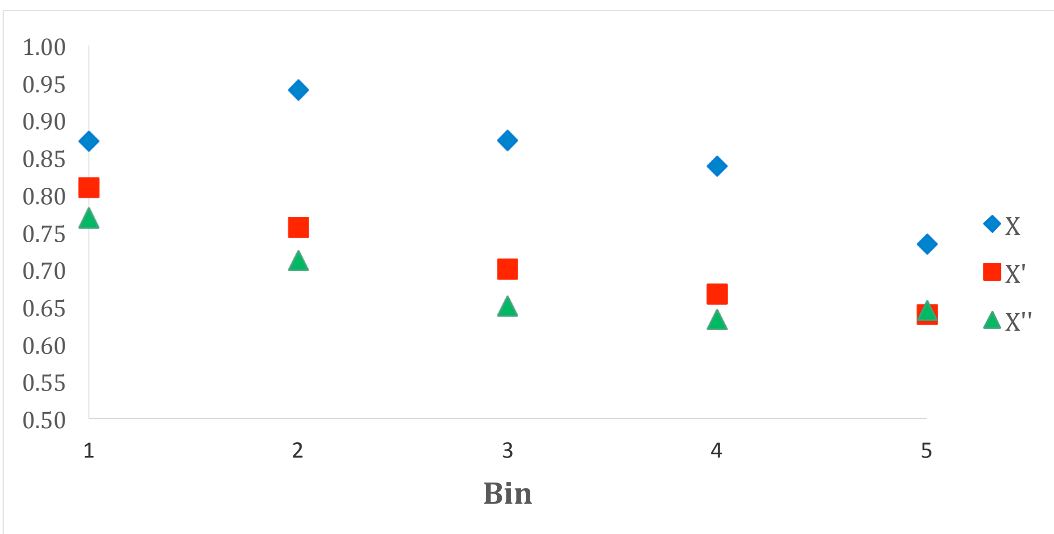
* This Table computes the ratio of the standard deviation of the average price across week in the samples of regular prices to the standard deviation in the samples of all prices. The columns 3a/3 use Tables 3 and 3a to compute the ratios. The columns 3a'/3' use Tables 3' and 3a' and the columns 3a''/3'' use Tables 3'' and 3a''. The average in the last column is across the cells in the row.

Table 7 shows that removing temporary sales reduces our measure of price flexibility by a substantial amount. We may therefore conclude that from the point of view of the Bental-Eden model, temporary sale prices are important.

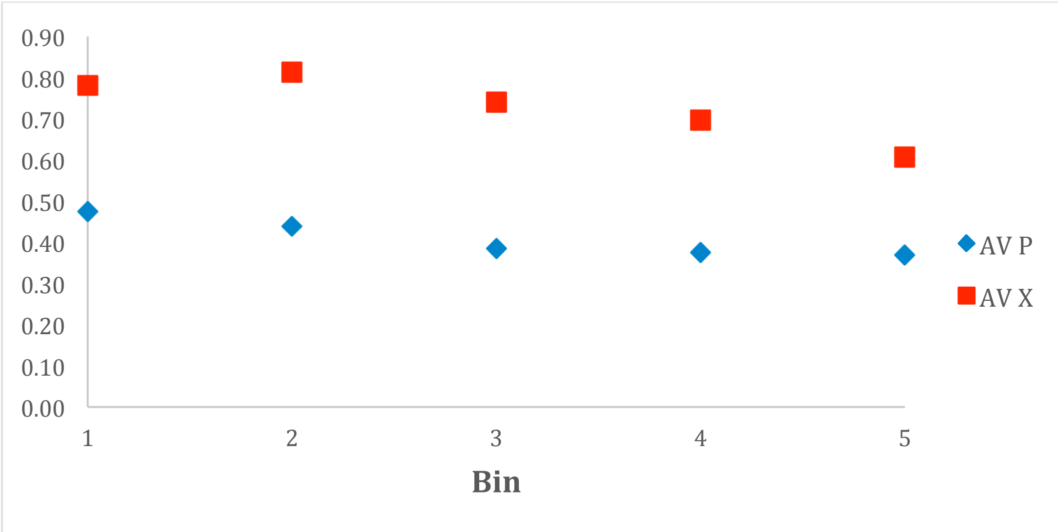
The version of the UST model in section 3.2 suggests that temporary sales are relatively more important for lower price bins. (In the example of Figure 2B removing temporary sale will affect the variances in the low price bin but will not affect the variances in the high price bin). To examine this prediction we look at the 5 bins division in the 2005 sample (not reported in Table 7). Figure 7A is the ratio of the standard deviation of the average regular price to the standard deviation of the average price (regular and sale). In the highest price bin (bin 1) the standard deviation of the average regular price is about 55% of the standard deviation of the average price. In the lowest price bin it is about 45%. Figure 7B is about quantities. In the highest price bin, the standard deviation of the average quantity in the sample of regular prices is about 85% of the standard deviation in the sample of all prices. In the lowest price bin the number is about 65%. Figure 7C use the average over samples and methods as the last column in Table 7. For price the average ratio is 0.47 for bin 1 and 0.37 for bin 5. It thus appear that removing temporary sale prices has a larger effect on the variation of the average price in the low price bin.



A. Ratios for SD Prices in the 2005 sample (P uses the original variables, P' uses the residuals when controlling for store effects and P'' uses the residuals when controlling for UPC specific store effects)



B. Ratios for SD Quantities in the 2005 sample (X uses the original variables, X' uses the residuals when controlling for store effects and X'' uses the residuals when controlling for UPC specific store effects)



C. Average over samples and methods

Figure 7: The ratio of the standard deviation (over weeks) of the cross-sectional average price in the sample of regular price to the standard deviation in the sample of all prices using the 5 bins division.

We may conclude that temporary sales have a larger effect on variations over weeks in low price bins as suggested by the example in Figure 2B.

8.1 Variations over weeks by bins.

The example in Figure 2B also suggests that variations over weeks in the lowest price bin are larger than in the highest price bin. To examine this hypothesis, Table 8 computes the ratio of the average standard deviation in the lowest price bin to the average standard deviation in the highest price bin (averages across samples). The first column (P) reports the ratio of the standard deviations of prices when using the sample of all prices (Table 3a). When using the 2 bins division, the standard deviation in the low price bin is 42% larger than the standard deviation in the high price bin. This difference is 52% when controlling for a store effect (Table 3a') and 53% when controlling for a UPC specific store effect (Table 3a''). When using the 3 and 5 bins divisions the differences are larger. The percentage differences in the standard deviations are lower when using the sample of regular prices (RP in the second column).

The third column in Table 8 is the ratio of the standard deviation of the quantity sold by stores in the lowest price bin to the quantity sold by stores in the highest price bin. When using the 2 bins division, the standard deviation in the low price bin is 40% larger than the standard deviation in the high price bin. This difference is about 30% when controlling for a store effect and for a UPC specific store effect (the last rows of the Table). Also here the ratios are lower when using the sample of regular prices but the ratios are still greater than 1.

Table 8: Ratio of the average standard deviation in the lowest price bin to the average standard deviation in the highest price bin.

	P	RP	X	RX
no store eff. Tables 3				
2 bins	1.42	1.42	1.40	1.36
3 bins	1.65	1.57	1.59	1.35
5 bins	1.80	1.62	1.61	1.36
store eff. Tables 3'				
2 bins	1.52	1.26	1.30	1.03
3 bins	1.74	1.37	1.36	1.04
5 bins	1.91	1.44	1.38	1.05
upc specific Tables 3"				
2 bins	1.53	1.22	1.34	1.02
3 bins	1.81	1.30	1.42	1.03
5 bins	2.01	1.36	1.47	1.05

* The Table reports the ratio of the average standard deviation in the lowest price bin to the average standard deviation in the highest price bin. Averages are over samples. The first column (P) is the ratio of the standard deviations of prices in the samples of all prices. The second column (RP) is this ratio in the samples of regular prices. The third column (X) is the ratio of the standard deviations of quantities and the last column (RX) is this ratio in the sample of regular prices.

We may therefore conclude that variations over weeks are relatively large in the low price bin. Removing temporary sales observations tends to reduce the difference in variations especially when controlling for UPC specific store effects.

9. PROBABILITIES

We have examined two predictions of (23): the quantity elasticity is between zero and unity and the cross price elasticity is less than the absolute value of the own price elasticity. Equation (23) has an additional prediction: The ratio of the cross price elasticity to the absolute value of the own price elasticity (C/O) is the same as the quantity elasticity (QE). This prediction can be examined by comparing two alternative calculations of the probability of attracting shoppers by the low price stores. The two alternative methods do not yield similar numbers when using the original variables or the store effect residuals. But they yield similar numbers when using the UPC specific residuals. Here we present the calculations for the UPC specific residuals.

Table 9 uses the estimated elasticities for the samples of all prices in Tables 4"-6" and 2 methods for computing the probability. The first (Pr 1) is 1-QE where QE is the quantity elasticity. The second (Pr 2) is 1 - C/O, where C/O is the ratio of the cross price elasticity to the absolute value of the own price elasticity. There is a substantial agreement between the two methods and the probability of attracting shoppers by stores in lower price bins is higher.

Table 9*: The probability of attracting shoppers by bin

	Prob. 1	Prob. 2
2 bins division		
bin 2	0.65	0.68
3 bins division		
bin 2	0.58	0.59
bin 3	0.77	0.81
5 bins division		
bin 2	0.60	0.60
bin 3	0.71	0.71
bin 4	0.79	0.81
bin 5	0.86	0.89

* This Table uses the 2005 sample of all prices in Tables 4"-6". The second column (Pr 1) is one minus the quantity elasticity. The third column (Pr 2) is one minus the ratio of the cross price elasticity to the absolute value of the own price elasticity.

10. CONCLUDING REMARKS

We provide results about elasticities within UPC-week cells, variations over weeks within UPC and the role of temporary sales.

The results about elasticities are obtained by dividing the stores in each UPC-week cell into bins and running the average quantity sold by stores in the highest price bin on the average quantity and price in a lower price bin. Our main findings are: (a) The elasticity of the quantity sold by stores in the high price bin with respect to the quantity sold by stores in a low price bin (the quantity elasticity) is between zero and unity; (b) This quantity elasticity is higher when the explanatory variables are from bins closer in price to the highest price bin; (c) The elasticity of the quantity sold by stores in the high price bin with respect to the price in a low price bin (the cross price elasticity) is positive but less than the absolute value of the own price elasticity; (d) The cross price elasticity is higher when the explanatory variables are from bins closer in price to the highest price bin.

Observations (b) and (d) say that for the purpose of predicting the quantity sold by stores in the highest price bin, the quantity and price in medium price stores is more relevant than the quantity and price in low price stores.

We computed the average quantity sold and the cross sectional average price for each UPC-week-bin cell and found that: (e) Variations over weeks in the average price and quantity are lower for higher price bins.

We also make the following observations about temporary sales: (f) The fraction of stores that offer an item on sale fluctuates over weeks in a way that is not consistent with the mixed strategy hypothesis; (g) Temporary sales contribute substantially to variations over weeks in the average posted price and the quantity sold; (h) The contribution of temporary sales to variations over weeks is large for all bins and somewhat larger for lower price bins.

Using our largest 2005 sample and controlling for UPC specific store effects the following estimates support the above conclusions:

(a) The quantity elasticity is 0.35 in the sample of all prices and 0.56 in the sample of regular prices (Table 4", 2 bins).

(b) The elasticity of the quantity sold by stores in bin 1 with respect to the quantity sold by stores in bin 2 is 0.4 while the elasticity with respect to the quantity sold by stores in bin 3 is 0.2 (Table 5", 3 bins).

(c) The cross price elasticity is 0.84 and the absolute value of the own price elasticity is 2.65 (Table 4", 2 bins).

(d) The elasticity with respect to the price posted by stores in bin 2 is 1.0 while the elasticity with respect to the price posted by stores in bin 3 is 0.5 (Table 5", 3 bins).

(e) The standard deviation of the average price over weeks in the low price bin is 23% higher than the standard deviation of the average price in the high price bin. The number for quantity is 20% (Table 3a", 2 bins).

The following numbers (again, using the UPC specific 2005 sample) support the conclusions about temporary sales:

(f) For the average UPC, none of the stores have temporary sales in 43% of the weeks. The mixed strategy hypothesis implies that this number should be around 1%.

(g) The standard deviation of the (cross sectional) average price over weeks in the sample of regular prices is only 41.9% of the standard deviation in the sample of all prices (Tables 3a" and 3b", 1 bin). The standard deviation of the quantity sold over weeks in the sample of regular prices is 64% of the standard deviation in the sample of all prices (Tables 3a" and 3b", 1 bin).

(h) For bin 1, the standard deviation of the average price over weeks in the sample of regular prices is 42.2% of the standard deviation in the sample of all prices. The number for bin 2 is 38.3% (Tables 3a" and 3b", 2 bins). For bin 1, the standard deviation of the quantity sold over weeks in the sample of regular prices is 70% of the standard deviation in the sample of all prices. This number is 60% for bin 2 (Tables 3a" and 3b", 2 bins).

The main findings are consistent with a UST model that allows for storage and non-shoppers (but are not consistent with the simple version of the UST model in section 3.1 and the simple version of the monopolistic competition model in section 2).

The intuition for the observations about elasticities ([a]-[d]) is as follows. The amount sold by stores depends on a random shock that is common to all buyers and on the number of shoppers (buyers who shop across stores). From the point of view of predicting the quantity sold by stores in the highest price bin the common shock is relevant and the number of shoppers is a "noise". Therefore shoppers' activity reduces the quantity elasticity. Since in the absence of shoppers the quantity elasticity is unity, we find a quantity elasticity that is less than one. The quantity sold by stores in the medium price bin is less influenced by shoppers' activity and therefore it provides a better signal for the common shock. As a result the elasticity with respect to the quantity sold by stores in the medium price bin is higher than the elasticity with respect to the quantity sold by stores in the low price bin.

We have assumed that the demand of shoppers is less stable than the demand of non-shoppers. This may be the result of storage activity by shoppers as in Hendel and Nevo (2013). Shoppers who find the item at a low price buy a large quantity and store most of it. They then stay out of the market until the level of inventories at home is low. We think that explicitly modeling this behavior will lead to the result that the demand of shoppers is relatively unstable and this will lead to the result about variations over week ([e]) because shoppers are more important for low price stores.

In section 3.2 temporary sales occur when demand in the previous period was low and stores that post the high regular price accumulate inventories. The prevalence of weeks with no temporary sales ([f]) is consistent with this model.

Observation (g) is relevant to the question of whether temporary sales are important for price flexibility. The measure of price flexibility (or price rigidity) depends on the underlying model. In UST models with storage the behavior of the entire cross sectional distribution is important but the behavior of prices at the store level is not. We have focused on the average cross sectional price and found that temporary sales have a large effect on its variability over weeks. Thus, from the point of view of UST models, temporary sales are important for macro.

Observation (h) complements observation (f) in suggesting that temporary sales are correlated across stores. The UST model in Bental and Eden (1993) may account for this observation. In this model an increase in inventories depresses all prices including the prices in the top of the distribution. Over time the level of inventories go back to "normal" and prices go back to their "regular level".

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APPENDIX A: AN EXISTENCE PROOF

We now turn to show the following Claim.

Claim A1: If $(ka_t)^{-1}\Pi_t$ is small, there exists a unique solution to (5) that satisfies: $\lambda_t \le P_{1t} < P_{2t} < \ldots < P_{mt}$.

Proof: Let

$$A(P_{it}) = \frac{(k+1)\lambda_t}{k+q_i} + \frac{\Pi_t}{(k+q_i)a_t P_{it}^{\theta}} = C + BP_{it}^{-\theta}$$

We look for a fixed point: $P_{it} = A(P_{it})$. Since $\theta = \frac{1}{\gamma - 1} < 0$ and $1+\theta = \frac{\gamma}{\gamma - 1} < 0$, we can sign the following derivatives:

$A'(P_{it}) = -\theta BP_{it}^{-\theta-1} = -\theta BP_{it}^{-(1+\theta)} > 0$ and

$A''(P_{it}) = \theta(1+\theta)BP_{it}^{-(1+\theta)-1} > 0$.

Note that $A'(0) = 0$. Since $B \le (ka_t)^{-1}\Pi_t$ is small, the function $A(P_{it})$ will intersect the 45 degree line twice. We choose the lower intersection in Figure A1. Note that the function $A(P_{it})$ is decreasing in q_i and therefore an increase in q_i will shift the curve downward and the fixed point will be lower. Therefore: $P_{1t} < P_{2t} < \ldots < P_{mt}$. Since $C \ge \lambda_t$ it follows that $P_{it} \ge \lambda_t$. □

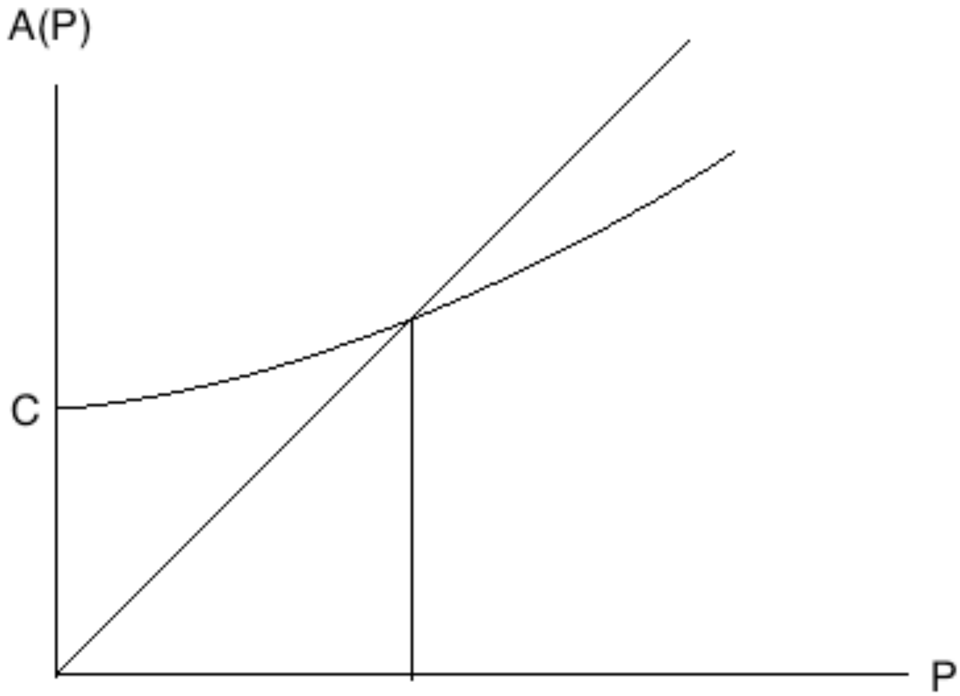


Figure A1

The monopoly price charged by the non-advertisers is:

(A1) $$P_t^m = \arg\max_P ka_t P^\theta (P - \lambda_t) = \frac{\theta \lambda_t}{\theta + 1} = \frac{\lambda_t}{\gamma}$$

The monopoly profits are:

(A2) $$\Pi_t^m = ka_t (\lambda_t)^{\theta+1} (1-\gamma) \gamma^{-(1+\theta)}$$

We require that advertisers will make the same profits as non-advertisers:

(A3) $$\Pi_t = \Pi_t^m$$

Equilibrium.

We define equilibrium as a vector $(P_{1t},...,P_{Zt}; P_t^m; \Pi_t, \Pi_t^m)$ that satisfies (A1)-(A3) and $\lambda_t \le P_{1t} < P_{2t} < ... < P_{mt}$.

Claim A2: There exists an equilibrium if

(A4) $$\frac{\Pi_t^m}{ka_t} = \frac{ka_t (\lambda_t)^{\theta+1} (1-\gamma) \gamma^{-(1+\theta)}}{ka_t} = (1-\gamma) \left(\frac{\gamma}{\lambda_t} \right)^{\frac{\gamma}{1-\gamma}}$$

is small.

To show this Claim note since $\Pi_t = \Pi_t^m$, (A4) insures that the condition in Claim A1 is satisfied for all q_i.

The expression (A4) is decreasing in γ and in λ_t. Therefore the sufficient condition is satisfied when either γ is large or λ is large.

Figure A2 provides a numerical example. In the figure there are three curves. The curve labeled "lambda/q" describes the standard UST prices which corresponds to the case $k=\Pi=0$. The curve labeled P(teta=-3) computes the equilibrium prices under the assumption that the own price elasticity is $\theta=-3$ and the curve labeled P(teta=-2) computes the equilibrium prices under the assumption $\theta=-2$. As can be seen having non-shoppers in the model increase prices and profit. In general when θ is lower in absolute value there is more monopoly power and prices are higher. This seems to be the case when the probability of selling to shoppers is high. In our example, the price when $q=0.6$ is an exception to the rule. The monopoly price is 1.5 when $\theta=-3$ and 2 when $\theta=-2$. In this example, the monopoly price is the highest price when $q\geq 0.7$.

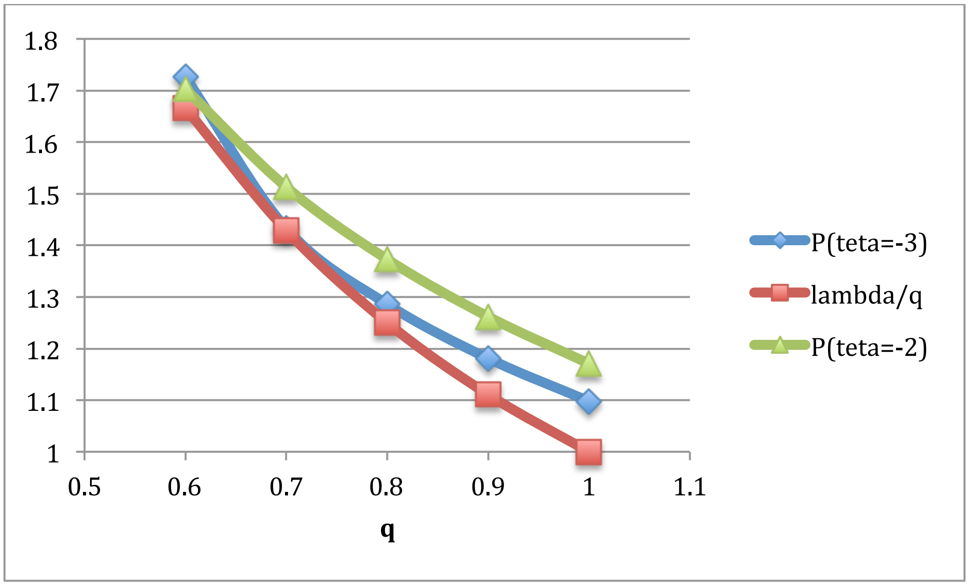


Figure A2: The probability of making a sale to shoppers (q) is on the horizontal axis. Equilibrium prices are on the vertical axis. All three curves assume $\lambda = a = 1$. The curve lambda/q (λ/q) is the prices of the standard UST model with $k = \Pi = 0$. The curve P assume $k = 1$. The curve P(teta=-3) assumes $\gamma = 2/3$, $\theta = -3$ and $\Pi_t = \Pi_t^m = (1-\gamma)\gamma^{-(1+\theta)}$ = 0.15. The curve P(teta=-2) assumes $\gamma = 1/2$, $\theta = -2$ and $\Pi_t = \Pi_t^m = (1-\gamma)\gamma^{-(1+\theta)}$ = 0.25.

<u>Deviation from equilibrium behavior</u>.

Suppose that an advertiser increases his price from say P_{it} to $P_{it} + \varepsilon < P_{i+1t}$. In this case a non-advertiser will fill the gap in the equilibrium price distribution by advertising P_{it}. As a result the deviant advertiser will be able to sell only if $\tilde{s} > i$ with probability q_{i+1}. Will he increase his expected profits? To answer this question, let

$$\Pi(q,P) = (k+q)aP^{1+\theta} - (k+1)\lambda a P^{\theta}$$

denote the expected profits as a function of the probability of making a sale to shoppers and the price. The function $\Pi(q,P)$ is increasing in q. Under the assumption that $P \geq \frac{\lambda}{q}$ and q is large the function $\Pi(q,P)$ is also increasing in P. When $\Pi(q,P)$ increases in both its arguments: $\Pi(q_{i+1}, P_i + \varepsilon < P_{i+1}) < \Pi(q_{i+1}, P_{i+1}) = \Pi(q_i, P_i)$ and the above deviation reduces expected profits.

APPENDIX B: GENERALIZING THE RESULTS IN CLAIM 2

Changing the dependent variable makes a big difference in this case. Substituting $\ln(a_t) = -\ln(k) + \ln(x_t^m) - \theta\ln(P_t^m)$ in (22) leads to:

(B1) $$\ln(x_{it}) = \ln(\tilde{\omega}_i) - \ln(k) + \ln(x_t^m) - \theta\ln(P_t^m) + \theta\ln(P_{it})$$

Here there is no correlation between the quantity sold by the monopoly $\ln(x_t^m)$ and the number of buyers served by the advertiser $\ln(\tilde{\omega}_i)$ and therefore when running a regression based on (B1) we expect the quantity elasticity to equal unity and the cross price elasticity to equal the absolute value of the own price elasticity.

<u>The relationship between the quantities sold by advertisers</u>.

We now turn to study the relationship between the quantities sold by stores in two different bins that are occupied by advertisers.

We start with two stores indexed $j < i \leq m$. Subtracting the quantity sold by advertiser j , $\ln(x_{jt}) = \ln(\tilde{\omega}_j) + \ln(a) + \theta\ln(P_{jt})$, from (22) leads to:

(B2) $$\ln(x_{it}) = \ln(x_{jt}) + \theta\ln(P_{it}) - \theta\ln(P_{jt}) + D_{ij}$$

where $D_{ij} = \ln(\tilde{\omega}_i) - \ln(\tilde{\omega}_j)$ is the difference in the number of shoppers. Since $j < i$, when $s < j$ the number of shoppers is zero for both stores and $D_{ij} = 0$. It is also zero when $s \geq i$ because in this case the number of shoppers is 1 for both stores. The difference D_{ij} is negative when $j \leq s < i$ because in this case a shopper arrives in the low index store but does not arrive in the high index store. Thus,

(B3) $$D_{ij} = \{\ln(k) - \ln(1+k) = \ln(k) - \ln\left(\frac{x_{jt}}{aP_{jt}^{\theta}}\right) \text{ when } j \leq s < i \text{ and 0 otherwise}\}.$$

Since $q_i = \sum_{s=i}^{m} \pi_s$ and $q_j = \sum_{s=j}^{m} \pi_s$,

(B4) $$\Pr ob(j \leq s < i) = \sum_{s=j}^{i-1} \pi_s = q_j - q_i$$

The expected difference in the number of shoppers is:

(B5) $$E(D_{ij}) = \psi_{ij} + (q_j - q_i)\left(-\ln(x_{jt}) + \theta\ln(P_{jt})\right)$$

where $\psi_{ij} = (q_j - q_i)\left(\ln(k) + E(\ln\tilde{a})\right)$. We can therefore write:

(B6) $$D_{ij} = \psi_{ij} + (q_j - q_i)\left(-\ln(x_{jt}) + \theta\ln(P_{jt})\right) + \varepsilon_{ijt}$$

where ε_{ijt} is an iid random variable with zero mean.

Substituting (B6) in (B2) leads to:

(B7) $$\ln(x_{it}) = \psi_{ij} + (1 + q_i - q_j)\ln(x_{jt}) + \theta\ln(P_{it}) - (1 + q_i - q_j)\theta\ln(P_{jt}) + \varepsilon_{ijt}$$

Since $q_i < q_j$, $0 < 1 + q_i - q_j < 1$, the quantity elasticity is between zero and unity and the own price elasticity is higher in absolute value than the cross price elasticity.

<u>Claim B1</u>: (a) the quantity elasticity is between zero and unity, (b) the own price elasticity is higher in absolute value than the cross price elasticity, (c) the quantity elasticity and the cross price elasticity are decreasing with the distance between the bins.

Parts (a) and (b) follow from $0 < 1 + q_i - q_j < 1$. To show (c) note that the absolute value of the difference in the probabilities of selling to shoppers ($\left|q_i - q_j\right|$) is larger for bins that are further apart.

We now turn to show that Claim 4 holds also for the case: $j > i$.

When $j > i$, $D_{ij} = 0$ if $s \geq j$ or if $s < i$. Thus,

(B8) $D_{ij} = \{\ln(1+k) - \ln(k) = \ln(1+k) - \ln\left(\frac{x_{jt}}{a_t P_{jt}^{\theta}}\right)$ when $i \leq s < j$ and 0 otherwise}

The expected value of (B8) is:

(B9) $$E(D_{ij}) = \psi^*_{ij} - (q_i - q_j)\left(\ln(x_{jt}) - \theta\ln(P_{jt})\right)$$

where $\psi^*_{ij} = (q_i - q_j)\left(\ln(1+k) + E(\ln\tilde{a})\right)$. We can therefore write:

(B10) $$D_{ij} = \psi^*_{ij} + (q_j - q_i)\left(\ln(x_{jt}) - \theta\ln(P_{jt})\right) + \varepsilon_{ijt}$$

Substituting (B10) in (B2) leads to:

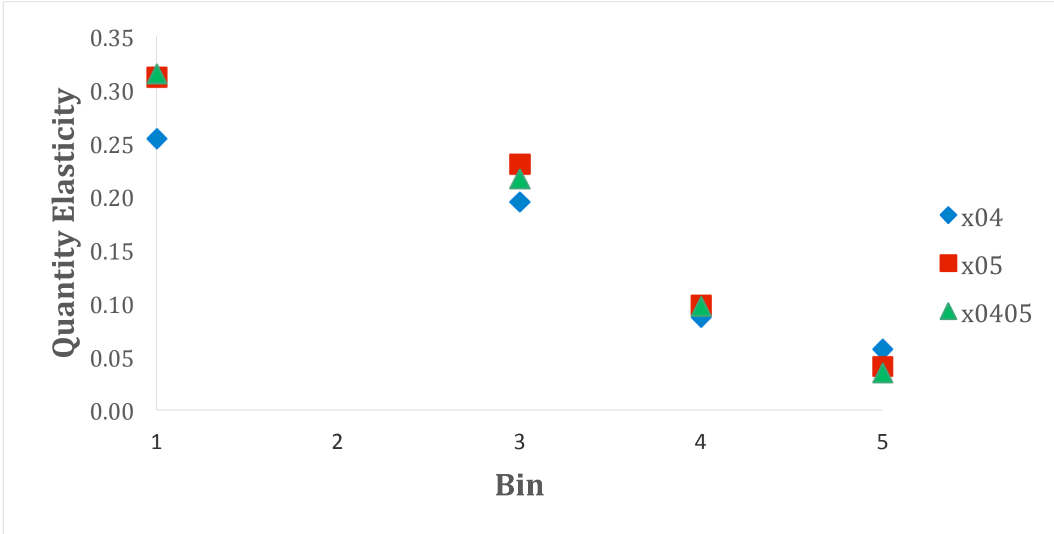
(B11) $$\ln(x_{it}) = \psi^*_{ij} + (1 + q_j - q_i)\ln(x_{jt}) + \theta\ln(P_{it}) - (1 + q_j - q_i)\theta\ln(P_{jt}) + \varepsilon_{ijt}$$

Since $q_j < q_i$, Claim B1 holds also for this case.

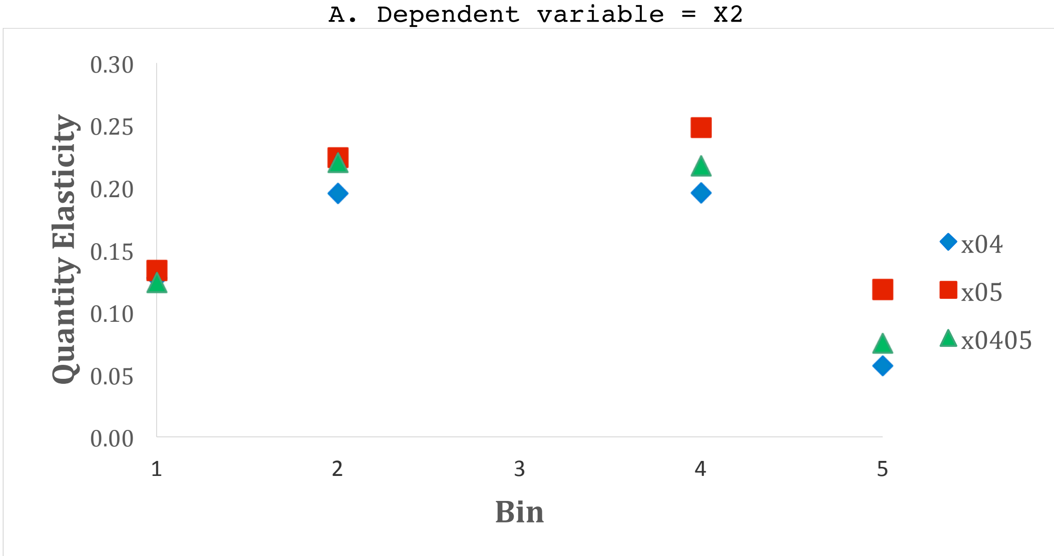
The theory says that the quantity elasticity and the cross price elasticity declines with the index of the explanatory bin. We have seen that this is the case when the dependent variable is the quantity sold by stores in the first bin. Does it holds for the case where the dependent variable is X2 or X3?

We ran X2 on 9 explanatory variables: X1,X3,X4,X5,P1,P2,P3,P4,P5. We expect that the coefficient of X3 will be larger than the coefficient of X4 and X5. We also expect that the coefficient of P3 will be larger than the coefficient of P4 and P5. We also ran X3 on X1,X2,X4,X5,P1,P2,P3,P4,P5. In this regression we expect that the coefficient of X4 is larger than the coefficient of X5 and the coefficient of P4 is larger than the coefficient of P5.

We ran these regressions using the original variables, the variables net of store effects and the variables net of UPC specific store effects. The results support the above hypotheses. Figures B1 and B2 describe the results when using the variables net of UPC specific store effects.



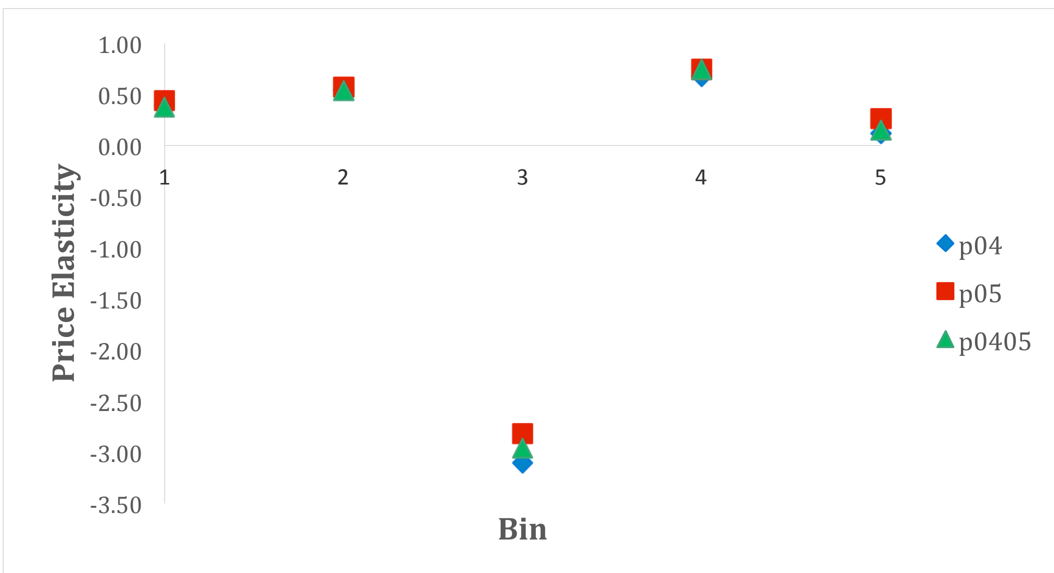
A. Dependent variable = X2



B. Dependent variable = X3

Figure B1: Quantity Elasticities based on 9 explanatory variable regressions with UPC specific store effects

A. Dependent variable = X2



B. Dependent variable = X3

Figure B2: Price Elasticities based on a regression with 9 explanatory variables with UPC specific store effect