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PRICE DISPERSION AND DEMAND UNCERTAINTY: EVIDENCE FROM US SCANNER DATA

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Abstract

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This is a revised version of a working paper by the same title (VUECON-13-00015, October 2013). I would like to thank PJ Glandon, Maya Eden and Saul Lach for useful comments on an earlier draft and especially to Vivian Ying Jiang for excellent research assistance.
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PRICE DISPERSION AND DEMAND UNCERTAINTY: EVIDENCE FROM US SCANNER DATA

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August 2016

I use the Prescott (1975) hotels model to explain variations in price dispersion across items sold by supermarkets in Chicago. The effect of demand uncertainty on price dispersion is highly significant and quantitatively important: My estimates suggest that more than 40% of the cross sectional standard deviation of log prices is due to demand uncertainty. I also find that price dispersion measures are negatively correlated with the average price but are not negatively correlated with the revenues from selling the good (across stores and weeks) and with the number of stores that sell the good. Temporary sales are modeled as a reaction to "unwanted inventories" that are accumulated when the realization of demand is low. The effect of demand uncertainty on the frequency of temporary sales is also highly significant and quantitatively important: Items with more demand uncertainty tend to accumulate "unwanted inventories" more often and tend to have temporary sales more often.

Key Words: Price Dispersion, Demand Uncertainty, Sequential Trade, temporary sales.

JEL Classification: D50, D80, D83, L10

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1. INTRODUCTION

Deviations from the law of one price are a challenge for the understanding of market-based economies. Among the explanation proposed are price discrimination, search frictions and sticky prices. Here I use scanner data on supermarket prices in Chicago to study the role of aggregate demand uncertainty.

I find that on average, more than 40% of the cross sectional standard deviation of log prices is due to demand uncertainty. This finding is consistent with Prescott (1975) type models that focus on demand uncertainty as the reason for price dispersion.

The original Prescott (1975) model assumed that prices are set in advance and cheaper goods are sold first. In Eden (1990) I relax the price rigidity assumption and describe a sequential trade process in which cheaper goods are sold first. In this model, that I call the 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 must make irreversible selling decisions before they know the realization of aggregate 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.[1]

Although prices are completely flexible, they may appear to be sticky. In Eden (1994), I argued that to maintain the equilibrium price distribution it is enough that only some sellers will change their prices. A seller who does not change his price may find that his real price has been eroded by inflation. But if the price remains in the equilibrium range, this seller is fully compensated by an increase in the probability of

[1] There are versions of the Prescott model that assume price rigidity. See for example, Dana (1998, 1999, 2001) and Deneckere and Peck (2012).

making a sale. This type of reasoning holds also for the Burdett and Judd (1983) model used by Head et.al. (2012). In their model, a seller whose price has been eroded by inflation is compensated by an increase in the volume of sales. Head et.al go further and show that a model that delivers equilibrium price dispersion can account for many of the stylized fact about price changes. Since their results depend mainly on the assumption that sellers are indifferent among prices in the equilibrium price range they should also hold for the UST model.[2]

There are, however important differences between the predictions of the UST model and menu cost models regarding the behavior of the cross sectional price distribution. Menu cost models tend to imply a positive relationship between inflation and measures of cross sectional price dispersion. In Eden (2001) I examined high and moderate inflation periods in Israel and found no relationship between the cross sectional price dispersion and inflation. Ahlin and Shintani (2007) compared price dispersion in Mexico under two regimes. They found that price dispersion is lower in the high inflation regime but argue that this may be due to decrease establishment heterogeneity.

A related issue is the speed of adjustment of the cross sectional price distribution. Menu cost models and time dependent models imply a slow adjustment to shocks while equilibrium price dispersion models imply a fast adjustment. Baharad and Eden (2004) used a VAR impulse response analysis and find that a shock that leads to an increase in the average (across stores) rate of price change does not affect the standard deviation of the cross sectional price distribution. This supports the hypothesis that the adjustment of the cross sectional price distribution is fast.

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[2] There are of course some unresolved puzzles about price changes. One is the finding that the probability of a price change declines with the time since the last price change. See, Campbell and Eden (2014). In menu cost models sellers adjust prices when the distance from the desired price is large. Since the distance from the desired price is likely to be small for prices that were recently changed, the finding of a declining hazard function is a challenge for menu costs models. It is less of a challenge for equilibrium price dispersion models that assume no costs for changing prices.

As was said above, the UST model uses uncertainty about aggregate demand to generate equilibrium price dispersion.[3] Here I use variations in the predictability of aggregate demand across goods to assess the importance of demand uncertainty in price dispersion.

An important by-product of the analysis is a theory of temporary sales. In a UST model that allows for storage, a good that is not sold is carried as inventories to the next period. Since in the model some units are sold and some are not, typically there is heterogeneity in the "age" of the units. Units that are closer to their expiration date are offered at a low price to maximize the probability of making a sale and minimize the probability that they will reach the expiration date before being sold. A store may therefore start at a relatively high "regular price" and then if it fails to make a sale switch to a low price until the level of inventories get back to "normal". This is related to Aguirregabiria (1999) who focused on fixed costs for changing prices and fixed delivery costs. It is also related to Kehoe and Midrigan (2015) who argue that the cost of temporary price changes is lower than the cost of regular price changes and therefore a store will use temporary sales to respond to temporary shocks.

I use the data set from Information Resources, Inc. (IRI) on supermarket prices. This data set is large and has a very narrow definition of goods (at the UPC-week level). The narrowness of the good definition has been a problem in other studies of price dispersion. For example, Lach (2002) reviewed the list of products in

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[3] There is no uncertainty about aggregate demand in search models of price dispersion and therefore getting price dispersion in search models is a challenge. Diamond (1971) was the first to point out the difficulty. In his model the equilibrium price distribution is degenerate and all firms post the monopoly price. Diamond assumed that buyers sample one firm at a time. Burdett and Judd (1983) allowed for sampling more than one selling offer per period and show that price dispersion will arise if the probability of sampling more than one seller is between zero and one. If however the probability of sampling more than one seller goes to one we will converge to a single price equilibrium in which all firms post the competitive price. If the probability of sampling more than one seller goes to zero we will converge to a single price equilibrium in which all firms post the monopoly price (as in the Diamond model). For other search models of price dispersion, see Reinganum (1979), Rob (1985) and Stahl (1989).

the Israeli CPI and found 31 products with precise labels. Out of these 31 products he chose 5 (refrigerator and 4 food items) that had also a weight measure.

Kaplan and Menzio (2015) use the Kilts-Nielsen data set that tracks the shopping for food behavior of approximately 50,000 households. They define a good by its bar code and the quarter that it was sold. Their study focuses on characterizing the typical price distribution and the characteristics of the households who get cheap deals.

The tradeoff between the narrowness of the good definition and the sample size is also present in studies of price dispersion in the airline industry. Escobari (2012) collected data on ticket prices for 81 flights (route-date combinations). Gerardi and Shapiro (2009) and Cornia, Gerardi and Shapiro (2012) use large publicly available data on airline tickets (the DB1B data set) but unlike Escobari's data, a flight is a route-quarter combination. Here the data set is large and the definition of the good is as narrow as one can hope for.[4]

Section 2 is about the underlying theory. Section 3 discusses implementation issues. Section 4 describes the data. Section 5 is the estimation results. Robustness checks are in section 6 and the quantitative importance of demand uncertainty is in Section 7. Concluding remarks are in the last section.

[4] Unlike airline tickets, food prices are easy to interpret. Two airline tickets may have different prices because one has a refund option and the other does not. Similarly the price of a hotel room may be different because of differences in cancellation policy. The refund or cancellation policy is important when studying the role of aggregate demand uncertainty because the question of who pays for an "empty seat" or an "empty hotel room" is central to the investigation. Furthermore, the difference in cross sectional price dispersion across food items is not likely to emerge as a result of price discrimination because people who buy say milk also buy hotdogs. This is different from the case of the airline industry where it is often argued that buyers who purchase tickets close to the departure date are business travelers with relatively inelastic demand. As a result, in the airline industry it is difficult to distinguish between the demand uncertainty and the price discrimination models of price dispersion.

2. THEORY

I start with a simplified version of Bentals and Eden (BE, 1993) and derive a relationship between specific measures of price dispersion and specific measures of demand uncertainty.[5]

Sellers

The economy lasts forever. There are many goods and many sellers who can produce the goods at a constant unit cost.[6] The unit cost of producing good j is λ_j. Production occurs at the beginning of each period before the beginning of trade. The seller knows the distribution of demand but at the time of production he does not know the realization.

Sellers face a tradeoff between the probability of making a sale and the price: The lower the price, the higher is the probability of making a sale. In each period, sellers of good j have to choose between Z_j price tags: $P_{1j} < ... < P_{Zj}$. In what follows I drop the good index and consider a good with prices $P_1 < ... < P_Z$.[7]

The probability of making a sale at the price P_i is q_i, where $1 = q_1 > ... > q_Z > 0$. The seller takes these probabilities as given. Units that are not sold are carried as inventories to the next period. A unit stored can be used to reduce production next period and the value of a unit of inventories is $\beta\lambda$, where $0 < \beta < 1$ reflects the cost of delay, storage cost and depreciation.

Sellers will put the price tag P_i on $0 < x < \infty$ units only if:

(1) $$q_i P_i + (1 - q_i)\beta\lambda = \lambda$$

[5] For exposition see Eden (2004, ch. 14). Chapter 14 is on my webpage: http://www.vanderbilt.edu/econ/faculty/Eden/documents/chapter-14.pdf

[6] The constant unit cost assumption simplifies the analysis relative to the BE model that assumes a strictly convex cost function.

[7] There is no incentive in equilibrium to announce a price $P_i < p < P_{i+1}$ because the probability of making a sale at this price is the same as the probability of making a sale at the price P_{i+1}.

The arbitrage condition (1) is key. The left hand side of (1) is the expected revenues from a unit with a price tag P_i. With probability q_i the seller will get the posted price and with probability $1-q_i$ he will get the value of inventories. The right hand side is the unit production cost. The seller will put the price tag P_i on $0 < x < \infty$ units, only if the two are equal. Otherwise, if $q_i P_i + (1-q_i)\beta\lambda > \lambda$ he will choose $x = \infty$ and if $q_i P_i + (1-q_i)\beta\lambda < \lambda$ he will choose $x = 0$.

In what follows I assume Z hypothetical markets and use the following language. A seller who puts the price tag P_i on a unit, supplies the unit to market i. The unit is sold if market i opens and is carried as inventories if market i does not open. Market i opens with probability q_i.

<u>Buyers</u>

At the price P the individual buyer demands $D(P)$ units where $D(P)$ is a downward sloping demand curve that does not intersect the axis. Buyers arrive at the market place after sellers have already made their production decisions. Upon arrival they see all available offers and buy at the cheapest available price.[8]

The number of active buyers that arrive in the market place in a typical period ($\tilde{N}$) is an *iid* random variable that may take Z realizations: $0 < N_1 < \dots < N_Z$. For notational convenience I use $N_0 = 0$. All realizations occur with equal probabilities: State s occurs when $\tilde{N} = N_s$ with probability $\pi = 1/Z$. The difference between two consecutive realizations is denoted by: $N_i - N_{i-1} = \Delta_i > 0$.

Buyers arrive in a sequential manner. The first batch of Δ_1 buyers buys in the first market at the price P_1. If $s = 1$, no more buyers arrive and trade is over for the period. If $s > 1$, an additional batch of Δ_2 buyers arrives and buys in the second market at the price P_2. Again, if $s = 2$ no more buyers arrive and trade is over for the

[8] Unlike Burdett et.al. (2001), here buyers observe both the price and availability. We may think of trade as occurring on the internet where each store deletes its price offer when it is stocked out.

period. Otherwise, if $s > 2$ a third batch arrives and buys in the third market at the price P_3 and so on.

Equilibrium

Using x_i to denote the supply to hypothetical market i, I define equilibrium as follows.

Equilibrium is a vector of prices $(P_1,...,P_Z)$, a vector of probabilities $(q_1,...,q_Z)$ and a vector of supplies $(x_1,...,x_Z)$ such that (a) the probability that market i will open and goods with price tag P_i will be sold is: $q_i = \Pr ob(\tilde{N} \geq N_i) = (Z-i+1)\pi$, (b) the arbitrage condition (1) is satisfied and (c) the supply to market i is equal to the potential demand: $x_i = \Delta_i D(P_i)$ for all i.

Note that the hypothetical markets open sequentially. When $\tilde{N} = N_s$, the first s markets open and the goods allocated to these markets are sold. The goods allocated to the last $Z-s$ markets are not sold and are carried as inventories to the next period. In equilibrium markets that open are cleared. Sellers in this model are "contingent price takers": They assume that they can sell any amount at the price P_i if market i opens. Production in each period is $\sum_i x_i - I$, where I is the beginning of period inventories. In equilibrium production is strictly positive because some goods are sold in each period and therefore some production is required to keep the available supply at the level $\sum_i x_i$.[9]

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[9] The assumption of a downward sloping demand curve captures some aspect of storage behavior on the part of the buyers as in Pesendorfer (2002) and Hendel and Nevo (2013). A buyer who arrives early will face a low price and will buy a relatively large quantity. Part of it he will consume in the same week and the rest he will store and consume in weeks that he arrives late and face a relatively high price. In Eden (July 2013) I allow for heterogeneity among buyers. This case is relevant because the demand of the buyer depends on the amount of storage he has.

Empirical implications

When $Z=1$, only one market opens and there is no price dispersion. Price dispersion occurs when $\tilde{N}$ is not a degenerate random variable and $Z>1$. This suggests a relationship between price dispersion and Z. Armed with this intuition, I now derive an approximate linear relationship between a measure of price dispersion and a measure of unit dispersion that I later estimate.

I start by showing that Z is proportional to the ratio of the maximum aggregate sales to the minimum aggregate sales. In state s, when exactly s markets open, $\sum_{i=1}^{s} x_i$ units are sold and $\sum_{i=s+1}^{Z} x_i$ units are carried as inventories to the next period. The maximum amount sold is: $H=\sum_{i=1}^{Z} x_i = Z\bar{x}$, where $\bar{x}$ is the average supply per market. The minimum amount sold is: $L=x_1$. Using the maximum weekly amount sold as an estimate of H and the lowest weekly amount sold as an estimate of L, I compute the ratio $HLU = H/L$ (= High-Low-Units):

(2) $$HLU=\frac{Z\bar{x}}{x_1}=Z\alpha \text{ or } Z=\frac{HLU}{\alpha}$$

where $\alpha = \bar{x}/x_1$ is a constant equal to the ratio of the average supply per market to the first market's supply.

To derive the relationship between price dispersion and Z, I use (1) to get:

(3) $$P_i=\beta\lambda+(1-\beta)\frac{\lambda}{q_i}$$

Since the probability that all the Z markets will open is $q_Z=\pi$, in any given week the highest price is:

(4) $$P^H=P_Z=\beta\lambda+(1-\beta)\frac{\lambda}{q_Z}=\beta\lambda+(1-\beta)\frac{\lambda}{\pi}$$

Since the probability that the first market will open is 1, the lowest price in any given week is:

(5) $$P^L=P_1=\lambda$$

Dividing (4) by (5) leads to:

$$HLP = \frac{P^H}{P^L} = \beta + (1-\beta)\frac{1}{\pi} = \beta + (1-\beta)Z \tag{6}$$

where the last equality uses $\pi = \frac{1}{Z}$ and HLP stands for High-Low-Price. Using (2) leads to: $HLP = \beta + (1-\beta)(\frac{1}{\alpha})HLU$ which is equivalent to:

$$HLP - 1 = (1-\beta)\left(\frac{HLU}{\alpha} - 1\right) \tag{7}$$

The left hand side of (7) is the percentage difference between the high and the low price. It is common to use the log difference as an approximation for the percentage difference. Using $\ln(HLP)$ as a proxy for $HLP - 1$ and $\ln(HLU) - \ln(\alpha)$ as a proxy for $\frac{HLU}{\alpha} - 1$ leads to:[10]

$$\ln(HLP) = -(1-\beta)\ln(\alpha) + (1-\beta)\ln(HLU) \tag{8}$$

This is a linear relationship between the range measure of price dispersion, $\ln(HLP)$, and the range measure of unit dispersion, $\ln(HLU)$.

I extend this result in the appendices. In Appendix A, I allow for cost shocks and derive the relationship between the standard deviation measures of dispersion. In Appendix B, I show that the relationship between price dispersion and unit dispersion holds even when allowing for non-shoppers and monopoly power.

I now turn to another extension in an attempt to capture the phenomena of temporary sales.

2.1 Temporary Sales and One-hoss-shay depreciation

Temporary sales deserve special attention because they are in the center of the debate about price rigidity. Here I argue that they emerge rather naturally in a UST model that allows for storage.

[10] A Taylor approximation of ln(HLP) around average HLP also leads to a linear relationship between ln(HLP) and ln(HLU).

The Bental-Eden model is a good starting point. In their model equilibrium prices and quantities are functions of the beginning of period inventories. When inventories are accumulated prices (in all hypothetical markets) go down and the quantities supplied (to all hypothetical markets) go up. This leads to a negative co-movement between the average posted price and the quantity sold, a phenomenon that was documented by several authors including Warner and Barsky (1995), MacDonald (2000) and Chevelier, Kashyap and Rossi (2003).

Temporary sales are consistent with the Bental-Eden model but so are many other price-setting behaviors.[11] To get sharper predictions and to keep the constant unit cost assumption, I replace the exponential decay in the Bental-Eden model with one-hoss-shay depreciation.

The one-hoss-shay depreciation is a natural assumption for supermarket items that have an expiration date. It implies that the value of inventories depends on the age of the unit: An "old" unit that is closer to its expiration date is worth less if it is not sold than a "young" unit because there is a higher chance that it will become worthless before being sold. Since relatively young units have a higher value when they are not sold, a store with a relatively large amount of young units will post a relatively high price. If the units do not sale it switches to a low price until it sells all or most of the "old units". It will then get newly produced units and switch again to the high price. Thus, one-hoss-shay depreciation can lead to temporary sales even when the marginal cost is constant.[12]

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[11] Since in the Bental-Eden model shocks are iid, the model cannot explain why prices are lower in weekends (Warner and Barsky) and in holidays. It is possible that in periods of high demand the distribution of the active number of buyers ($\tilde{N}$) is less dispersed. For example if in holidays all potential buyers are active and $\tilde{N} = N_Z$, there will be one market and sales will occur at a relatively low price. In general, it is enough that the minimum number of buyers N_1 is larger in weekends and holidays with no change in Δ_i.

[12] As was said before, this is consistent with Aguirregabiria (1999) who used data on both inventories and prices and found that the markup is negatively related to the level of inventories. Anderson et.al (2013) argue that temporary sales do not respond to cost shocks and present institutional evidence that

To illustrate, I assume that: (a) Each unit lives for two periods. If it is not sold in the first period it can still be sold in the second period but after that it becomes worthless. (b) All units within a store are of the same age.[13] And (c) The number of buyers in period t, $\tilde{N}_t$, can take two possible realizations: N with probability $1-q$ and $N+\Delta$ with probability q.

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 (No I) 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 treatment and the equilibrium definition are in Appendix C. The main idea is that older goods get a "priority" in the supply to the first market (and

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. The main finding that temporary sales do not respond to cost shocks is in line with our focus on demand shocks. The fact that a "trade deal window" is allowed is consistent with the hypothesis that temporary sales are used to react to the level of unwanted inventories.

[13] Alternatively, we can think of a model in which each unit has its own price tag and there can be many price tags within a store.

younger units get a priority in the supply to the second market) because younger units have a "relative advantage" in bearing the risk of not being sold.

Given prices the allocation rule is as follows. If the number 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 number 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.

Figure 1 captures the main idea. In Figure 1A, the first market price does not depend on the level of inventories. When the second market does not open $I = \Delta D(P_2)$ units are carried as inventories and are sold in the next period's first market at the price $P(1,I) = \lambda$. The supply to the second market is of newly produced goods and the price in the second market is determined by:

$$qP_2 + (1-q)\beta\lambda = \lambda \qquad (9)$$

The left hand side of (9) is the expected present value of per unit revenues. If the second market opens (with probability q) the seller gets P_2. Otherwise he will get in the next period the first market price, λ. The right hand side of (9) is the unit cost of production and therefore (9) insures zero profits. The solution to (9) is:

$$P_2 = \frac{\lambda\left(1-(1-q)\beta\right)}{q} \qquad (10)$$

In both states newly produced units are supplied to the first market and therefore the price in the first market is λ.

In Figure 1B, the amount of inventories that will be carried when market 2 does not open is large. When inventories are accumulated (in state I) only old units are supplied to the first market and therefore the price in this market can be below cost. Since newly produced units are supplied to the first market in state NI, the first market price in this state is λ. The first market price in state I and the price in market 2 are determined by the following two equations:

(11) $$qP_2 = P(1,I) \text{ and } qP_2 + (1-q)\beta P(1,I) = \lambda$$

The first equation 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 second equation is similar to equation (9). It says that the expected revenue from supplying a new unit to the second market is λ. The solution to the two equations in (11) is:

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

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

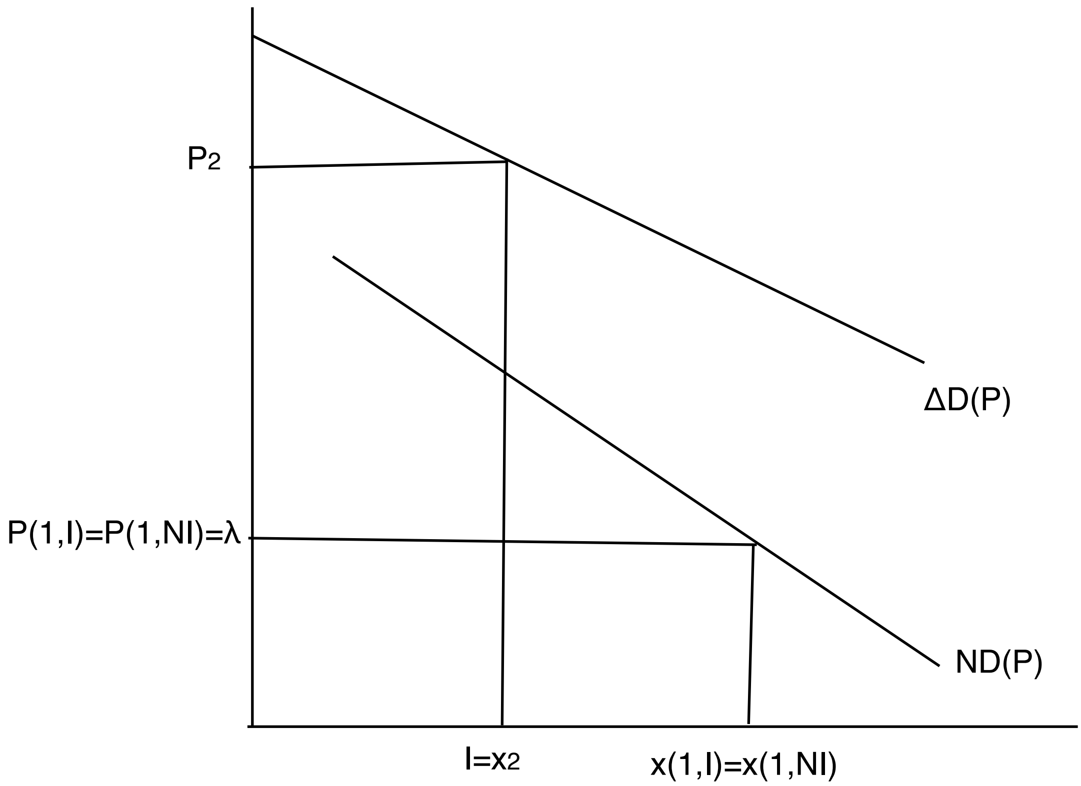
In Figure 1C, all inventories are absorbed by market 1 and prices must satisfy:

(13) $$qP_2 \le P(1,I) \text{ and } qP_2 + (1-q)\beta P(1,I) = \lambda$$

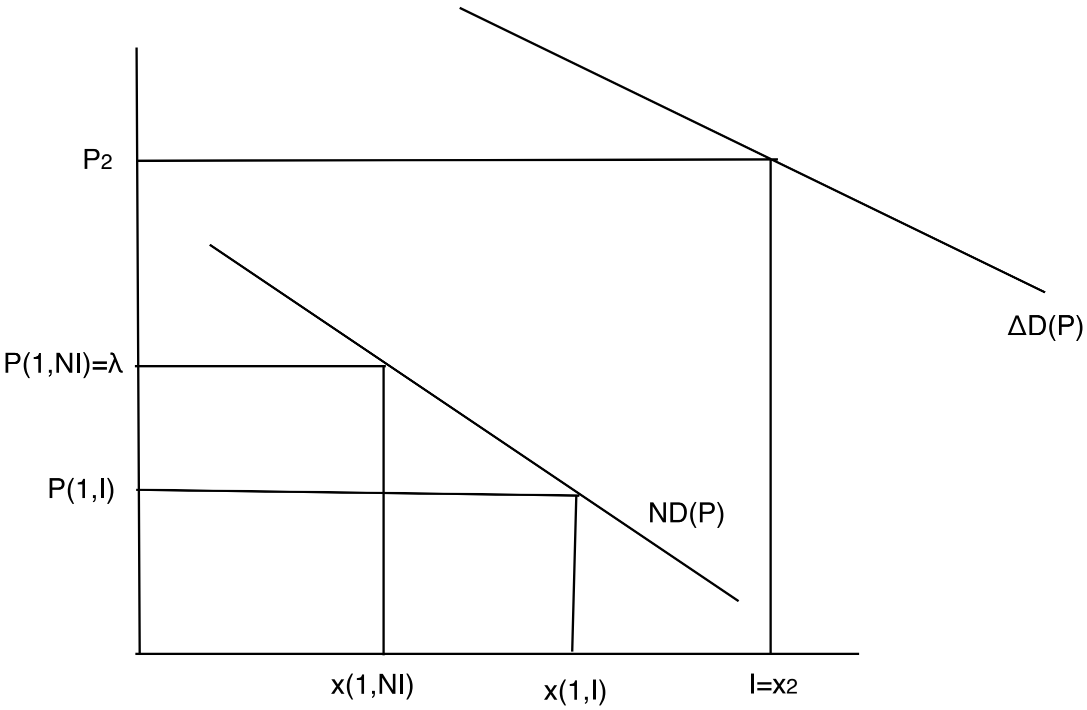
The inequality requires that an old unit will on average earn more in the first market. The solution to (13) is:

(14) $$\frac{\lambda}{1+(1-q)\beta} \le P(1,I) \le \lambda \text{ and } P_2 = \frac{\lambda-(1-q)\beta P(1,I)}{q}$$

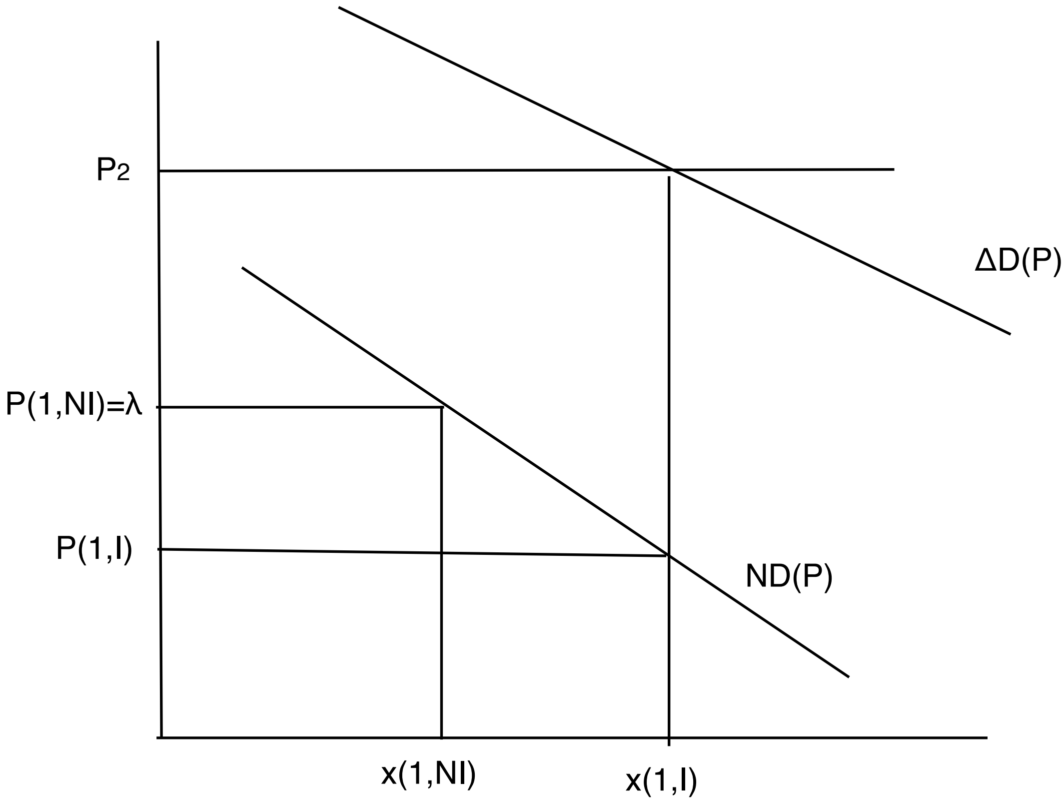
The model described by Figure 1 may account for temporary sales. Some stores offer newly produced units at the high ("regular") price of market 2. Then if demand is low they accumulate inventories and offer the units for sale at the low price of market 1. The model is extended in Appendix C to the case in which $\tilde{N}$ can take many possible realizations. It is shown there that also in this case of one-hoss-shay depreciation we get a positive relationship between HLP and HLU.



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.



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



C. In state I, the supply to the first market is equal to the beginning of period level of inventories.

Figure 1: Possible Equilibria

Note that in cases B and C there is a negative correlation between the average posted price and the quantity sold.[14] This correlation arises because the "temporary sale price" is lower than the cost of production and at this price the quantity purchased by first-market buyers is large.

The frequency of temporary sales

Goods with perfectly predicted demand will be traded in a single standard Walrasian market at the price λ. For these goods, sellers will sell everything they produce at the market-clearing price, "unwanted inventories" will not be accumulated and temporary sales that are aimed at reducing inventories will not occur. As was argued in the previous section this is not the case for goods that face uncertain demand. Thus, differences in demand uncertainty can lead to differences in the frequency of temporary sale.

I now show this possibility for two cases. I start with the equilibrium in Figure 1A where all the "old units" are supplied to the first market and are on a "temporary sale". The number of units that are on "temporary sale" in state I is x_2 and the fraction of units that are on sale in state I is: $x_2/(x_1+x_2)$, where here $x_1 = x(1,I)$. Since state I occurs with probability $1-q$, the average sale frequency is: $SF = (1-q)x_2/(x_1+x_2)$. The measure of unit dispersion HLU is: $HLU = (x_1+x_2)/x_1$. This leads to:

(15) $$\frac{1}{SF} = \frac{x_1+x_2}{(1-q)x_2} = \frac{1}{1-q} + \frac{1}{1-q}\frac{x_1}{x_2} = \frac{1}{1-q} + \frac{1}{(1-q)(HLU-1)}$$

Variations in x_2/x_1 across goods can arise as a result of differences in the parameters N and Δ. When variations across goods are the result of variations in x_2/x_1 and not q, there is a perfect correlation between $1/SF$ and $1/(HLU-1)$ and a positive correlation between SF and HLU.

[14] The average posted price is over units not stores. If the number of stores in each market does not change over time it should hold also when the average is over stores.

I now turn to the case in which the number of buyers is uniformly distributed and each buyer has a demand for one unit. I assume that units supplied out of inventories are on temporary sale and $\tilde{N}$ can take Z possible realizations where $N_s = s$ is a typical realizations. Thus, $\Delta_i = x_i = 1$, $\alpha = 1$ and $\Pr ob(\tilde{N} = s) = \pi = \frac{1}{Z}$. When s markets open, $Z - s$ units are not sold and are carried as inventories to the next period where they are on temporary sale. The fraction of items on temporary sale when s markets were open in the previous period is:

$$FS_s = \frac{Z-s}{Z} = 1 - \frac{s}{Z}$$

The expected value of the fraction of items on temporary sale:

(15') $$FS = \pi \sum_{s=1}^{Z} FS_s = 1 - \pi \sum_{s=1}^{Z} \frac{s}{Z} = 1 - \frac{1}{Z^2} \sum_{s=1}^{Z} s = 1 - \frac{1}{Z^2} \frac{Z(Z+1)}{2} = \frac{1}{2} - \frac{1}{2Z} = \frac{1}{2} - \frac{1}{2HLU}$$

The last equality uses (2) and $\alpha = 1$. Also in this example, FS is increasing in HLU.

3. IMPLEMENTATION

I start with the relationship (8) between measures of price dispersion and measures of unit dispersion. This linear relationship depends on β that is a key parameter for determining the value of inventories. Since β depends on storage cost and the rate of depreciation, it may vary across categories. I therefore include category dummies and size variables that may be correlated with storage cost. I add classical measurement error to (8) and run:

(16) $$\ln(HLP_i) = b_0 + b_1 \ln(HLU_i) + \sum_j d_{ji} CD_{ji} + \sum_j s_{ji} SD_{ji} + e_i$$

where b_1 is the parameter of interest, CD are category dummies ($CD_j = 1$, if product i belong to category j and $CD_j = 0$ otherwise), SD are category specific normalized size measures and e is an error term. The size variables will be described later. They are included in the regression as a proxy for shelf space and the cost of trade delays.

I also use a linear approximation to (A5) in Appendix A and run:

(17) $$SDP_i = b_0 + b_1 SDU_i + \sum_j d_{ji} CD_{ji} + \sum_j s_{ji} SD_{ji} + e_i$$

To check robustness, I add variables suggested by other models: The average price, total revenues and the number of stores that sold the good. The average price was used by Pratt et.al (1979) in an earlier study. Sorensen (2000) used the purchase frequency and the average wholesale price. Here I have data only from the sellers' side and I therefore use aggregate revenues to capture the importance of the goods in the buyers' budget (aggregate revenues = aggregate spending). The number of stores that offer the good may be a proxy for monopoly power and is analogous to the number of airlines in the route used by Gerardi and Shapiro (2009) when studying price dispersion in the airline industry.

Adding the above variables to (16) and (17) leads to:

(16') $$\ln(HLP_i) = b_0 + b_1 \ln(HLU_i) + b_2 \ln(\mathrm{Re}\,v_i) + b_3 \ln(AvP_i) + b_4(\#Stores_i) + \sum_j d_{ji} CD_{ji} + \sum_j s_{ji} SD_{ji} + e_i$$

(17') $$SDP_i = b_0 + b_1 SDU_i + b_2 \ln(\mathrm{Re}\,v_i) + b_3 \ln(AvP_i) + b_4(\#stores) + \sum_j d_{ji} CD_{ji} + \sum_j s_{ji} SD_{ji} + e_i$$

where $\ln(\mathrm{Re}\,v)$ is the log of total revenues (over stores and weeks), $\ln(AvP)$ is the log of average price (averaged over stores and weeks) and $\#Stores$ is the number of stores that sold the product.

To test the relationship between the average frequency of temporary sales and unit dispersion suggested by (15) and (15'), I run (16) and (17) after replacing the dependent variable with the average sale frequency.

4. DATA

I use the Information Resources, Inc. (IRI) data set that contains weekly observations of the revenues from each good and the number of units sold. I identify a product with a Universal Product Code (UPC) and obtain prices by dividing revenues by the number of units sold. There are 31 categories in 50 different markets and there are both grocery stores and drug stores from several different chains during the years 2001-2011. A full utilization of this huge data set is beyond the scope of this paper. Here I look at the sample of grocery stores in Chicago during the years 2004 and 2005.[15]

I exclude from the sample store-UPC combinations (cells) with zero revenues in some of the sample's weeks, UPCs that were sold by less than 11 stores and categories with less than 10 UPCs. The first exclusion is employed because zero-revenue observations may occur when the item is not on the shelf rather than being on the shelf and not being sold. The second is aimed at reliable measures of cross sectional price dispersion, and the last allows for within category comparison and economizes on the number of category dummies and size variables. After applying these exclusions I get "semi balanced" samples in which the number of stores vary across UPCs but the number and the identity of stores within a UPC cell do not vary over weeks. After implementing the exclusions, I get 1084 UPCs for the 2005 sample and 665 UPCs for the 2004 sample. I also use a sample of both years with 104 weeks. This 04-05 sample has only 324 UPCs because a store-UPC cell is included only if the cell's revenues were positive in all the 104 weeks.

The requirement that the product will be sold continuously by more than 11 stores leads to a sample of fairly popular brands. The focus on fairly popular items is

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[15] Initially, I thought of using 2 years of the Chicago market as a pilot study and then add years and cities. But the results turned out to be robust to the choice of specification and sample and the paper got too long. It therefore seems that adding years and cities should be done in a different paper.

likely to reduce the problem of close substitutes that have different UPCs.[16] In addition, the 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.[17]

The summary statistics for the 3 samples are in Table 1. These are by category for the largest 2005 sample and the averages across UPCs for the other two samples. The column after the category name is the number of UPCs. There are for example, 56 UPCs in the beer category. The third column is the average (maximum, minimum) number of stores per UPC. The average number of stores in the beer category is 21, the maximum number of stores is 35 and the minimum number of stores is 11. The next four columns provide the averages of the main variables.

The columns ln(HLU) and SDU are unit dispersion measures used as proxies for aggregate demand uncertainty. With the risk of repetition I now describe the construction of the main variables in detail. The variable HLU_i is constructed as follows. U_{it} is the aggregate amount (over all stores) of UPC i sold in week t, $H_i = \max_t\{U_{it}\}$ is the maximum weekly amount sold during the year (or during the sample period when the 04-05 sample of 2 years is used) and $L_i = \min_t\{U_{it}\}$ is the minimum weekly amount sold during the year. $HLU_i = H_i / L_i$ is the ratio between the amount sold in the highest sale week and the lowest sale week. The fourth column in Table 1 is the average of the log of this variable, $\ln(HLU)$, over the UPCs in the category. For beer the average log difference is 1.01 implying that on average the

[16] The focus on popular items is not unique to this paper. As was mentioned in the introduction, 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.

[17] To get a sense of the effect of the sample exclusion on the result I study, in Eden (October 2013), 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.

quantity sold in the highest sale week was almost 3 times the quantity sold in the lowest sale week (the average ratio is HLU = 2.73).

The variable SDU_i is the standard deviation of $\ln(U_{it})$ over weeks. (Over 52 weeks in the yearly samples and 104 weeks in the 04-05 sample). Column 5 is the average of SDU_i over the UPCs in the category. For beer the average is 0.25.

The columns ln(HLP) and SDP are price dispersion measures.
The variable HLP is constructed as follows. P_{its} is the price of UPC i in week t store s. $P_{it}^H = \max_s\{P_{its}\}$ is the highest price of UPC i in week t and $P_{it}^L = \min_s\{P_{its}\}$ is the lowest price. $HLP_{it} = P_{it}^H / P_{it}^L$ is the ratio in week t and $\ln(HLP_i) = (1/52)\sum_{t=1}^{52}\ln(HLP_{it})$, is the average of the log of this ratio over 52 weeks (over 104 weeks in the 04-05 sample). The average reported in column 6 is over all the UPCs in the category. For beer it is 0.19.

The variable SDP was constructed as follows. SDP_{it} is the standard deviation of $\ln(P_{its})$ over stores. The variable $SDP_i = (1/52)\sum_{t=1}^{52} SDP_{it}$ is the average of SDP_{it} over weeks. In column 7 we have the average of SDP_i over the UPCs in the category. For beer the average standard deviation is 0.06.

There are substantial variations in the measures of dispersion across categories. The lowest ln(HLU) is for milk (ln[HLU] = 0.78) implying that for an average UPC in the category the aggregate (over stores) amount sold in the highest sale week is 2.18 times the aggregate amount sold in the lowest sale week. The highest ln(HLU) is for hot dogs (ln[HLU] = 2.36) implying that for an average UPC in this category, the aggregate amount sold in the highest sale week is 10.6 times the aggregate amount sold in the lowest sale week. The lowest ln(HLP) is for paper towels (ln[HLP] = 0.15) implying that for an average UPC in this category the highest price in an average week is 16% higher than the lowest price. The highest ln(HLP) is for margarine (ln[HLP] = 0.49) implying that for an average UPC in this category the highest price in an average week is 63% higher than the lowest price.[18]

I also attempted to include proxies for the value of a product that was not sold. Ideally we would like to have information on the shelf life of each UPC and the storage space that it takes. In the data there is only a size measure that may serve as a proxy for “shelf space”. But the size measures are not comparable across categories. They are in terms of a fraction of a “regular pack” and the size of a “regular pack” is sometimes in units of volume (for example, rolls for toilet paper), sometimes in terms of square feet (100 square feet is the regular pack for paper towel) and sometimes in units of weights (the regular pack of beer is 288 oz). For this reason I constructed 18 “size dummy” variables. The “size dummy” for beer was constructed as follows. First I normalized the size of all the 56 UPCs in the beer category so that the largest size is 1. I then assigned the value of zero to UPCs that are not in the beer category and the normalized beer size to UPCs within the beer category. Similar treatment was applied to other categories. The column before the last in Table 1 is the average normalized size. The maximum is 1 by construction. The minimum normalized size is in parentheses. For example, the average size in the beer category is 0.46 implying that on average the size of a UPC is about half the size of the largest UPC in the category.

The last column in Table 1 is the frequency of temporary sales. I assume that a sale occurs when a drop in the price of at least 10% is followed by a price that is equal to or above the pre-sale price within 4 weeks. Similar definitions were used by Nakamura and Steinsson (2008) and by Coibion et al. (2015).[19] The frequency of sale

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[18] For the week studied in Eden (October, 2013), about 70% of the UPCs have ln(HLP) less than 0.4 (HLP less than 1.5).

[19] I also tried 3 alternative measures of sales. One alternative required that the price returns to *exactly* the pre-sale price within 4 weeks (as opposed to a price that is *above or equal* to the pre-sale price). The other 2 definitions required that the sale period will be less than 2 weeks as opposed to less than 4 weeks. The correlation of the 4 measuers of the frequency of sale and the dispersion measures are similar and I therefore report here the results for one measure only. There is also a sale tag in the IRI data. The IRI sale definition requires only 5% price reduction and therefore it labels more prices as "sale prices". The frequency of sale according to the IRI definition is 35% that is almost twice the

is defined by the percentage of the UPC-store-week cells that are labeled as sales out of the total number of UPC-store-week cells. There is a large variation in the frequency of sale across categories. The lowest frequency of sale is for beer (4%) and the highest is for hotdogs (32%).

The last 3 rows are averages across all UPCs. In the 2005 sample the average UPC is sold in 20 stores, has ln(HLU) of 1.46, SDU of 0.34, ln(HLP) of 0.35, SDP of 0.11 and the average size is 0.49. The frequency of sale for the entire 2005 sample is 20%. These averages do not vary much across samples.

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frequency that I get. The correlation between the frequency of sale according to the IRI definition and the frequency of sale according to my definition is 0.8.

Table 1*: Summary Statistics

	# UPC	# stores	ln(HLU)	SDU	ln(HLP)	SDP	Size	Freq. Sale
paper towels	19	20(31,11)	0.95	0.21	0.15	0.05	0.31(0.13)	9%
beer	56	21(35,11)	1.01	0.25	0.19	0.06	0.46(0.07)	4
facial tissue	18	18(26,11)	1.54	0.38	0.24	0.08	0.29(0.1)	17
frozen dinners/entrees	75	16(28,11)	1.61	0.36	0.32	0.1	0.62(0.41)	26
milk	64	22(34,11)	0.78	0.16	0.32	0.1	0.50(0.13)	9
mustard & ketchup	21	20(32,11)	1.59	0.36	0.33	0.1	0.32(0.13)	10
salty snacks	120	22(35,11)	1.26	0.3	0.3	0.1	0.47(0.16)	21
toilet tissue	19	21(34,11)	1.51	0.35	0.32	0.1	0.32(0.04)	24
frozen pizza	53	18(29,11)	1.49	0.32	0.36	0.11	0.52(0.18)	15
peanut butter	24	21(31,14)	1.3	0.26	0.34	0.11	0.61(0.30)	15
yogurt	152	23(35,11)	1.16	0.26	0.31	0.11	0.36(0.13)	26
carbonated beverages	144	23(35,11)	1.55	0.37	0.37	0.12	0.38(0.04)	26
mayonnaise	19	23(32,11)	1.29	0.3	0.39	0.12	0.63(0.25)	14
soup	74	19(35,11)	2.06	0.49	0.39	0.12	0.51(0.40)	13
spaghetti/Italian sauce	32	16(29,11)	1.37	0.31	0.38	0.13	0.55(0.29)	18
cold cereal	133	21(34,11)	2.03	0.49	0.45	0.15	0.59(0.21)	19
margarine/butter	40	25(35,11)	1.22	0.27	0.49	0.15	0.37(0.17)	27
hotdog	21	20(34,11)	2.36	0.56	0.43	0.16	0.96(0.75)	32
	Total	Av.	Av.	Av.	Av.	Av.	Av.	Av.
2005	665	20	1.46	0.34	0.35	0.11	0.49	20
2004	1084	15	1.61	0.38	0.38	0.13	0.50	20
04-05	324	15	1.62	0.35	0.37	0.13	0.45	21

* The statistics about individual categories use the 2005 sample. The first column is the category name. The second is the number of UPCs in the category. The third is the average number of stores per UPC in the category (maximum and minimum in parentheses). The next two columns are measures of demand uncertainty and the following two columns are measures of price dispersion. The last two columns are the average (minimum) normalized size and the frequency of temporary sales. The last three rows are averages for the three samples (2005, 2004 and 2004-05).

The correlations between the main variables in the 3 samples are in Table 2. The correaltions between the price dispersion measures (ln[HLP]&SDP) and between the unit dispersion measures (ln[HLU]&SDU) are both very high (in the range 0.95-0.97). The correlation between the price dispersion measures and the unit dispersion measures (HLU&HLP, SDU&HLP, HLU&SDP, SDU&SDP) are in the 0.43-0.60 range. The correlation between the unit and price dispersion measures and the frequency of temporary sale measure is in the range 0.36-0.56.

Table 2*: Correlation between the main variables

2004	lnHLU	SDU	lnHLP	SDP	Freq. Sale
lnHLU	1.00				
SDU	0.96	1.00			
lnHLP	0.56	0.59	1.00		
SDP	0.57	0.60	0.97	1.00	
Freq. Sale	0.44	0.50	0.51	0.53	1.00
# of UPCs = 665					
2005	lnHLU	SDU	lnHLP	SDP	Freq. Sale
lnHLU	1.00				
SDU	0.96	1.00			
lnHLP	0.43	0.45	1.00		
SDP	0.48	0.50	0.96	1.00	
Freq. Sale	0.42	0.43	0.46	0.50	1.00
# of UPCs = 1084					
04-05	lnHLU	SDU	lnHLP	SDP	Freq.Sale
lnHLU	1.00				
SDU	0.97	1.00			
lnHLP	0.47	0.51	1.00		
SDP	0.50	0.53	0.97	1.00	
Freq.Sale	0.36	0.39	0.54	0.56	1.00
# of UPCs = 324					

* This Table contains 3 correlation matrices followed by the number of UPCs. The first matrix is for the 2004 sample with 665 UPCs, the second is for the 2005 sample with 1084 UPCs and the last is for the 04-05 sample with 324 UPCs. The variables are the log difference between the highest and lowest weekly aggregate sales ln(HLU), the standard deviation of the log of aggregate sales (SDU), the average log difference between the highest and the lowest price ln(HLP), the average cross sectional standard deviation of log prices (SDP) and the frequency of temporary sales. See the text for detailed definitions.

5. ESTIMATION

As described in the data section, I use two measures of dispersion: The range measure and the standard deviation measure. Here I report the results when using the range measures. The regressions that use the standard deviation measures are reported in Appendix D.

I start with running price dispersion on unit dispersion for categories with more than 50 UPCs and for the samples as a whole. Thus, I run (16) for each category separately without the category and size dummies. As can be seen from Table 3, 8 out of the 9 coefficients of ln(HLU) in the 2005 sample are positive and 6 out of the 8 are significant. In the 2004 sample, 3 out of the 4 coefficients are significant and positive. In the 04-05 sample, all 3 coefficients are positive and 2 are significant. The last row for each year is the regression that uses all observations (without dummies). The coefficients when using all variables is highly significant and in the range of 0.088-0.106.

I also ran the regressions in Table 3 with the following additional explanatory variables: ln(revenues), the number of stores, ln(average price) and the size variable. To economize on space these regressions are not reported here but similar regressions that use the standard deviations measures of dispersion are in Table D2 in Appendix D. In the regressions that are not reported here, the coefficient of ln(HLU) is positive for all the 9 categories in the 2005 sample, all the 4 categories in the 2004 sample and for 2 out of the 3 categories in the 04-05 sample. The coefficient of ln(HLU) is significant and positive in 12 out of the 16 regressions and the single negative coefficient is not significant. On the whole, the category regressions, provide strong support for a positive ln(HLU) coefficient, a somewhat weaker support for a negative average price coefficient and even weaker support for a positive revenues and number of stores coefficients. The results with respect to the size variables are mixed.

Table 3*: Running ln(HLP) on ln(HLU) for selected categories.

2005 sample	Intercept	ln(HLU)	#UPC	Adj R^2
beer	0.165***	0.023	56	0.005
carbbev	0.308***	0.040**	144	0.049
coldcer	0.190***	0.127***	133	0.321
fzdinent	0.217***	0.063*	75	0.044
fzpizza	0.247***	0.074**	53	0.141
milk	0.343***	-0.024	64	-0.012
saltsnck	0.059*	0.194***	120	0.454
soup	0.311***	0.040*	74	0.059
yogurt	0.283***	0.027	152	0.001
All	0.209***	0.095***	1084	0.185
2004 sample	Intercept	ln(HLU)	#UPC	Adj R^2
carbbev	0.411***	-0.005	86	-0.011
coldcer	0.151***	0.149***	93	0.561
saltsnck	0.107***	0.138***	94	0.457
yogurt	0.229***	0.068*	92	0.060
All	0.207***	0.106***	665	0.318
04-05 sample	Intercept	HLRU	#UPC	Adj R^2
carbbev	0.348***	0.030*	58	0.058
coldcer	0.164***	0.147***	53	0.601
yogurt	0.385***	0.002	65	-0.016
All	0.276***	0.088***	324	0.230

* One star (*) denotes p-value of 5%, two stars (**) denote p-value of 1% and three stars (***) denote p-value of 0.1%. The first 10 rows are the results when using the 2005 sample. The following 5 rows are the results when using the 2004 sample and the last 4 rows are the results when using the 04-05 sample.

Table 4 uses all observations. It reports the results of running the price dispersion measure ln(HLP) on category dummies, “size dummies” and various combinations of the following main variables: The unit range dispersion measure ln(HLU), revenues, the number of stores and the average price. Only the coefficients of the main variables are reported. The first column reports the results of running (16) and the following columns are the results when adding the variables in (16').

The first 5 rows in the Table describe the regression results when using the 1084 observations in the 2005 sample. The regression reported in Column 1 uses only the unit dispersion measures ln(HLU), intercept, category dummies and size variables. The reported coefficient 0.082 is highly significant. This coefficient is somewhat lower than the coefficient I get when running this regression without the category dummies and the size variables (0.095 - reported in the row labeled "all" in Table 3). The coefficient of ln(HLU) does not change much when we add other explanatory variables in columns 2-6 and it is in the range 0.078 - 0.094.

The coefficient of the average price is negative and significant. It is in the range of -0.089 to -0.55. The coefficients of revenues are positive but not always significant. The coefficients of the number of stores are positive and significant.

The next 5 rows describe the regression results when using the 665 observations in the 2004 sample. Also here the coefficients of the unit dispersion measure are highly significant and stable. The range of the estimated elasticity is 0.097-0.105 and is slightly higher than the range in the 2005 sample.

The coefficients of the average price in the 2004 sample are significant and are in the range -0.062 to -0.055. The coefficients of revenues and the number of stores are positive but not always significant.

The last five rows report the regression results when using the 04-05 sample with 104 weeks and 324 UPCs. The coefficients of the unit dispersion measure are in the range (0.078 - 0.089) that is similar to the range in the 2005 sample and slightly less than the range in the 2004 sample. The coefficients of the average price are in the range (-0.142 to -0.103) that is lower than the range in the previous two samples. The coefficients of revenues and the number of stores are positive but not always significant.

On the whole, the estimated elasticity of the price dispersion measure with respect to the unit dispersion measure is close to 0.1 and is not sensitive to adding variables to the regression.

Table 4*: The Main Explanatory Variables; Dependent variable = ln(HLP)

2005	1	2	3	4	5	6
ln(HLU)	0.082*** (0.007)	0.082*** (0.007)		0.078*** (0.006)		0.094*** (0.007)
ln(Revenues)			0.077*** (0.005)	0.074*** (0.004)	0.043*** (0.01)	0.005 (0.009)
#Stores					0.004*** (0.001)	0.009*** (0.000)
ln(Av. Price)		-.059*** (0.013)	-.089*** (0.012)	-.089*** (0.012)	-.072*** (0.013)	-.055*** (0.012)
Adj. R^2	0.3306	0.3432	0.415	0.4851	0.4228	0.5171
2004	1	2	3	4	5	6
ln(HLU)	0.104*** (0.007)	0.105*** (0.007)		0.097*** (0.007)		0.102*** (0.007)
ln(Revenues)			0.052*** (0.007)	0.036*** (0.006)	0.049*** (0.011)	0.008 (0.010)
#Stores					0.001 (0.002)	0.009*** (0.000)
ln(Av. Price)		-.055*** (0.014)	-.061*** (0.015)	-.062*** (0.013)	-.060*** (0.015)	-.056*** (0.013)
Adj. R^2	0.4905	0.5028	0.3746	0.5312	0.3737	0.5393
04-05	1	2	3	4	5	6
ln(HLU)	0.089*** (0.009)	0.083*** (0.009)		0.078*** (0.009)		0.083*** (0.009)
ln(Revenues)			0.040*** (0.007)	0.031*** (0.007)	0.034** (0.013)	0.007 (0.012)
#Stores					0.002 (0.003)	0.008* (0.003)
ln(Av. Price)		-.111*** (0.021)	-.142*** (0.023)	-.119*** (0.021)	-.139*** (0.024)	-.103*** (0.022)
Adj. R^2	0.5351	0.5721	0.4874	0.594	0.4863	0.6015

* This Table reports the results of 6 regressions in 3 different samples. The 6 regressions include different combinations of the explanatory variables in (16'). The samples are 2005, 2004 and 04-05. The first column is the name of the explanatory variables. Each column reports the coefficients of a different regression. Standard errors are in parentheses. The dependent variable in all 6 regressions is the average (over weeks) log difference between the highest and the lowest price. All 6 regressions have category dummies (17 + intercept) and 18 size variables. One star (*) denotes p-value of 5%, two stars (**) denote p-value of 1% and three stars (***) denote p-value of 0.1%. The main explanatory variable in regression 1 is the log difference between the aggregate number of units sold in the week of highest sales and the week of lowest sales (HLU). Regression 2 adds the average log of the price. Regression 3 replaces HLU with the log of total revenues. Regression 4 has both HLU and revenues. Regression 5 replaces HLU with the number of stores and regression 6 uses all the explanatory variables.

As a robustness check I ran the regressions in Table 4 after eliminating "temporary sale" observations. The results in Table 5 show that the coefficients of the ln(HLU) variable are smaller than in Table 4 but are still highly significant. These coefficients are relatively stable across specifications but not across samples.

Table 5: **Dependent variable = ln(HLP); the samples of regular prices.**

2005	1	2	3	4	5	6
ln(HLU)	0.022***	0.025***		0.027***		0.022***
	(0.005)	(0.004)		(0.004)		(0.004)
ln(Revenues)			0.060***	0.061***	-0.01	-0.003
			(0.004)	(0.004)	(0.008)	(0.008)
#Stores					0.009***	0.008***
					(0.001)	(0.001)
ln(Av. Price)		-0.080***	-0.096***	-0.103***	-0.065***	-0.073***
		(0.011)	(0.011)	(0.010)	(0.010)	(0.010)
Adj. R^2	0.205	0.241	0.352	0.378	0.411	0.428
2004	1	2	3	4	5	6
ln(HLU)	0.038***	0.040***		0.041***		0.039***
	(0.005)	(0.005)		(0.005)		(0.005)
ln(Revenues)			0.025***	0.028***	-0.004	0.007
			(0.006)	(0.006)	(0.009)	(0.009)
#Stores					0.008***	0.006***
					(0.002)	(0.002)
ln(Av. Price)		-0.067***	-0.065***	-0.072***	-0.061***	-0.069***
		(0.013)	(0.013)	(0.012)	(0.013)	(0.012)
Adj. R^2	0.356	0.383	0.344	0.406	0.36	0.414
04-05	1	2	3	4	5	6
ln(HLU)	0.042***	0.038***		0.037***		0.036***
	(0.006)	(0.006)		(0.006)		(0.006)
ln(Revenues)			0.017**	0.016**	-0.006	-0.002
			(0.007)	(0.006)	(0.010)	(0.009)
#Stores					0.007***	0.006***
					(0.002)	(0.002)
ln(Av. Price)		-0.087***	-0.111***	-0.094***	-0.093***	-0.080***
		(0.017)	(0.018)	(0.018)	(0.019)	(0.018)
Adj. R^2	0.493	0.53	0.474	0.538	0.488	0.547

*This Table is comparable to Table 4. The only difference is that observations that were labeled as "temporary sales" were removed.

Frequency of temporary sales

Equations (15) and (15') suggest that goods with more demand uncertainty will also have higher frequency of temporary sales. To test this hypothesis, I replaced the dependent variable in (16) and (17) by the frequency of sale measure. Consistent with the theory, the coefficients of the lnHLU measure of price dispersion are strongly significant and positive. These coefficients are stable over specifications but not over samples. When all the variables are in the regressions the coefficient of ln(Revenue) is not significant for the 2004 and 2005 samples and barely significant for the 2004-05 sample. This does not support the loss-leader model in Lal and Matutes (1994).[20]

[20] Chevalier, Kashyap and Rossi (2003) argue that the loss-leader model implies more temporary sales for more popular items.

Table 6*: **Dependent variable = Frequency of temporary sales**

2004 sample	**1**	**2**	**3**	**4**	**5**	**6**
lnHLU	0.073***	0.073***		0.067***		0.071***
	(0.006)	(0.006)		(0.006)		(0.006)
lnrev			0.038***	0.027***	0.033***	0.004
			(0.005)	(0.005)	(0.009)	(0.008)
NumofStores					0.001	0.006***
					(0.002)	(0.002)
lnavgprice		0.005	0.0003	-0.0005	0.001	0.004
		(0.011)	(0.012)	(0.011)	(0.012)	(0.011)
Adjusted R2	0.485	0.484	0.398	0.509	0.398	0.517
2005 sample	**1**	**2**	**3**	**4**	**5**	**6**
lnHLU	0.079***	0.079***		0.078***		0.083***
	(0.005)	(0.005)		(0.005)		(0.005)
lnrev			0.023***	0.020***	0.031***	-0.002
			(0.004)	(0.003)	(0.008)	(0.008)
NumofStores					-0.001	0.003***
					(0.001)	(0.001)
lnavgprice		0.007	-0.002	-0.002	-0.006	0.01
		(0.009)	(0.010)	(0.009)	(0.011)	(0.010)
Adjusted R2	0.505	0.505	0.416	0.521	0.416	0.525
0405 sample	**1**	**2**	**3**	**4**	**5**	**6**
lnHLU	0.055***	0.051***		0.045***		0.048***
	(0.009)	(0.008)		(0.008)		(0.008)
lnrev			0.041***	0.036***	0.035***	0.020*
			(0.007)	(0.007)	(0.011)	(0.011)
NumofStores					0.002	0.005*
					(0.003)	(0.003)
lnavgprice		-0.084***	-0.107***	-0.094***	-0.104***	-0.083***
		(0.020)	(0.020)	(0.019)	(0.021)	(0.020)
Adjusted R2	0.499	0.524	0.519	0.562	0.518	0.566

* The explanatory variables are the same as in Table 4 but the dependent variable is different. It is the average frequency of temporary sale within the UPC.

An alternative model assumes that temporary sales are the result of discrimination practices. See, Varian (1980), Guimaraes and Sheedy (2011) and Chevalier and Kashyap (2011). When stores use mixed strategy to determine the time of temporary sales as in Varian (1980), it is possible that some items will be on sale more often than others. In this case, the items that are on sale more often will also have more variability in the amount sold. This suggests that temporary sales cause both price dispersion and demand uncertainty. To investigate this possibility I include the frequency of sale (FreqSale) variable as an explanatory variable in the regression. The results in Table 4a show a significant coefficient for this variable as predicted by the discrimination hypothesis. The coefficient of the unit dispersion variable (lnHLU) is still highly significant. This finding is also consistent with the UST model. From the point of view of the UST model in section 2.1, temporary sales are an endogenous response to demand uncertainty and the total effect of unit dispersion on price dispersion (the direct effect and the indirect effect through the frequency of sales variable) is the same as in Table 4.

Table 4a: Dependent Variable = ln(HLP)

	lnHLU	lnrev	#Stores	lnavgprice	FreqSale	Adj. R2
2004	0.066***	0.006	0.004**	-0.058***	0.505***	0.622
	(0.007)	(0.009)	(0.002)	(0.012)	(0.043)	
2005	0.059***	0.006	0.007***	-0.059***	0.428***	0.575
	(0.007)	(0.009)	(0.001)	(0.011)	(0.036)	
2004-05	0.057***	-0.003	0.005*	-0.059***	0.530***	0.700
	(0.008)	(0.010)	(0.003)	(0.019)	(0.053)	

* This Table adds the frequency of sales variable to the list of explanatory variables in Table 4.

To further investigate the mixed strategy hypothesis and to address possible endogeneity problems I use the 04-05 sample with 104 weeks and compute the independent variables on the basis of the first 52 weeks and the dependent variable on the basis of the last 52 weeks. The coefficient of ln(HLU) in Table 7 are similar to the coefficients in Table 4 and 6 and support the view that demand uncertainty is UPC specific rather than the outcome of a mixed strategy.[21]

[21] I also ran a 2SLS regression using ln(HLU) that is based on the first 52 weeks as an instrument for ln(HLU) that is based on the last 52 weeks. The results did not change the coefficients of the unit dispersion measure by much suggesting that endogeneity is not a problem.

Table 7*: Dependent variables from 2005, explanatory variables from 2004

Dependent variable = ln(HLP) from 2005; explanatory variables from 2004						
ln(HLU.04)	0.102*** (0.011)	0.095*** (0.011)	0.088*** (0.011)		0.091*** (0.011)	0.063*** (0.011)
ln(Rev. 04)			0.027*** (0.008)	0.035* (0.014)	0.011 (0.013)	-0.002 (0.012)
#Stores				0.001 (0.004)	0.005 (0.003)	0.004 (0.003)
ln(AvP. 04)		-0.130*** (0.023)	-0.137*** (0.023)	-.158*** (0.026)	-.127*** (0.024)	-0.077*** (0.023)
FreqSale.04						0.463*** (0.062)
Adj. R^2	0.5112	0.557	0.5712	0.478	0.5738	0.639
Dependent variable = frequency of sale from 2005, explanatory variables from 2004						
ln(HLU.04)	0.070*** (0.010)	0.068*** (0.010)		0.061*** (0.010)		0.064*** (0.010)
ln(Rev. 04)			0.037*** (0.008)	0.029*** (0.007)	0.025** (0.012)	0.007 (0.012)
#Stores					0.004 (0.003)	0.007** (0.003)
ln(AvP. 04)		-0.052** (0.021)	-0.08*** (0.022)	-0.059*** (0.021)	-0.07*** (0.022)	-0.046** (0.021)
Adj. R^2	0.551	0.558	0.527	0.578	0.528	0.585

* This Table uses the 04-05 sample. The dependent variable is computed from the last 52 weeks in the sample (in 2005) while the explanatory variables are computed from the first 52 weeks (in 2004).

Week effect and Unit surprise measures

Seasonality may be a problem because the model assumes *iid* demand shocks. To address this problem, I used the 04-05 sample with 104 weeks and ran the units in the year 2005 on the same week units in the year 2004 and other lags. I then used the residuals from these regressions instead of the original variables.

I used U_{it-L} to denote the aggregate number of units sold from good i in week $t-L$ and ran the following regressions[22]:

(18) $$\ln(U_{it}) = a_i + b_{i52}\ln(U_{it-52}) + \varepsilon_{it}$$

(18') $$\ln(U_{it}) = a_i + b_{i52}\ln(U_{it-52}) + b_{i1}\ln(U_{it-1}) + b_{i2}\ln(U_{it-2}) + b_{i3}\ln(U_{it-3}) + \varepsilon_{it}$$

[22] I measure price dispersion by the average (over weeks) cross sectional dispersion. Therefore, running prices on a weekly dummy will change all the prices in the week by a (week specific) constant and will not change the results. I measure unit dispersion by the dispersion of the aggregate amount sold over weeks. Therefore, running units on a UPC specific weekly dummy is not possible.

Note that in (18) there is only one lag of 52 weeks designed to capture seasonality. In (18') I added the most recent 3 lags. The week effect is UPC specific because each good has its own seasonality pattern.

After running the above regressions, I look at the difference between the highest and the lowest residuals from the regression and define $HLRU_i = \varepsilon_i^H - \varepsilon_i^L$, where $\varepsilon_i^H = \max_t\{\varepsilon_{it}\}$ is the highest value of the residual in (18) and $\varepsilon_i^L = \min_t\{\varepsilon_{it}\}$ is the lowest value of the residual. I use $HLRU$ (high-low residual unit) as a range measure of demand uncertainty. The residual standard deviation measure of uncertainty, $SDRU_i$, is the standard deviation of ε_i.[23]

Table 8 replaces the unit dispersion measure in Table 7 with the residual range measure of demand uncertainty. When ln(HLP) is the dependent variable, the coefficients of HLRU are similar to the coefficients of HLU in Table 4 and are in the range of 0.08 to 0.114. The coefficients of the unit surprise measure when the frequency of temporary sales is the dependent variable are higher than in Table 6 and are now close to 0.08.

[23] When using (18') the average HLRU is 1.25 which is 33% less than the average ln(HLU) reported in Table 1 (for the sample 04-05 the average reported in Table 1 is 1.62). The average SDRU is 0.27 and is also 33% less than the average of SDU reported in Table 1 (0.35). Thus, seasonality and recent sales contribute about a third to our measures of unit dispersion.

Table 8*: Allowing for a week effect in the range measure of demand uncertainty

Dependent variable = ln(HLP.05)				
HLRU	0.114*** (0.010)	0.103*** (0.010)	0.105*** (0.010)	0.082*** (0.010)
Ln (Rev.04)		0.031*** (0.008)	0.012 (0.012)	-0.001 (0.011)
#Stores			0.006* (0.003)	0.005* (0.003)
Ln (Av. P.04)		-.128*** (0.022)	-.117*** (0.022)	-0.073*** (0.021)
FreqSale.04				0.415*** (0.059)
Adj. R^2	0.5631	0.6207	0.6245	0.677
Dependent variable = frequency of sale.05				
HLRU	0.079*** (0.009)	0.077*** (0.009)	0.073*** (0.009)	0.076*** (0.009)
Ln (Rev.04)			0.031*** (0.007)	0.008 (0.011)
#Stores				0.008*** (0.003)
Ln (Av. P.04)		-0.045** (0.020)	-0.053*** (0.020)	-0.039* (0.020)
Adj. R^2	0.582	0.588	0.612	0.62

* This Table uses the 04-05 sample. The dependent variables are based on the last 52 weeks of the sample. The explanatory variable HLRU is the residual unit dispersion measure obtained from (18'). Ln (Av. Price) and Ln (Revenues) are computed on the basis of the first 52 weeks in the sample.

Store effect

Different stores may provide different services. Unfortunately, in the UST model (and in other equilibrium price dispersion models) it is difficult to distinguish between a store that is indifferent among all prices in the equilibrium range but consistently chooses to be at the low price range to a store that is in the low price range because it provides low services.[24] A "store dummy" may therefore capture differences in services and differences in the average choice among prices that promise the same expected profits or price inertia.

[24] It is not easy to distinguish between the two possibilities even in principle. The "quality" of the store may be judged by the variety of the product it offers and more generally, by the probability of a stock-out: At the same price, a buyer prefers a store that he can find everything that is on his shopping list. But according to our model, the probability of a stock-out is higher for a low price store. We should therefore think of a store quality as attributes like location, cleanliness, average length of the line at the exit and parking availability.

To estimate an upper bound on the differences in services, I used the 04-05 sample with 324 UPCs and 104 weeks and ran 324 regressions of price logs on store dummies.

(19) $$\ln(P_{ijt}) = a_i + b_{ij}(store - dummy) + e_{ijt}$$

Here i is a UPC index, j is a store index and t indexes the week. Similar to the "week effect", the “store effect” is UPC specific. The reason is in product placement: A store can consistently place one UPC in a relatively visible location and another UPC in a place that is not easy to find.[25]

I replace the log of prices by the residuals from (19). Using notation that are similar to the “week effect” notation we have:

$e_{it}^H = \max_j(e_{ijt})$ = the highest residual for UPC i in week t

$e_{it}^L = \min_j(e_{ijt})$ = the lowest residual for UPC i in week t

The log difference of the price residuals is: $\ln(HLRP_{it}) = e_{it}^H - e_{it}^L$. The variable $\ln(HLRP_i)$ is the average of $\ln(HLRP_{it})$ over 104 weeks. Table 9 provides summary statistics. The column ln(HLRP) is the average of $\ln(HLRP_i)$ over all the UPCs in the category. The average log difference, reported in the last row of Table 9 is 0.31. This is 6 percentage points less than the average log difference when not controlling for a store effect reported in the last row of the column ln(HLP). The last column in Table 9, labeled “SDRP” is the average of $SDPR_i$ over all the UPCs in the category. The average standard deviation over all UPCs is 0.11 (in the last row of the last column). This is 2 percentage points less than the average standard deviation when not controlling for store effect (SDP).

[25] Kaplan and Menzio (2015) find that about 10% of price dispersion are attributed to "store effect". They distinguish between “store effect” and “store specific good effect”. The first is a measure of the average price of the basket of goods sold by the store relative to the average price of the same basket in other stores. The second is the average price of the specific good relative to the average price of other products sold by the store.

The upper bound on the amount of price dispersion caused by difference in services is thus 16% (= 6/37) if we use the range measure and 15% (= 2/13) if we use the standard deviation measure.

Table 10 is a correlation matrix that repeats the correlations in Table 2 for the 04-05 sample and adds the correlations with the new price dispersion measures that control for “store effects”. The correlation between the “old” measure ln(HLP) and the “new” measure ln(HLRP) is about 0.9. The correlation between the “new” measures ln(HLRP) and SDRP is 0.98 and is similar to the correlation between the “old” measures. What is striking is that the correlation between the unit dispersion measures and the “new” price dispersion measures is higher than the correlation between the unit dispersion measures and the “old” dispersion measures. For example, the correlation between SDU and SDP is 0.53 and this is less than the correlation between SDU and SDRP that is 0.62. This suggests that the “store effect” dummy captures some differences in services and not merely price inertia.

Table 11 is comparable to the last rows in Table 3. It reports the results of running ln(HLRP) on ln(HLU). The coefficients of ln(HLU) are now higher than before. Table 12 is comparable to the last rows in Table 4. The coefficients of ln(HLU) are now larger and the coefficient of ln(avgPrice) are smaller (higher in absolute value).

Table 9: Summary statistics for the 04-05 sample with and without fixed "store effect"

	#UPC	ln(HLU)	SDU	ln(HLP)	SDP	ln(HLRP)	SDRP
beer	20	1.27	0.27	0.18	0.06	0.13	0.04
carbbev	58	1.80	0.39	0.39	0.13	0.34	0.12
coldcer	53	2.31	0.51	0.45	0.17	0.40	0.14
fzpizza	12	1.66	0.32	0.40	0.14	0.30	0.10
margbutr	18	1.53	0.32	0.53	0.19	0.41	0.14
milk	23	0.85	0.17	0.36	0.12	0.25	0.08
peanbutr	11	1.44	0.28	0.35	0.12	0.24	0.08
saltsnck	42	1.50	0.32	0.31	0.11	0.29	0.10
soup	22	1.99	0.43	0.40	0.13	0.29	0.09
yogurt	65	1.29	0.27	0.35	0.13	0.32	0.11
Total	324						
average		1.62	0.35	0.37	0.13	0.31	0.11

* The first column is the category name. The second is the number of UPCs in the category. The next two columns are measure of demand uncertainty and the following two columns are measures of price dispersion that are comparable to the measures in Table 1 for the 04-05 sample. The last two columns are measures of price dispersion that control for a "store effect". The last row is the average across all the 324 UPCs.

Table 10*: Correlations between unit dispersion measures, "old" price dispersion measures and "new" price dispersion measures

	lnHLU	SDU	lnHLP	SDP	lnHLRP	SDRP
lnHLU	1					
SDU	0.97	1				
lnHLP	0.47	0.51	1			
SDP	0.5	0.53	0.97	1		
lnHLRP	0.55	0.6	0.91	0.9	1	
SDRP	0.58	0.62	0.87	0.9	0.98	1

* This correlation matrix uses the 04-05 sample with 324 UPCs. The "new" price dispersion measures (lnHLRP and SDRP) use the residuals from the regression of price log on store dummies. The "old" price dispersion measures (lnHLP and SDP) use price logs and do not control for store effects. The unit dispersion measures (lnHLU and SDU) are based on aggregate amounts sold.

Table 11*: Running ln(HLRP) on ln(HLU)

I	Intercept	lnHLU	#UPC	Adj. R^2
carbbev	0.266***	0.044**	58	0.144
coldcer	0.087	0.134***	53	0.472
yogurt	0.242***	0.060*	65	0.077
All	0.161***	0.095***	324	0.306

* Comparable to the last rows in Table 3.

Table 12*: Running ln(HLRP) on ln(HLU) and other variables.

	1	2	3	4	5	6
lnHLU	0.103*** (0.010)	0.097*** (0.009)		0.091*** (0.009)		0.096*** (0.009)
ln(Rev)			0.046*** (0.009)	0.035*** (0.008)	0.040** (0.013)	0.008 (0.012)
#Stores					0.002 (0.003)	0.009** (0.003)
ln(avgPrice)		-0.133*** (0.022)	-0.169*** (0.024)	-0.142*** (0.021)	-0.165*** (0.025)	-0.123*** (0.022)
Adj. R^2	0.497	0.550	0.437	0.580	0.436	0.590

* Comparable to the last rows in Table 4.

7. QUANTITATIVE IMPORTANCE

The coefficients of the measures of demand uncertainty are statistically significant and relatively stable across specifications and samples. To get a sense of their economic significance I ask what will be the average price dispersion in a hypothetical world in which there is no demand uncertainty and the aggregate amount sold per week is perfectly predictable. Here I assume that the services provided are the same across stores. In Appendix E, I consider the case in which services varies across stores.

I estimate the effect of eliminating demand uncertainty for an "average" UPC: A UPC with the average unit dispersion and the average price dispersion measures.

Table 13 focuses on the range measures. The name of the sample used is in the first column. The second column (C1) is the coefficient of ln(HLU) in the regression of ln(HLP) on ln(HLU) and other variables (taken from Table 4).[26] This coefficient is 0.094 for the 2005 sample, 0.102 for the 2004 sample and 0.083 for the 04-05 sample. The third column is the average of the log of the high to low price ratio, lnHLP, in the sample (in the last rows of Table 1). These are 0.35, 0.38 and 0.37. (The average ratios HLP are 1.4, 1.46 and 1.45). The forth column ln(HLPH) is the hypothetical log

[26] The total (direct and indirect) effect of demand uncertainty on price dispersion is the coefficient of lnHLU in the regressions in Table 4 that exclude the frequency of sales variables.

difference computed as: ln(HLPH) = ln(HLP) - C1*ln(HLU), where HLU is the average in the sample (in the last rows of Table 1). For example, in 2005 the average ln(HLU) is 1.46 and the hypothetical log difference is: 0.35-0.094*1.46 = 0.21. The hypothetical log differences are 0.21, 0.21 and 0.24. (The hypothetical ratios, HLPH, are 1.23, 1.23 and 1.27). The fifth and the sixth columns are the estimated percentage reduction in price dispersion that will follow the elimination of demand uncertainty. The fifth column uses the logs while the sixth column uses the actual ratio (the anti-logs). As we can see from the last column, the percentage reduction is between 41 and 48 percent.

The calculations in Table 13 assume that temporary sales are endogenous and will not exist in a hypothetical world in which there is no demand uncertainty. An alternative assumption is that temporary sales are used as a discrimination device and eliminating demand uncertainty will not affect the frequency of temporary sales. To calculate the importance of demand uncertainty under the alternative assumption, I used for C1 the coefficient of ln(HLU) from Table 4a in which the frequency of sale is in the list of explanatory variables. These coefficients are 0.059 for the 2005 sample, 0.066 for the 2004 sample and 0.057 for the 2004-05 sample. The estimated percentage reduction in price dispersion that will follow the elimination of demand uncertainty under the alternative hypothesis is in the range of 0.28 to 0.32. Thus, even when temporary sales are not related to demand uncertainty, the effect of removing demand uncertainty on price dispersion is not small.

Table 14 focuses on the standard deviation measure of dispersion. The second column is the coefficient (C2) of SDU in a regression of SDP on SDU and other variables. The third column is the average SDP in the sample. The forth column is the hypothetical SDP calculated as: SDPH = SDP - C2*SDU, where SDU is the average in the sample. The last column is the estimated effect of demand uncertainty on price dispersion. The elimination of demand uncertainty will reduce the standard deviation by 39-44 percent.

Tables 15 and 16 repeat the hypothetical experiment after controlling for "store effect". In this case, eliminating demand uncertainty will reduce price dispersion by 54 percent.

Table 13*: The hypothetical range measure

Sample	C1	$\ln HLP$	$\ln HLPH$	$\frac{\ln HLP - \ln HLPH}{\ln HLP}$	$\frac{HLP - HLPH}{HLP - 1}$
2005	0.094 (0.087,0.101)	0.35	0.21 (0.20,0.23)	0.39 (0.37,0.42)	0.44 (0.41,0.47)
2004	0.102 (0.095,0.109)	0.38	0.21 (0.20,0.23)	0.43 (0.40,0.46)	0.48 (0.45,0.51)
04-05	0.083 (0.074,0.092)	0.37	0.24 (0.22,0.25)	0.36 (0.32,0.40)	0.41 (0.37,0.45)

*The first column is the sample used. The second is the coefficient of ln(HLU) taken from Table 4. In parenthesis are the lower and upper bounds of the estimated coefficients. Thus for example, in 2005 the estimated coefficient is 0.094 and the standard error is 0.007. The lower bound of the coefficient is 0.094-0.007 = 0.087 and the upper bound is 0.094+0.007 = 0.101. The third column is the average lnHLP in the data. The fourth is the hypothetical lnHLP calculated as:
Ln(HLPH)=ln(HLP) - C1*Ln(HLU), where Ln(HLU) is the average of the log HLU in the data. In parenthesis are the calculation when using the lower and upper bound of C1. The fifth and sixth columns is the percentage decline in price dispersion. The fifth is the ratio of the log difference (lnHLP-lnHLPH) to lnHLP and the last column is the ratio of the percentage difference HLP-HLPH to HLP-1. In parentheses are the computation when using the lower and upper bounds of C1.

Table 14*: The hypothetical standard deviation measure

Sample	C2	SDP	$SDPH$	$\frac{SDP - SDPH}{SDP}$
2005	0.147 (0.139,0.155)	0.11	0.063 (0.061,0.066)	0.44 (0.41,0.46)
2004	0.152 (0.143,161)	0.13	0.077 (0.073,0.080)	0.43 (0.40,0.46)
04-05	0.145 (0.133,0.157)	0.13	0.079 (0.075,0.083)	0.39 (0.36,42)

* The second column is the coefficient of SDU taken from Table D1 (upper and lower bounds in parenthesis). The third is the average SDP in the data. The fourth is the hypothetical SDP calculated as: SDPH = SDP - C2*SDU. The last column is the ratio of the difference SDP-SDPH to SDP.

Table 15*: Hypothetical range measure after controlling for "store effects"

Sample	C1	ln(HLRP)	ln(HLRPH)	$\frac{\ln HLRP - \ln HLRPH}{\ln HLRP}$	$\frac{HLRP - HLRPH}{HLRP - 1}$
04-05	0.096 (0.087,0.105)	0.31	0.15 (0.14,0.17)	0.5 (0.45,0.55)	0.54 (0.49,0.59)

* The Table reports the hypothetical experiment results after controlling for "store effect". The coefficient of ln(HLU) is from Table 12 (lower and upper bounds in parenthesis), the ratio of the residual ln(HLRP) is 0.31 (Table 10), the hypothetical ratio is Ln(HLRPH) = ln(HLRP)-(C1)ln(HLU) = 0.31-(0.096)(1.62)= 0.15 and the percentage reduction in the dispersion measures due to the elimination of unit dispersion are 0.5 and 0.54.

Table 16*: Hypothetical st. deviation measure after controlling for "store effects"

Sample	C2	SDRP	SDRPH	$\frac{SDRP - SDRPH}{SDRP}$
04-05	0.169 (0.157,0.181)	0.11	0.051 (0.047,0.055)	0.54 (0.50,0.58)

* The second column is the coefficient of SDU taken from Table D7 in Appendix D. The third column is the standard deviation of the residuals taken from Table 10. The fourth column is the hypothetical standard deviation calculated as SDRPH = SDRP - (C2)SDU = 0.051 where SDU = 0.35 is from Table 10. The last column is the percentage reduction in the standard deviation that will follow the elimination of demand uncertainty.

Using the results in Appendix E that allows for differences in services across stores, the above estimates are lower bounds. We may thus say that eliminating demand uncertainty will reduce the standard deviation measure of "true" price dispersion by more than 54 percent. This is a big effect.

Table 17 calculates the hypothetical frequencies of temporary sales. Using the 2005 sample, the average frequency of sale is: FS = 0.20. Average ln(HLU) = 1.46. The coefficient of ln(HLU) when running FS on lnHLU and other variables is 0.08 (Table 6). In a hypothetical world with no demand uncertainty, the frequency of sales will be: FSH = FS - 0.08* ln(HLU) = 0.2 - 0.08*1.46 = 0.083

This suggest that the elimination of demand uncertainty will reduce the frequency of sales by more than half: (FS-FSH)/FS = (0.2 - 0.083)/0.2 = 0.59. For the 2004 sample FSH is 0.087 and for the 2004-05 sample it is 0.13. The last column is the estimated effect of demand uncertainty on the frequency of sales. The elimination of demand uncertainty will reduce the frequency of sales by 38-59 percent.

Table 18 uses the standard deviation measure of unit dispersion to repeat the calculations in Table 17. The average SDU for the 2005 sample is 0.34. The coefficient of SDU when running the frequency of sales on SDU and other variables is 0.38 (Table D4 in Appendix D). The hypothetical frequency of sale is: FSH = FS - 0.38*0.35 = 0.07. For the 2004 sample it is 0.08 and for the 2004-05 sample it is 0.13. The quantitative effect is large. The elimination of demand uncertainty will reduce the frequency of sales by 40 to 65 percent.

Table 17*: Hypothetical Frequencies of Temporary Sales (range measure)

Sample	FS	Average lnHLU	Coef of ln(HLU)	FSH	$\frac{FS-FSH}{FS}$
2005	0.2	1.46	0.08	0.083	0.59
2004	0.2	1.61	0.07	0.087	0.57
04-05	0.21	1.62	0.05	0.13	0.38

* The first column is the sample. The second is the frequency of temporary sales. The third is the average ln(HLU) in the sample. The fourth is the coefficient of ln(HLU) from Table 6. The fifth column is the hypothetical frequency of sales computed as: FSH = FS - (coef)(Average lnHLU). The last column is the percentage reduction in the frequency of sales.

Table 18*: Hypothetical Frequencies of Temporary Sales (st. deviation measure)

Sample	FS	Average SDU	Coef of SDU	FSH	$\frac{FS-FSH}{FS}$
2005	0.2	0.34	0.38	0.07	0.65
2004	0.2	0.38	0.32	0.08	0.61
04-05	0.21	0.35	0.24	0.13	0.40

*This Table uses the standard deviation measure of unit dispersion to repeat the calculations in Table 17. The coefficient of SDU is from Table D4 in Appendix D. The hypothetical frequency is: FSH = FS - (coef)(Average SDU).

8. CONCLUDING REMARKS

In the UST model and other versions of the Prescott (1975) model, price dispersion arises as a result of uncertainty about aggregate demand and temporary sales emerge rather naturally when items have expiration dates ("one-hoss-shay" depreciation). We may observe that newly produced units are offered at a relatively high "regular" price. When demand is low, inventories are accumulated and the store posts a relatively low "sale" price until inventories are back to normal.

An item with perfectly predictable demand will be sold in a standard (single) Walrasian market in which sellers always sell their entire supply at the market-clearing price. An item with unpredictable demand will be sold at many prices and "unwanted" inventories will accumulate whenever demand is not at its highest possible realizations. These inventories trigger temporary sales. This suggests that items with less predictable demand will have more price dispersion and more temporary sales. I have verified this conjecture for two special cases.

Following the model, I assume that the distribution of demand varies exogenously across UPCs. Under this assumption, and consistent with the theory, I find that price dispersion is increasing in measures of unit dispersion. To check for robustness, I include in the regressions three variables suggested by search and discrimination theories: The number of stores that sell the good, total revenues from selling the good and the average price of the good. The inclusion of the additional variables does not change the unit dispersion coefficient by much. Out of the additional variables used, the average price is the only one with a stable and significant effect. As in Pratt et. al. (1979), items with higher average price have less price dispersion.

The effect of unit dispersion on the frequency of temporary sales is also highly significant. Also here the inclusion of the additional variables does not change the coefficient of the unit dispersion by much. Out of the additional variables the number of stores that sell the good has a significant positive effect.

The effect of unit dispersion measures on price dispersion and the frequency of sales has economic significance in addition to the statistical significance. Our estimates suggest that eliminating demand uncertainty will on average, reduce the cross sectional standard deviation of the price log and the frequency of temporary sales by more than 40%.

There are alternative explanations for the findings in this paper. One possible explanation assumes that temporary sales are not related to demand uncertainty.[27] It is possible, for example, that temporary sales are discrimination devices that are used more in some goods and less in other goods. Following this theory, I ran price dispersion on unit dispersion and the frequency of temporary sales. The introduction of the frequency of sales variable reduces the size of the unit dispersion coefficient but the coefficient is still highly significant and quantitatively important: Eliminating demand uncertainty will reduce the range measure of price dispersion by about 30% even when temporary sales do not depend on demand uncertainty.[28]

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[27] Some may also argue that causation may be in the opposite direction: differences in price dispersion cause differences in unit dispersions. It seems that this reaction fails to distinguish between variations over weeks and variations over stores within a week. For example, it is reasonable to assume that there are large fluctuations in the cost of supplying fresh fruits and vegetables over weeks and these cost shocks lead to large variations in the average weekly price and the quantity sold. I do not have items like fresh fruits and vegetables in the data. More importantly, I measure price dispersion over stores in an average week while this explanation refers to the dispersion of the average price over weeks.

[28] Since this calculation assumes no differences in services, the estimated effect may be a lower bound. See Appendix E.

APPENDIX A: COST SHOCKS AND THE STANDARD DEVIATION MEASURES

In this Appendix I derive the relationship between the range measures of dispersion when there are cost shocks and between the standard deviation measures of dispersion.

Cost shocks

I assume that at the time the seller makes the production decisions in week t, he knows the unit cost for this period, λ_t, and the distribution of the unit cost next period. The next period's cost is a random variable, $\tilde{\lambda}_{t+1}$, and its expected value is denoted by: $\lambda^e_{t+1} = E(\tilde{\lambda}_{t+1})$. Since a unit of inventories can be used to cut next period's production, the value of inventories is the expected discounted cost in the next period, $\beta\lambda^e_{t+1}$. We can therefore modify the arbitrage condition (1) as follows.

(A1) $$q_i P_{it} + (1-q_i)\beta\lambda^e_{t+1} = \lambda_t$$

Using $\psi_t = \dfrac{\lambda^e_{t+1}}{\lambda_t}$, we can write (A1) as:

(A2) $$P_{it} = \beta\psi_t\lambda_t + (1-\beta\psi_t)\frac{\lambda_t}{q_i}$$

which leads to:

(A3) $$\frac{P^H_{it}}{P^L_{it}} = \beta\psi_t + (1-\beta\psi_t)Z$$

Taking the average of (A3) over weeks leads to a relationship that is similar to (8). Consistent with this reasoning, I estimate HLP by the average ratio of the highest to lowest price over weeks.

The standard deviation measures

To derive a relationship between the standard deviation measures of dispersion, I assume that each buyer demands one unit and the number of buyers is uniformly distributed so that $\Delta_s = x$ for all $s = 1,...,Z$. The fraction of stores that post the price P_s is the same for all s and is given by $\pi = \frac{x}{Zx} = \frac{1}{Z}$. The probability of making a sale at the price P_s is: $q_s = 1 - \frac{s-1}{Z} = 1-(s-1)\pi$. Substituting in (3) and rearranging leads to:

(A4)
$$\frac{P_s - \beta\lambda}{1-\beta} = \frac{\lambda}{q_s} = \frac{\lambda}{1-(s-1)\pi} = \frac{\lambda Z}{Z+1-s}$$

Under the assumption that for the same good λ, β and Z do not change over weeks, we get:

(A5)
$$Var\left(\ln(P_s - \beta\lambda)\right) = Var\left(\ln(Z+1-s)\right) = Var(\ln s)$$
$$= \tfrac{1}{12}(Z-1)^2 = \tfrac{1}{12}(HLU-1)^2$$

The number of units sold in state s is: sx. Since x is a constant, the variance of the log of units is $Var(\ln s)$ and is equal to (A5). Thus in this example there is a correlation between the standard deviation dispersion measures. The correlation is perfect when storage is not possible and $\beta = 0$.

APPENDIX B: A UST MODEL WITH NON-SHOPPERS

Salop and Stiglitz (1977), Shilony (1977) and Varian (1980) introduced the important distinction between shoppers and non-shoppers. In the standard UST model all buyers are shoppers. Here I outline a UST model that allows for the distinction between shoppers and non-shoppers under the assumption of no storage possibilities ($\beta = 0$).

Buyers arrive in batches. In batch i there are $\phi\Delta_i$ shoppers and $(1-\phi)\Delta_i$ non-shoppers. They all see posted prices but non-shoppers may not choose the cheapest available offer because the location of the cheapest store may not be convenient.

A non-shopper buys in the store of his choice $D(P)$ units at the store's price P if the store is not stocked out. If the store is stocked-out he goes home empty handed. (He may consume out of storage or buy a close substitute, but this is not modeled here). I assume that the fraction of the non-shoppers that go to market i (choose a store with the price P_i) is γ_i where $\sum_i \gamma_i = 1$.

Shoppers see availability in addition to posted prices. They go to the cheapest store out of all the stores that are not stocked-out. In a more realistic model getting the best possible deal requires some search: The shoppers will typically visit more than one store while non-shoppers visit a single store.

The store chooses the stock-out state. It can choose to stock out only when demand is at its highest possible realization (state Z). It can also choose to stock out at state $s < Z$ with a higher probability. A store that stock out sells its entire supply and therefore a high stock out probability is a benefit. To stock out with high probability the store must post a low price and the tradeoff is therefore between the stock out probability and the price. This is different from the tradeoff we had before (between the probability of making a sale and the price) because now the store will always sell part of its supply to non-shoppers.

I assume one store per market. The store in market i stocks-out when $s>i$. The amount it sells (at the price P_i) to the non-shoppers is:

(B1) $$\gamma_i(1-\phi)N_s D(P_i) \text{ if } s<i \text{ and } \gamma_i(1-\phi)N_i D(P_i) \text{ if } s \geq i$$

The amount it sells to shoppers is:

(B2) $$\phi\Delta_i D(P_i) \text{ if } s \geq i \text{ and zero otherwise.}$$

Since the store in market i is stocked out in state i, the supply to market i is:

(B3) $$CAP_i = \left(\phi\Delta_i + \gamma_i(1-\phi)N_i\right)D(P_i)$$

The expected profits in market i is:

(B4) $$V_i = P_i D(P_i)\left\{q_i\left(\phi\Delta_i + \gamma_i(1-\phi)N_i\right) + \gamma_i(1-\phi)\sum\nolimits_{s<i}\pi_s N_s\right\} - \lambda(CAP_i)$$

Equilibrium is a non-negative vector $(P_1,...,P_Z;V_1,...,V_Z,V)$ that satisfies $V_i = V$ for all i and $P_1 < ... < P_Z$.

Note that the standard UST model is a special case of this equilibrium in which $\phi=1$, $CAP_i = \Delta_i D(P_i)$ and $V_i = (q_i P_i - \lambda)\Delta_i D(P_i) = 0$. In this case $q_i P_i = \lambda$ and the expected revenue is the same across markets.

As in the standard UST model if there is no aggregate demand uncertainty there is no price dispersion. To get the linear relationship (7) I assume that each buyer has a high reservation price and demand one unit. I assume further that the number of buyers is uniformly distributed and $\Delta_i = \Delta$ for all i. Under these assumptions: $L=\Delta$, $H=Z\Delta$ and $HLU = \frac{H}{L} = Z$, which is a special case of (2) that leads to (7).

APPENDIX C: A MODEL OF TEMPORARY SALES

I start with a formal treatment of the case in which demand can take two possible realizations as in Figure 1. Here, state 1 is the state in which there are inventories and state 2 is the no inventories state. The superscript is used for the state and the subscript for the market. Thus for example, P_1^1 is the first market price in state 1 and P_1^2 is the first market price in state 2.

Equilibrium is a vector
$(P_1^1, P_1^2, P_2, P_2^1, P_2^2, x_1^1, x_1^2, x_2, x_2^1, x_2^2, x_1^{1,old}, x_2^{1,old}, x_1^{1,young}, x_2^{1,young}, I^1, I^2)$
of non-negative magnitudes that satisfies:

(C1) $P_2 = P_2^1 = P_2^2$, $P_1^2 = \lambda$, $x_2 = x_2^1 = x_2^2$

(C2) $x_1^1 = x_1^{1,old} + x_1^{1,young}$, $x_2^1 = x_2^{1,old} + x_2^{1,young}$

(C3) $x_1^{1,old} + x_2^{1,old} = I^1 = \Delta D(P_2)$, $I^2 = 0$

(C4) $x_1^{1,old} = \min\left\{x_1^1, I^1\right\}$

(C5) $P_1^1 \geq qP_2$ with equality if $x_2^{1,old} > 0$

(C6) $P_1^1 \leq \lambda$ with equality if $x_1^{1,young} > 0$

(C7) $qP_2 + (1-q)\beta P_1^1 = \lambda$

(C8) $x_1^1 = ND(P_1^1)$

(C9) $x_1^2 = N_1 D(P_1^2)$

(C10) $x_2 = \Delta D(P_2)$

Equations (C1)-(C3) are definitional. Equation (C1) says that the amount supplied to the second market and its price, do not depend on the state. Equation (C2) says that the supply to each of the two markets in state 1 is the sum of old units and newly produced units. Equation (C3) is the level of the beginning of period inventories. When demand in the previous period was low the entire supply to the second market was carried as inventories and the beginning of period inventories is $\Delta D(P_2)$. When the demand in the previous period was high everything was sold and the beginning of period inventories is zero.

Condition (C4) says that "old units" are supplied to the first market first. They are supplied to the second market only if the level of inventories is larger than the demand in the first market. Condition (C5) says that the price in the first market must equal the cost of production when there are no inventories but maybe below cost when the level of inventories is high. I require $P_1^1 \geq qP_2$ and therefore supplying goods out of storage to the first market ($x_1^{1,old} > 0$) is optimal. When goods are supplied to both markets and $x_2^{1,old} > 0$, the price in the first market must equal the expected price in the second market $(P_1^1 = qP_2)$ because otherwise it is optimal to move "old units" from the second to the first market. Condition (C6) requires that the price in the first market is less than λ and is equal to λ when new units are supplied to this market. Equation (C7) assumes that some newly produced goods are supplied to the second market and that the value of newly produced goods that are not sold is βP_1^1 , where β is a discount factor $(0 < \beta < 1)$. The left hand side of (C7) is the expected revenues from supplying a newly produced unit to the second market. With probability q the second market opens and the seller gets P_2. With probability $1-q$ the second market does not open and the unit will be sold in the next period's first market at the price P_1^1 . The right hand side of (C7) is the cost of production and therefore (B6) says that the expected discounted revenue must equal the cost of production.

Extension to the case in which demand can take many possible realizations

I now consider the case in which $\tilde{N}$ has Z possible realizations. The equilibrium magnitudes depend on the beginning of period inventories I. I assume that in equilibrium there is a positive level of production and old units are allocated to lower index markets first. Therefore some young units are supplied to the last market. I expect that this assumption can be derived as a result in a more complete treatment.

I define equilibrium as follows.

Equilibrium is a vector of functions
$\left(P_1(I),...,P_Z(I);x_1(I),...,x_Z(I),x_1^{old}(I),...,x_Z^{old}(I);x_1^{young}(I),...,x_Z^{young}(I)\right)$

that satisfies the following conditions:

(C11) $x_i(I)=x_i^{old}(I)+x_i^{young}(I)$

(C12) $\sum_i x_i^{old}(I)=I$

(C13) $x_i^{old}(I)=\min\left\{x_i(I),I-\sum_{s\leq i}x_s^{old}(I)\right\}$

(C14) $q_iP_i(I)\leq q_{i-1}P_{i-1}(I)$ with equality if $x_i^{old}(I)>0$ and $x_{i-1}^{old}(I)>0$

(C15) $q_iP_i(I)+\beta\sum_{s<i}\pi_sP_1\left(\sum_{j>s}x_j(I)\right)\leq\lambda$ with equality if $x_i^{young}(I)>0$

(C 16) $q_iP_i(I)=P_1(I)$ if $x_i^{young}(I)=0$

(C17) $x_i(I)=\Delta_iD\left(P_i(I)\right)$

for all I and i.

Condition (C11) says that total supply to each market is the sum of the supply of old units and newly produced units. Condition (C12) says that the supply of old units across markets must equal the beginning of period level of inventories. Condition (C13) says that inventories are allocated to lower index markets in a sequential manner. They are allocated to the first market, first. Then if there is no sufficient demand in the first market to absorb all inventories, the remaining old units are allocated to the second market and so on. Condition (C14) ensures that old units are allocated according to (C13). It says that the expected price must decline with the index of the market. Otherwise, if $q_iP_i(I)>q_{i-1}P_{i-1}(I)$, the seller may allocate all the old units to the higher index market. The left hand side of (B15) is the expected revenue per unit. If market i opens and the good is sold, the seller gets $P_i(I)$. Otherwise, if the good is not sold the seller gets the price in the next period's first market. Condition (B15) says that expected revenue per unit must be less than λ.

Otherwise, if $P_i(I) > \lambda$, an infinitely large amount of newly produced goods will be supplied to this market. When newly produced goods are supplied to this market the expected revenue per unit must equal λ. Condition (C16) requires the clearing of markets that open.

Let

$I^* = N_1 D(\lambda)$

denote the maximum amount of inventories that the first market can absorb at the price λ. If $I < I^*$ then newly produced goods must be supplied to the first market and $P_1 = \lambda$. Otherwise, if $I \geq I^*$, $P_1 < \lambda$ and no young units are supplied to the first market.

Assume that

$\Delta_Z D\left(\frac{\lambda}{q_Z}\right) > I^*$

Since $P_Z < \frac{\lambda}{q_Z}$, this assumption insures that either $I = 0$ or $I > I^*$.

Claim C1: There exists equilibrium with

(C18) $$P_i = \frac{\lambda}{q_i\left(1+(1-q_Z)\beta\right)}$$

(C19) $$P_1(0) = \lambda$$

Proof: Substituting $q_1 = 1$ in (C18) leads to:

(C20) $$P_1(I>0) = \frac{\lambda}{1+(1-q_Z)\beta} = q_i P_i$$

Therefore (C18) solves:

(C21) $$q_i P_i + (1-q_i)\beta P_1(I>0) = \lambda$$

And both (C15) and (C16) are satisfied. □

As in the text, I assume that $\pi_s = \pi = \frac{1}{Z}$. Under this assumption:

(C22) $$HLP = \frac{P_Z}{\min\{P_1(I)\}} = \frac{1}{q_Z} = \frac{1}{\pi} = Z$$

The quantity sold is highest when all markets open and is equal to $Z\bar{x}$, where $\bar{x}$ is the average amount sold per market when the beginning of period's inventories is strictly positive. The quantity sold is lowest when there are no inventories and only the first market opens. In this case it is equal to I^*. It follows that

(C23) $$HLU = \frac{Z\bar{x}}{I^*}$$

There is thus a positive relationship between HLP and HLU.

APPENDIX D: REGRESSIONS WITH THE STANDARD DEVIATION MEASURES

This Appendix replaces the range dispersion measures (HLP, HLU) in Tables 4 - 7 with the standard deviation dispersion measures (SDP, SDU).

Table D1*: The Main Explanatory Variables; Dependent variable = SDP

2005	1	2	3	4	5	6
SDU	0.136*** (0.009)	0.136*** (0.009)	0.129*** (0.008)		0.147*** (0.008)	0.097*** (0.009)
ln(Revenues)			0.016*** (0.001)	0.014*** (0.01)	-0.002 (0.003)	-0.001 (0.003)
#Stores				0.000 (0.000)	0.002*** (0.000)	0.002*** (0.000)
ln(Av. Price)		-.016*** (0.004)	-.022*** (0.004)	-.021*** (0.004)	-.013*** (0.004)	-0.015*** (0.004)
FreqSale						0.132*** (0.012)
Adj. R^2	0.4203	0.429	0.4963	0.3754	0.5179	0.571
2004	1	2	3	4	5	6
SDU	0.159*** (0.009)	0.160*** (0.009)	0.151*** (0.009)		0.152*** (0.009)	0.104*** (0.010)
ln(Revenues)			0.008*** (0.002)	0.024*** (0.004)	0.007* (0.003)	0.007** (0.003)
#Stores				-0.002** (0.001)	0.000 (0.001)	-0.001 (0.001)
ln(Av. Price)		-.018*** (0.004)	-.019*** (0.004)	-.020*** (0.005)	-.019*** (0.004)	-0.019*** (0.004)
FreqSale						0.149*** (0.015)
Adj. R^2	0.57	0.5807	0.5912	0.402	0.5907	0.645
04-05	1	2	3	4	5	6
SDU	0.154*** (0.012)	0.147*** (0.011)	0.143*** (0.012)		0.145*** (0.012)	0.104*** (0.011)
ln(Revenues)			0.004 (0.002)	0.015*** (0.004)	0.001 (0.004)	-0.001 (0.003)
#Stores				-0.002 (0.001)	0.001 (0.001)	-0.0002 (0.001)
ln(Av. Price)		-.030*** (0.006)	-.031*** (0.006)	-.046*** (0.008)	-.029*** (0.007)	-0.017*** (0.006)
FreqSale						0.166*** (0.017)
Adj. R^2	0.6402	0.6631	0.6654	0.5019	0.6651	0.744

* See notes to Table 4.

Table D2*: Separate regressions for selected categories; dependent variable = SDP

2005	SDU	ln(Rev)	# stores	ln(Av. P)	Size	Adj. R^2
beer	0.061*	0.012	-0.001	-0.044***	0.023	0.4571
carbbev	0.075**	-0.017*	0.003***	0.012	-0.009	0.1205
coldcer	0.152***	0.029*	0.001	-0.083***	0.020	0.6525
fzdinent	0.135**	0.028	-0.002	0.007	-0.028	0.3403
fzpizza	0.135**	0.004	0.001	-0.037	0.002	0.3608
milk	0.124*	0.003	0.004***	-0.035	0.085	0.3851
saltsnck	0.251***	0.000	0.001	-0.003	-0.015	0.607
soup	0.147***	-0.022	0.002	-0.012	0.092*	0.3697
yogurt	0.084**	0.015	0.002***	0.012*	-0.044**	0.6344
2004	SDU	ln(Rev)	# stores	ln(Av. P)	Size	Adj. R^2
carbbev	0.044	0.011	-0.005	-0.013	-0.069	0.071
coldcer	0.142***	0.054***	-0.003	-0.096***	0.039	0.8089
saltsnck	0.168***	0.008	0.002	-0.002	0.025	0.6056
yogurt	0.016	0.025***	-0.003***	-0.021***	-0.056***	0.8471
04-05	SDU	ln(Rev)	# stores	ln(Av. P)	Size	Adj. R^2
carbbev	0.094***	-0.017*	0.004	-0.004	0.003	0.2116
coldcer	0.186***	0.028*	0.002	-0.049*	-0.004	0.8177
yogurt	-0.016	0.010***	-0.001*	-0.041***	0.028	0.8227

* This Table was not reported in the text for the range measures. See the discussion that follows Table 3.

Table D3*: **Dependent variable = SDP, only regular prices**

2004 sample						
SDlnUnit	0.088***	0.091***		0.092***		0.092***
	(0.010)	(0.010)		(0.010)		(0.010)
lnrev			0.006***	0.007***	0.002	0.006**
			(0.002)	(0.002)	(0.003)	(0.003)
NumofStores					0.001	0.0001
					(0.001)	(0.001)
lnavgprice		-0.023***	-0.022***	-0.025***	-0.022***	-0.025***
		(0.004)	(0.005)	(0.004)	(0.005)	(0.004)
Constant	0.063***	0.044***	0.03	-0.025	0.050**	-0.022
	(0.007)	(0.008)	(0.022)	(0.021)	(0.025)	(0.025)
Adjusted R2	0.377	0.403	0.335	0.414	0.336	0.413
2005 sample						
SDlnUnit	0.034***	0.041***		0.046***		0.040***
	(0.007)	(0.007)		(0.006)		(0.006)
lnrev			0.012***	0.013***	-0.006**	-0.003
			(0.001)	(0.001)	(0.003)	(0.003)
NumofStores					0.002***	0.002***
					(0.000)	(0.000)
lnavgprice		-0.026***	-0.027***	-0.031***	-0.020***	-0.024***
		(0.004)	(0.003)	(0.003)	(0.004)	(0.004)
Constant	0.079***	0.055***	-0.047***	-0.080***	0.079***	0.036
	(0.006)	(0.006)	(0.015)	(0.015)	(0.021)	(0.022)
Adjusted R2	0.21	0.248	0.276	0.31	0.316	0.342
0405 sample						
SDlnUnit	0.104***	0.097***		0.097***		0.097***
	(0.012)	(0.012)		(0.012)		(0.012)
lnrev			0.002	0.001	-0.002	-0.003
			(0.002)	(0.002)	(0.004)	(0.003)
NumofStores					0.001	0.001
					(0.001)	(0.001)
lnavgprice		-0.032***	-0.038***	-0.032***	-0.035***	-0.029***
		(0.006)	(0.007)	(0.006)	(0.007)	(0.006)
Constant	0.048***	0.029***	0.059**	0.024	0.078***	0.042
	(0.008)	(0.008)	(0.026)	(0.024)	(0.030)	(0.028)
Adjusted R2	0.523	0.562	0.464	0.561	0.465	0.562

* Comparable to Tables 6 and C1. Observations labeled as "sale" were deleted.

Table D4*: **Dependent variable = Frequency of sales**

2004 sample						
SDlnUnit	0.327***	0.327***		0.302***		0.320***
	(0.021)	(0.021)		(0.022)		(0.022)
lnrev			0.038***	0.022***	0.033***	-0.003
			(0.005)	(0.005)	(0.009)	(0.008)
NumofStores					0.001	0.007***
					(0.002)	(0.002)
lnavgprice		0.001	0.0003	-0.003	0.001	0.002
		(0.011)	(0.012)	(0.011)	(0.012)	(0.011)
Adjusted R2	0.525	0.524	0.398	0.539	0.398	0.549
2005 sample						
SDlnUnit	0.357***	0.357***		0.349***		0.377***
	(0.020)	(0.020)		(0.020)		(0.021)
lnrev			0.023***	0.018***	0.031***	-0.01
			(0.004)	(0.003)	(0.008)	(0.007)
NumofStores					-0.001	0.004***
					(0.001)	(0.001)
lnavgprice		0.006	-0.002	-0.001	-0.006	0.013
		(0.009)	(0.010)	(0.009)	(0.011)	(0.009)
Adjusted R2	0.534	0.534	0.416	0.546	0.416	0.553
0405 sample						
SDlnUnit	0.279***	0.261***		0.227***		0.244***
	(0.035)	(0.035)		(0.034)		(0.035)
lnrev			0.041***	0.031***	0.035***	0.013
			(0.007)	(0.007)	(0.011)	(0.011)
NumofStores					0.002	0.006**
					(0.003)	(0.003)
lnavgprice		-0.080***	-0.107***	-0.089***	-0.104***	-0.076***
		(0.020)	(0.020)	(0.019)	(0.021)	(0.020)
Adjusted R2	0.528	0.551	0.519	0.579	0.518	0.584

*Comparable to Table 7.

Table D5: Dependent variables from 2005, explanatory variables from 2004

Dependent variable = SDP.05						
SDU. 04	0.147*** (0.013)	0.140*** (0.012)	0.137*** (0.013)		0.138*** (0.013)	0.103*** (0.013)
ln(Rev. 04)			0.003 (0.003)	0.013** (0.005)	0.002 (0.004)	-0.001 (0.004)
#Stores				-0.002 (0.001)	0.000 (0.001)	-0.0002 (0.001)
ln(Av. P. 04)		-.035*** (0.007)	-.035*** (0.007)	-.048*** (0.009)	-.035*** (0.007)	-0.021*** (0.007)
FreqSale.04						0.134*** (0.021)
Adj. R^2	0.5839	0.6122	0.6125	0.4665	0.6114	0.659
Dependent variable = freqsale.05						
SDU. 04	0.284*** (0.036)	0.274*** (0.036)		0.247*** (0.036)		0.263*** (0.036)
ln(Rev. 04)			0.037*** (0.008)	0.027*** (0.007)	0.025** (0.012)	0.003 (0.012)
#Stores					0.004 (0.003)	0.008*** (0.003)
ln(Av. P. 04)		-0.050** (0.021)	-0.076*** (0.022)	-0.057*** (0.020)	-0.068*** (0.022)	-0.042** (0.021)
Adj. R^2	0.566	0.573	0.527	0.59	0.528	0.598

* Comparable to Table 8.

Table D6*: Allowing for week effect

Dependent variable = SDP.05				
SDRU	0.177*** (0.014)	0.170*** (0.013)	0.168*** (0.013)	0.135*** (0.013)
Ln (Av. P. 04)		-0.036*** (0.007)	-0.036*** (0.007)	-0.021*** (0.007)
Ln(Rev. 04)			0.003 (0.004)	-0.001 (0.004)
#Stores	0.099*** (0.006)	0.073*** (0.008)	0.036 (0.031)	0.0001 (0.001)
FreqSale.04				0.130*** (0.019)
Adj. R^2	0.615	0.646	0.647	0.694
Dependent variable = freqsale.05				
SDRU	0.353*** (0.039)	0.344*** (0.038)	0.322*** (0.038)	0.341*** (0.038)
Ln (Av. P. 04)		-0.052** (0.020)	-0.058*** (0.020)	-0.043** (0.020)
Ln(Rev. 04)			0.029*** (0.007)	0.003 (0.011)
#Stores				0.008*** (0.003)
Adj. R^2	0.589	0.597	0.617	0.627

* Comparable to Table 9.

Table D7*: Running SDRP on SDU and other variables.

	1	2	3	4	5	6
SDU	0.179*** (0.012)	0.171*** (0.012)		0.165*** (0.012)		0.169*** (0.012)
ln(Rev)			0.013*** (0.003)	0.006* (0.002)	0.017*** (0.005)	0.001 (0.004)
#Stores					-0.001 (0.001)	0.002 (0.001)
ln(avgPrice)		-0.033*** (0.007)	-0.048*** (0.008)	-0.035*** (0.007)	-0.050*** (0.009)	-0.031*** (0.007)
Adj. R^2	0.619	0.646	0.440	0.652	0.440	0.654

*Comparable to the last rows in Table D1.

APPENDIX E: QUANTITATIVE IMPORTANCE WHEN STORES PROVIDE DIFFERENT SERVICES

Ideally we should focus on the dispersion of services adjusted prices or "true" prices defined by:

(E1) $$P^*_{ijt} = \frac{P_{ijt}}{S_{ij}}$$

where P^*_{ijt} is the "true" price, P_{ijt} is the observed price and S_{ij} is a measure of services provided by the store. Thus a price of 1 dollar in store 1 is equivalent to a price of 1.1 dollars in store 2 if store 2 provides 10% more services. I assume that the "true" price is the relevant price for both the buyer and the seller.[29]

The "true" price has a regular price component (R_{ij}) and a temporary element (T_{ijt}):

(E2) $$P^*_{ijt} = R_{ij}T_{ijt}$$

The regular price reflects the choice between average capacity utilization and price. The temporary element may reflect changes that are required to achieve a UST equilibrium. It may also reflect the desire to discriminate between shoppers and non-shoppers as in Varian (1980).

I therefore assume that the temporary element in the price has two components: one that is required to achieve UST equilibrium (u_{ijt}) and one that reflects discrimination (d_{ijt}). I assume $T_{ijt} = u_{ijt}d_{ijt}$ and write (E2) as:

(E3) $$P^*_{ijt} = R_{ij}u_{ijt}d_{ijt}$$

In an hypothetical world with no demand uncertainty the first two components in (E3) are constants and we can write

(E4) $$P^{*H}_{ijt} = k_i d_{ijt}$$

[29] Thus a buyer in the UST model will choose to buy at the cheapest available "true" price. The seller will first choose the amount of services provided by the store. This cannot be easily changed and may be treated as a constant in the short run. He then chooses the price taking into account the probability of making a sale that is determined by the "true" price.

where k_i is a constant and the discrimination component d_{ijt} varies over stores and time.

The range measure

Using (E4) I write the ratio of the high to low hypothetical "true" prices as:

$$HLP^{*}H_{it} = \frac{\max_j\{P^{*H}_{ijt}\}}{\min_j\{P^{*H}_{ijt}\}} = \frac{\max_j\{d_{ijt}\}}{\min_j\{d_{ijt}\}} \quad \text{(E5)}$$

Using (E3) I write the ratio of the high to low "true" price as:

$$HLP^{*}_{it} = \frac{\max_j\{P^{*}_{ijt}\}}{\min_j\{P^{*}_{ijt}\}} == \frac{\max_j\{R_{ij}u_{ijt}d_{ijt}\}}{\min_j\{R_{ij}u_{ijt}d_{ijt}\}} \quad \text{(E6)}$$

Dividing (E5) by (E6) leads to:

$$\frac{HLP^{*}H_{it}}{HLP^{*}_{it}} = \frac{\max_j\{d_{ijt}\}}{\min_j\{d_{ijt}\}} \frac{\min_j\{R_{ij}u_{ijt}d_{ijt}\}}{\max_j\{R_{ij}u_{ijt}d_{ijt}\}} \quad \text{(E7)}$$

The ratio (E7) is a measure of the importance of demand uncertainty: The lower this ratio is the more important is demand uncertainty in determining price dispersion. Unfortunately, we do not observe the "true" price and its components. But under certain conditions we can use the observed price and its components to estimate (E7).

The "true" price is the price net of services. I define a gross price that includes services by $P^{*}_{ijt}S_{ij}$. The ratios of the gross prices that are analogous to (E5) and (E6) are:

$$HLPH_{it} = \frac{\max_j\{P^{*H}_{ijt}S_{ij}\}}{\min_j\{P^{*H}_{ijt}S_{ij}\}} = \frac{\max_j\{d_{ijt}S_{ij}\}}{\min_j\{d_{ijt}S_{ij}\}}; \quad HLP_{it} = \frac{\max_j\{R_{ij}u_{ijt}d_{ijt}S_{ij}\}}{\min_j\{R_{ij}u_{ijt}d_{ijt}S_{ij}\}} \quad \text{(E8)}$$

And the "importance" measure analogous to (E7) is:

$$\frac{HLPH_{it}}{HLP_{it}} = \frac{\max_j\{d_{ijt}S_{ij}\}}{\min_j\{d_{ijt}S_{ij}\}} \frac{\min_j\{R_{ij}u_{ijt}d_{ijt}S_{ij}\}}{\max_j\{R_{ij}u_{ijt}d_{ijt}S_{ij}\}} \quad \text{(E9)}$$

The measure (E9) is the same as the ideal measure (E7) if S_{ij} is a constant that does not vary across stores. It is also the same as (E7) if variation it can be "factored out" in the following way.

$$\max_j\{x_jS_j\} = \max_j\{x_j\}\max_j\{S_j\}; \ \min_j\{x_jS_j\} = \min_j\{x_j\}\min_j\{S_j\} \quad \text{(E10)}$$

where x_j denotes other components of the store's price. This says that when services dominates the store with the highest price has the highest level of services and the store with the lowest price has the lowest level of services.

The "factoring out" property (E10) is likely to hold when we have a large number of stores. To illustrate, I consider the case in which x_j and S_j are independently distributed. Let x^H denote the highest realization of x and S^H denote the highest realization of S. For a given store the probability that the product will not hit the maximum possible is:

$$prob\left(xS < x^H S^H\right) = 1 - \left(\Pr ob(x = x^H)\right)\left(\Pr ob(S = S^H)\right)$$

The probability that no store out of n stores will hit the maximum possible product is: $\left[prob\left(xS < x^H S^H\right)\right]^n$. The probability that the maximum product is the highest possible is therefore: $\Pr ob\{\max_j(x_j S_j) = x^H S^H\} = 1 - \left[prob\left(xS < x^H S^H\right)\right]^n$

that is increasing in n.

When the number of stores is sufficiently large we can therefore use the following approximation.

(E11) $$\frac{HLPH_{it}}{HLP_{it}} = \frac{\max_j\{d_{ijt}\}\max_j\{S_{ij}\}}{\min_j\{d_{ijt}\}\min_j\{S_{ij}\}} \frac{\min_j\{R_{ij}u_{ijt}d_{ijt}\}\min_j\{S_{ij}\}}{\max_j\{R_{ij}u_{ijt}d_{ijt}\}\max_j\{S_{ij}\}} = \frac{HLP^* H_{it}}{HLP^*_{it}}$$

I also use the price net of store effect. This is not the "true" price because controlling for "store effect" eliminates variation in both services and the regular price, rather than just variations in services.

The ratio of prices net of store effect that is analogous to (D5) and (D9) is:

(E12) $$HLRH_{it} = \frac{\max_j\{d_{ijt}\}}{\min_j\{d_{ijt}\}} \; ; \; HLR_{it} = \frac{\max_j\{u_{ijt}d_{ijt}\}}{\min_j\{u_{ijt}d_{ijt}\}}$$

And the ratio analogous to (E7) is:

(E13) $$\frac{HLRH_{it}}{HLR_{it}} = \frac{\max_j\{d_{ijt}\}}{\min_j\{d_{ijt}\}} \frac{\min_j\{u_{ijt}d_{ijt}\}}{\max_j\{u_{ijt}d_{ijt}\}}$$

This will equal (E7) only if there is no price inertia and R_{ij} is a constant that does not vary across stores or if we can "factor out" R_{ij} in a way similar to the "factoring out" of S_{ij} in (E10).

<u>The variance measure</u>

To simplify, I assume that the "true" price does not depend on the level of services. A store that provides good services can offer a good deal and have a low "true" price. I also assume that the three components of the "true" price are independently distributed. Thus the probability of a "sale" is the same for "high true regular price" store and for "low true regular price stores". This simplifies the exposition but the main results hold if we allow for a positive correlation between the "true price" and services.

Writing (E1) and (E3) in log terms leads to:

(E14) $$\ln(P_{ijt}) = \ln(S_{ij}) + \ln(R_{ij}) + \ln(u_{ijt}) + \ln(d_{ijt})$$

(E15) $$\ln(P^*_{ijt}) = \ln(R_{ij}) + \ln(u_{ijt}) + \ln(d_{ijt})$$

After removing "store effect" we are left with the temporary components of the price:

(E16) $$e_{ijt} = \ln(u_{ijt}) + \ln(d_{ijt})$$

The elimination of demand uncertainty will eliminate UST type reasons for price dispersion: The variation in regular true price and in temporary true price due to non-discrimination. We can therefore compute the variances of the hypothetical prices by substituting $Var(\ln R_{ij}) = Var(\ln u_{ijt}) = 0$ in (E14)-(E16). This leads to:

(E17) $$Var(\ln P^H_{ijt}) = Var(\ln S_{ij}) + Var(\ln d_{ijt})$$

(E18) $$Var(\ln P^{*H}_{ijt}) = Var(\ln e^H_{ijt}) + Var(\ln d_{ijt})$$

The ideal measure of the importance of demand uncertainty is:

(E19) $$\frac{Var(\ln P^{*H}_{ijt})}{Var(\ln P^*_{ijt})} = \frac{Var(\ln d_{ijt})}{Var(\ln P^*_{ijt})}$$

The measure that does not control for "store effect" is:

(E20) $$\frac{Var(\ln P_{ijt}^{H})}{Var(\ln P_{ijt}^{*})} = \frac{Var(\ln S_{ij}) + Var(\ln d_{ijt})}{Var(\ln S_{ij}) + Var(\ln P_{ijt}^{*})}$$

This measure is the same as the ideal measure (E19) when all stores provide the same services and $Var(\ln S_{ij}) = 0$. Otherwise it is higher than the ideal measure.

The measure that controls for "store effect" is:

(E21) $$\frac{Var(\ln e_{ijt}^{H})}{Var(\ln e_{ijt})} = \frac{Var(\ln d_{ijt})}{Var(\ln u_{ijt}) + Var(\ln d_{ijt})}$$

This measure is the same as the ideal measure (E19) if there is no price inertia and $Var(\ln R_{ij}) = 0$. Otherwise, it is higher than the ideal measure.

Since both (E20) and (E21) are larger than the ideal measure, it follows that:

(E22) $$1 - \frac{SD(\ln P_{ijt}^{H})}{SD(\ln P_{ijt})} < 1 - \frac{SD(\ln P_{ijt}^{*H})}{SD(\ln P_{ijt}^{*})} \text{ and } 1 - \frac{SD(\ln e_{ijt}^{H})}{SD(\ln e_{ijt})} < 1 - \frac{SD(\ln P_{ijt}^{*H})}{SD(\ln P_{ijt}^{*})}$$

The first inequality says that the percentage reduction in the standard deviation of the gross prices is less than the ideal measure of the percentage reduction. The second inequality says that the percentage reduction in the prices net of store effect is less than the ideal measure of the percentage reduction.

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