Vanderbilt University Department of Economics Working Paper Series
Nashville, TN 37235-1819

Vanderbilt University Department of Economics Working Papers 19-00003

Temporary sales in response to aggregate shocks

Benjamin Eden
Vanderbilt University

Maya Eden
Brandeis University

Jonah Yuen
Vanderbilt University

Abstract

This paper studies the role of temporary sales in the reaction to aggregate shocks. Using scanner data from supermarkets, we establish the following stylized facts: (a) The fraction of stores that offer sale prices fluctuate over weeks; (b) Goods with more fluctuations in regular prices have also more sales; (c) Temporary sales contribute substantially to the weekly variation of the average cross-sectional price of the typical good; (d) High prices appear to be more rigid than low prices. These findings can be rationalized by a model in which prices are completely flexible and temporary sales are reactions to unwanted inventories which accrue in response to aggregate demand shocks.

We would like to thank IRI for making the data available. All estimates and analysis in this paper based on data provided by IRI are by the authors and not by IRI.
Citation: Benjamin Eden and Maya Eden and Jonah Yuen, (2019) "Temporary sales in response to aggregate shocks", *Vanderbilt University Department of Economics Working Papers*, VUECON-19-00003.
Contact: Benjamin Eden - ben.eden@vanderbilt.edu, Maya Eden - mayeden@gmail.com, Jonah Yuen - jonah.j.yuen@Vanderbilt.Edu.
Submitted: February 11, 2019. **Published:** March 25, 2019.
URL:http://www.accessecon.com/Pubs/VUECON/VUECON-19-00003.pdf

TEMPORARY SALES IN RESPONSE TO AGGREGATE SHOCKS*

Benjamin Eden — Vanderbilt University
Maya Eden — Brandeis University
Jonah Yuen — Vanderbilt University

February 2019

Abstract

This paper studies the role of temporary sales in the reaction to aggregate shocks. Using scanner data from supermarkets, we establish the following stylized facts: (a) The fraction of stores that offer sale prices fluctuate over weeks; (b) Goods with more fluctuations in regular prices have also more sales; (c) Temporary sales contribute substantially to the weekly variation of the average cross-sectional price of the typical good; (d) High prices appear to be more rigid than low prices. These findings can be rationalized by a model in which prices are completely flexible and temporary sales are reactions to unwanted inventories which accrue in response to aggregate demand shocks.

Key Words: Temporary Sales, Unwanted Inventories, Sequential Trade
JEL Code: D40

* We would like to thank IRI for making the data available. All estimates and analysis in this paper based on data provided by IRI are by the authors and not by IRI.

1. INTRODUCTION

Temporary sales — defined as large price drops which quickly rebound — are a puzzling phenomenon from a macroeconomic perspective. Their large magnitude and short duration suggest that they have little to do with aggregate shocks. It is unlikely that a 20% drop in prices that rebounds within a month is indicative of a sharp temporary contraction in the money supply, or of a sharp temporary increase in total factor productivity.

In light of this, it has become standard practice in macroeconomics to focus on the behavior of regular prices. (See Nakamura and Steinsson (2008), Eichenbaum, Jaimovich, and Rebelo (2011), and Kehoe and Midrigan (2015)). Viewed as a tool for price discrimination (see Guimaraes and Sheedy (GS, 2011), Salop and Stiglitz (1977), Shilony (1977) and Varian (1980)), sales contain no information on macroeconomic conditions.

This paper begins by asking whether, indeed, this is the case: do sales cancel out in the aggregate, or do they contribute to aggregate price volatility? We examine a panel dataset of scanner prices from supermarkets. For a given item, a "sale" is defined as a large, temporary price drop in a given store. We find that sales do not cancel out in the aggregate. The frequency of sales is about 20% but the fraction of prices that are sale prices fluctuates over weeks. For the typical good, there are no sales in any of the stores in about 40% of the weeks.

We also looked at the behavior of the cross-sectional average price of a typical good over weeks, where the average is across stores. In general, if all prices are iid we would expect that the variance of the average price will decrease with the number of stores. In contrast, removing sale prices reduces the number of stores but increase the volatility of the average price by about 20%.

We propose a model in which temporary sales are reactions to unwanted inventories, which accrue in response to aggregate demand or supply shocks where an aggregate shock is not store specific, but may be good specific. The main insight of the model is that, if storage is associated with depreciation (as is the case with perishable goods that have expiration dates), then sharp, temporary reductions in prices can occur even in response to moderate macroeconomic shocks. Unlike standard models in which prices respond only to changes in cost and monetary conditions, large aggregate price changes are not necessarily reflective of large changes in the underlying fundamentals.

Our model is a flexible price version of Prescott (1975) motel model: The Uncertain and Sequential Trade (UST) model in Eden (1990).[1] Most closely related is Bental and Eden (BE, 1993) that allows for storage and assumes exponential decay. In their model, there are demand and supply shocks and the equilibrium price distribution depends on the current cost shock and the beginning of level inventories. Inventories are accumulated when demand in the previous period was low. The accumulation of inventories leads to a reduction in prices (the entire price distribution shifts to the left) and as a result the quantity sold increases on average. Roughly speaking, the reduction in prices is temporary and lasts until inventories are back to their "normal" level.

We adopt here the feature emphasized by Eden (2018), who assumed that 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".

Aguirregabiria (1999) used a unique data set from a chain of supermarket stores in Spain and found a significant and robust effect of inventories at the beginning of the month on the current price. He also provides a description of the negotiation between the chain's headquarter and its suppliers. The toughest part of the negotiation with suppliers is about the number of weeks during the year that the brand will be under promotion, and about the percentage of the cost of sales promotions that will be paid by the wholesaler

[1] For rigid price versions of the model see, Dana (1998, 1999) and Deneckere and Peck (2012).

(e.g. cost of posters, mailing, price labels). A similar description is in Anderson et.al (2013) who present institutional evidence that sales (accompanied by advertising and other demand generating activities) are complex contingent contracts that are determined substantially in advance. There is also some flexibility. For many promotions, manufacturers allow for a "trade deal window" of several weeks where the seller can execute the promotion. These descriptions are consistent with the hypothesis that temporary sales are used to respond to high inventories. Sometimes the delivery schedule allows the firm to predict the level of inventories and as a result, temporary sales are set in advance. The flexibility in the timing of sales reflects the need to respond to inventories that were accumulated as a result of demand shocks.

Our findings are related to the finding in Coibion et.al. (2015) and Glandon (2015). Both finds that consumer buy more at sale prices and therefore the price paid by the consumer fluctuates more than the price posted by stores. Here the focus is on the prices posted by stores. We argue that sale prices are used by the stores to react to negative demand shocks and are not merely a discrimination device.

2. STYLIZED FACTS

We start by establishing some stylized facts about the behavior of the cross-sectional price distribution. Our main findings are: (a) The fraction of stores that offer sale prices fluctuates over weeks; (b) the standard deviation of the (cross sectional) average price over weeks is larger than the standard deviation of the average regular price, where the average is over stores and the average regular price is obtained after excluding “sales” observations; (c) goods with less fluctuations in their regular price tend to have less sales.

We use a rich set of scanner data from Information Resources Inc. (IRI).[2] The complete data set covers 48 markets across the United States, where a market is sometimes a city (Chicago, Los Angeles, New York) and sometimes states (Mississippi). There are 31 diverse categories of products found in grocery and drug stores, such as carbonated beverages, paper towels, and hot dogs. We define goods by the Universal Product Code (UPC). The data provide information about the total number of units and total revenue for each UPC-store-week cell. We obtain the price for each cell by dividing revenue by the number of units sold. We use data from grocery stores in Chicago during the years 2004 and 2005. We use 3 samples. The 52 weeks in the year 2004, the 52 weeks in the year 2005 and the 104 weeks in the combined sample of 2004-2005.

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

(a) We drop all UPC-Store cells that do not have positive revenues in all of the sample's weeks.[3]

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

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

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

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

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

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

the number of stores varies across UPCs but stores that are in the sample sold their products in all of the sample's weeks.

The requirement that the product be sold continuously by more than 11 stores leads to a sample of fairly popular brands.[4] The focus on fairly popular items is likely to reduce the problem of close substitutes that have different UPCs. In addition, the exclusion of items sold by fewer than 11 stores significantly reduce the number of items with very high price dispersion that may arise as a result of measurement errors.[5]

Temporary Sales.

We assume that a temporary sale occurs when a price drop of at least 10% is followed by a price equal to or above the pre-sale price within four weeks.

Summary statistics are in Table 1. The rows in Table 1 are the number of UPCs and the number of observations for individual categories. In the 2004 sample there were 32 UPCs in the beer category. The number of observations (UPC-Week cells) is (32)(52)=1664. In 2005 there were 56 UPCs in the beer category. The number of observations is not equal to (56)(52) because in 3 cells there was no price dispersion. The total number of observations for each sample is in the bottom of the Table. The combined 04-05 sample has fewer UPCs because criterion (a) in our filtering procedure is harder to satisfy when there are 104 weeks. As a result, the combined sample includes relatively more popular brands.

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

[5] To get a sense of the effect of the sample exclusion on the result, Eden (2013) studies one week in detail. See the working paper version of Eden (2018): Vanderbilt University Department of Economics Working Papers 13-00015. 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.

Table 1*: Summary statistics

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

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

Table 2 provides summary statistics about sales. The first row after the sample name, repeats the number of UPCs in each sample. The second is the average number of stores per UPC-Week cell with the minimum and the maximum number of stores in parentheses. In the 2005 sample, there are 21 stores on average. The minimum number of stores is 11 and the maximum number of stores is 35. The third row is the average number of stores after eliminating sales observations. The average number of stores for the 2005 sample is now 17. The minimum number of stores is 1 and the maximum is 35. The fourth row (Freq Sales) is the frequency of sales calculated as the fraction of UPC-Week-Store cells with a sale price (in parentheses are the frequency of sale for the UPC with the lowest frequency and the UPC with the highest frequency). For the 2005 sample the average frequency of sale is 0.2, the minimum is zero (there are UPCs with no sale prices) and the maximum is 0.45. The fifth row (No Sales) is the fraction of weeks in which there is no sale in any store, averaged over UPCs. For the 2005 sample, the average fraction of weeks with no sale is 0.45. The sixth (Sales in all stores) is the fraction of weeks in which there are sales in all stores (averaged over UPCs). For the 2005 the average is 0.5 percent.

The seventh and the eighth rows reports standard deviations over weeks. We first calculate the average log price for each UPC-week cell. We then calculate the standard deviation of these averages for each UPC across weeks. The seventh row reports the average (over UPCs) standard deviation when using the entire sample. This is 9% in the 2005 sample. The eighth reports the standard deviation when using the sample of regular prices which we obtain after removing sale observations. This is 7.5% in the 2005 sample. The ninth row reports the ratio of the standard deviation of the average price to the standard deviation of the average regular price. This is 1.2 in the 2005 sample. The tenth row is the contribution of sales to the standard deviation relative to the average frequency of sale. For the 2005 sample this is 0.2/0.2 = 1. The last row reports the correlation between the frequency of sales and the standard deviation of the average regular price. This correlation is 0.65 in the 2005 sample.

Table 2*: Statistics about sales

Sample	2005	2004	2004-2005
# UPC	1084	665	324
# stores, All	20.98 (min=11,max=35)	15.42 (11,21)	14.56 (11,19)
# stores, Regular	16.95 (min=1,max=35)	12.50 (1, 21)	11.51 (1, 19)
Freq Sales (Av. Freq)	0.2 (0,0.45)	0.19 (0, 0.47)	0.21 (0, 0.41)
No Sales	0.45	0.42	0.39
Sales in all stores	0.0051	0.002	0.002
SD All	0.0908	0.0795	0.0837
SD regular	0.0755	0.0623	0.0708
Ratio	1.20	1.28	1.18
Relative	1	1.47	0.86
Corr	0.65	0.69	0.58

* The first row after the sample name, repeats the number of UPCs in each sample. The second is the average number of stores (per UPC-Week cell – the minimum and the maximum number of stores are in parentheses). The third is the average number of stores after eliminating sales observations. The fourth (Freq Sales) is the frequency of sales calculated as the fraction of UPC-Week-Store cells that their price is a sale price (in parentheses are the frequency of sale for the UPC with the lowest frequency and the UPC with the highest frequency). The fifth (No Sales) is the fraction of weeks in which there is no sale in any store, averaged over UPCs. The sixth (Sales in all stores) is the fraction of weeks in which there are sales in all stores (averaged over UPCs). The seventh and eighth rows reports standard deviations over weeks. We first calculate the average log price for each UPC-week cell. We then calculate the standard deviation of these averages for each UPC across weeks. The seventh row reports the average (over UPCs) standard deviation when using the entire sample. The eighth reports the standard deviation when using the sample of regular prices which we get after removing sale observations. The ninth row reports the ratio of the standard deviation of all prices to the standard deviation of regular prices. The tenth row is the contribution of sales to the standard deviation relative to the average frequency of sale. For the 2005 sample this is 0.2/0.2 = 1. The last row reports the correlation between the frequency of sales and the standard deviation of the average regular price.

Table 2 suggests three main observations. Temporary sales contribute to the variation of the average price over weeks, UPCs with more fluctuations in the average regular price tends to have more sales, and the fraction of weeks in which there is no sale in any of the stores is high.

The fact that temporary sales increase the standard deviation of the average price (by about 20%) suggests that temporary sale prices play an important role in price flexibility. Under the assumption that all prices are iid, eliminating randomly selected 20% of the prices that leads to a drop in the average number of stores, will increase the standard deviation of the cross-sectional average price.[6] Instead if we eliminate

[6] The variance of the average of n iid random variables with variance σ^2 is σ^2/n. As n decreases, the variance of the average increases.

temporary sale prices we get a substantial reduction in the standard deviation of the average price.

The correlation between the frequency of sale and the standard deviation of the average regular price says that UPCs with more fluctuations in regular prices also have more sales. This is consistent with the hypothesis that both temporary sales and regular price changes are responses to demand shocks and as a result UPCs that have more demand shocks have more fluctuations in regular prices and more sales. It is not consistent with the hypothesis that temporary sales and regular prices are chosen in an independent manner.

Table 2 suggests that the fraction of weeks in which there was no sale in any of the stores is high. If all stores use a mix strategy to choose sales and if they all use the same probability that is equal to the observed frequency of sale, the probability of no sale in any of the store is: 0.8^21=0.009 or 0.9 percent for the 2005 sample. This is very different from the observed frequency of 45%. Heterogeneity may lead to this result. It is possible that the phenomenon of no sale in any of the stores occurs primarily in UPCs with low sale probabilities. To examine this possibility, we divide the UPCs into five bins according to the frequency of sale.

This is done in Table 3. The first row defines the bin. The first bin contains all UPCs with frequency of sales between zero and 10 percent. The second bin contains all UPCs with frequency of sales between 11 and 20 percent and so on. The second row is the fraction of UPCs that are in the bin. Twenty-six percent are in the third bin which contains all UPCs with frequency of sale between 21 and 30 percent. The average frequency of sale is in the third row. For the third bin the average frequency of sale is 25%. The average number of stores is in the fourth row. It is close to 22 in the third bin. The fifth row is the fraction of weeks in which there were no sales in any of the stores. This fraction is 0.29 for the third bin. The sixth row is the probability of no sale in any of the stores calculated under the assumption that stores follow a mixed strategy and choose sales with probability equal to the average frequency in the bin. For example, in the 21-30 bin the average frequency is 0.25 and the average number of stores is close to 22. The probability of no sale in any of the 22 stores is 0.75^22 which is 0.2 percent. The average fraction of weeks in which there was no sales in any of the stores is 29 percent and is about 15 times higher than the predicted probability.

The last rows of Table 3 are about the standard deviation of the cross-sectional average price over weeks. The differences between the bins are large. For example, the average standard deviation for UPCs that are in the highest frequency of sale bin is 0.124, which is more than three times the average standard deviation for UPCs that are in the lowest frequency of sale bin. The ratio reported in the last row suggests that the contribution of sales to the standard deviation does not increase with the frequency of sale. For the highest frequency bin the standard deviation of the average price is 7% higher than the standard deviation of the average regular price. For the lowest frequency bin it is 17.2% higher. In the lowest frequency bin the average frequency of sale is 4%. Per percentage point the contribution of sales to the standard deviation is 17.2/4 = 4.3%. As can be seen from the last row (labelled "relative") the contribution per percentage point declines with the average frequency.

.

Table 3*: By frequency of sale bins

Freq of sale	0-10	11-20	21-30	31-40	41-50	All bins
Frac UPCs	0.27	0.25	0.26	0.20	0.01	1
Av. Freq	0.04	0.15	0.25	0.34	0.42	0.2
# of stores	20.25	19.44	21.82	23.17	14.71	21
No Sales	0.79	0.46	0.29	0.21	0.19	0.45
Prob.	0.47	0.04	0.00	0.00	0.00	0.01
SD All	0.046	0.093	0.113	0.116	0.133	0.091
SD Regular	0.040	0.070	0.093	0.105	0.124	0.076
ratio	1.172	1.321	1.221	1.110	1.069	1.203
relative	4.300	2.140	0.884	0.324	0.164	1.015

* This Table uses the 2005 sample. UPCs are divided into 5 bins. The first bin contains all UPCs with frequency of sales between zero and 10 percent. The second bin contains all UPCs with frequency of sales between 11 and 20 percent and so on. The first row is the fraction of UPCs that are in the bin. The second row is the average frequency of sale for the bin. The third is the average number of stores in the bin. The fourth is the fraction of weeks in which there were no sales in any of the stores. The fifth is the probability of no sale in any of the stores calculated under the assumption that stores follow a mixed strategy and choose sales with probability equal to the average frequency. The last four rows are about the standard deviation of the average price over weeks. The row before the last is the ratio of the standard deviation of the average price to the standard deviation of the average regular price. The last row is the per percentage point contribution to the standard deviation. For example, the average frequency of sale in the first bin is 4%. Sales increase the standard deviation by 17.2%. Per percentage point the contribution is 17.2/4 = 4.3%.

Smaller samples with at least 11 stores that post the regular price

To better understand the behavior of regular prices and the role of sales, we look at samples in which there are at least 11 stores that post the regular price. That is, UPCs were dropped if after removing temporary sales observations there were fewer than 11 stores in any week. This is an additional filter that drastically reduced the number of UPCs in the sample. In the 2005 sample it reduced the number of UPCs from 1084 to 215. It also reduced the frequency of sales in that sample from 0.2 to 0.05.

Table 4 provides some statistics about the smaller samples and should be compared with Table 2. The standard deviation of the average price in the smaller samples is much lower than the standard deviation in the larger samples. In the smaller 2005 sample (with 215 UPCs) the standard deviation of all prices is 0.043. In the larger sample of 2005 the standard deviation of all prices is 0.09, which is more than double that magnitude. The standard deviation of the average regular price in the smaller sample of 2005 is 0.039. In the larger sample it is 0.076 which is almost double that magnitude.

This suggests that UPCs with lower sale frequencies have also lower standard deviation of both the average price and the average regular price. It is consistent with the positive correlation between the standard deviation of the average regular price and the frequency of temporary sales. The contribution of sales to the standard deviation is large relative to the frequency of sale. In the smaller 2005 sample sales increase the standard deviation by 2% per percentage point of frequency. In the larger 2005 sample it is only 1% per percentage point. Thus, although there are fewer sales in the smaller sample the effect of each sale on the standard deviation is relatively large.

Table 4*: The smaller samples

Sample	2005	2004	2004-2005
# UPC	215	80	18
# stores, All	23.54 (min=11,max=35)	16.375 (11,21)	16.06 (13,19)
# stores, Regular	22.34 (min=11,max=35)	15.89 (11,21)	14.70 (11,19)
Av. Freq	0.05	0.03	0.02
No Sales	0.74	0.84	0.84
SD All	0.0434	0.0263	0.0347
SD Regular	0.0393	0.0220	0.0318
Ratio	1.1	1.2	1.09
Relative	2.00	6.67	4.50
Corr	0.51	0.52	0.11

* Similar to Table 2 but here we delete UPCs with less than 11 stores that post regular prices in any week.

3. SEQUENTIAL TRADE

We now turn to a model that is consistent with the above findings. We start with a simple version and then augment it to account for various features of the data.

3.1 A simple version

There are many goods and many sellers who can produce the goods at a constant unit cost. We focus on one good with a unit cost of λ. Production occurs at the beginning of the period before the arrival of buyers. Storage is not possible. The number of buyers $\tilde{N}$ is an iid random variable that can take two possible realizations: N with probability $1-q$ and $N+\Delta$ with probability q.

Sellers take prices and the probability of making a sale as given. They know that they can sell at the price P_1 for sure. They may also be able to sell at a higher price, P_2, if demand is high, with probability q. In equilibrium sellers are indifferent between the two price tags: The expected profits are the same for both tags.

It is useful to think of two hypothetical markets. The price in the first market is P_1 and the probability that this market opens is 1. The price in the second market is P_2 and the probability that it opens is q. From the seller's point of view, he can sell any quantity at the price announced in the market, if the market opens but cannot sell anything at that market if the market does not open. A unit with a price tag of P_1 will be sold in the first market. A unit with a price tag of P_2 will be sold in the second market, if this market opens.

Buyers arrive sequentially in batches. The first batch of N buyers buys in the first market at the price P_1. The second market opens only if the second batch of Δ buyers arrives. If this second batch arrives the second market opens at the price P_2.

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

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

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

And markets that open are cleared:

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

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

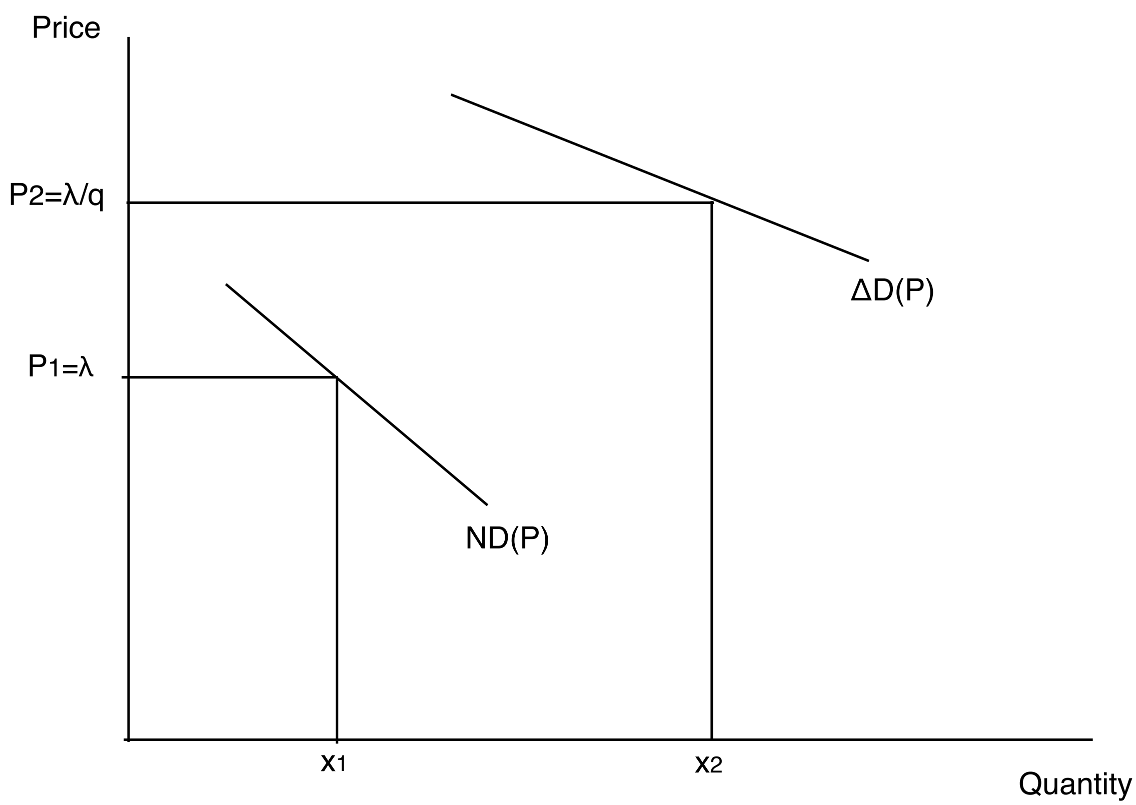


Figure 1: Prices and quantities in the simple version of the UST model

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

3.2 Storage

Bental and Eden (BE, 1993) study a UST model that allows for storage. In their model prices fluctuate as a result of both iid demand and supply shocks. A negative demand shock leads to the accumulation of inventories and a reduction in all prices. A temporary reduction in the cost of production has a similar effect. Thus, "temporary sales" may be the result of both demand and supply shocks.

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

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

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

At the beginning of period t the economy can be in one of two states. In state I (I for inventories) the demand in the previous period was low ($\tilde{N}_{t-1} = N$) and the second market did not open. As a result, inventories were carried from the previous period. In state NI (NI for no inventories) demand was high ($\tilde{N}_{t-1} = N+\Delta$) and there are no inventories. The price in the first market is $P(1,I)$ in state I (with inventories) and $P(1,NI)$ in state NI (with no inventories). The quantity offered for sales in market 1 is $x(1,I)$ in state I and $x(1,NI)$ in state NI. The price in the second market (P_2) and the supply (x_2) do not depend on the level of inventories. The quantity sold in the first market is equal to the quantity offered for sale. The quantity sold in the second market is zero if demand is low and x_2 if demand is high. Table 5 describes quantities as a function of last period's demand and this period's demand. Note that the quantity sold depends both on the last period's demand and on this period demand. Production depends only on the last period's demand. With some abuse of notation we write the level of inventories in state I, as $I = x_2$. Production in state I is equal to the demand in the first market while production in state NI is equal to the demand in both markets.

Table 5*: Quantities in period t as a function of the state at $t-1$ and the state at t

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

A formal analysis and the equilibrium definition is in Eden (2018, Appendix A.3). To make this paper self-contained we repeat here the description of the model. In allocating the available amount of goods (from new production and inventories) across the two markets, the older units receive "priority" in the first market (and the younger units receive "priority" in the second market). Given prices the allocation rule is as follows. If the amount of old units (from inventories) is less than the demand in the first market then all old units are supplied to the first market. If the amount of old units is greater than the demand in the first market then only old units are supplied to the first market. To motivate this allocation rule, we consider the following example. There are 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, store O does not sell and 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. It follows that the joint profits of both stores can be increased if they do not follow our allocation rule. This cannot occur in equilibrium.

A young unit that is not sold in the current period will be sold in the next period at the price $P(1,I)$. The value of a young unit that is not sold in the current period (the value of inventories) is $\beta P(1,I)$, where $0<\beta<1$ is a constant that captures discounting, storage costs and depreciation. The value of an old unit that is not sold is zero. Newly produced units are supplied to the second market and in equilibrium the following arbitrage condition must hold.

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

The left-hand side of (3) is the expected present value of revenues from a newly produced unit allocated to the second market. If the second market opens (with probability q) the seller gets P_2. Otherwise he will get the unit value of inventories, $\beta P(1,I)$. The right hand side of (3) is the unit cost of production. Thus, (3) says that the marginal cost is equal to expected revenues.

We now distinguish between two cases. In the first case, illustrated by Figure 2A, inventories in state I are relatively low and newly produced goods are supplied in state I to both markets. Since newly produced goods are supplied to the first market, the price in the first market is the marginal cost: $P(1,I)=P(1,NI)=\lambda$. Substituting this into (4) yields:

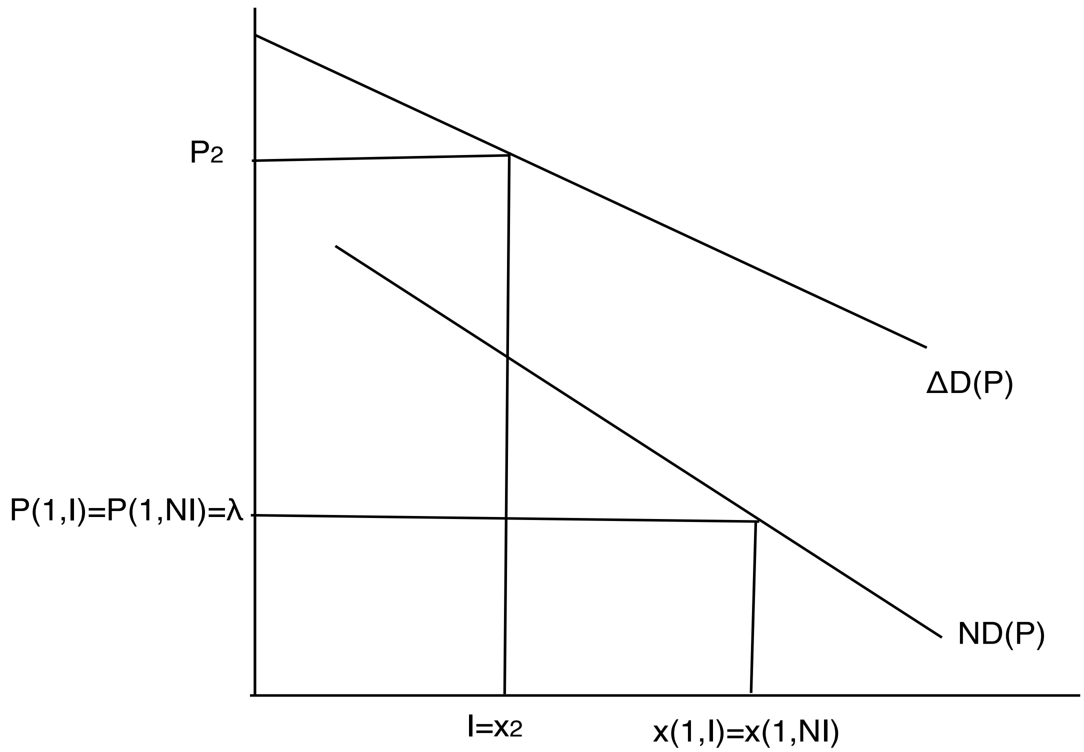
(4) $$P_2=\frac{\lambda\big(1-(1-q)\beta\big)}{q}$$

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

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

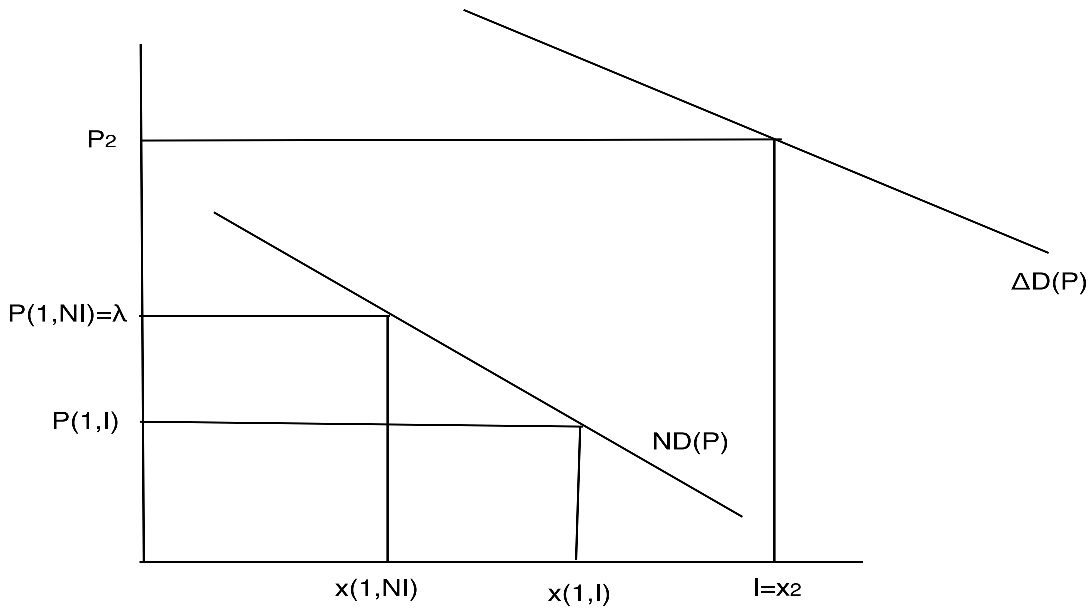
This says that the expected revenue of supplying an old unit to the second market is the same as the revenue from supplying it to the first market. The solution to (3) and (5) is[7]:

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



A. In state I, $I=x_2$ "old units" and $x(1,I)-I$ newly produced units are supplied to the first market.

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



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

Figure 2: Possible Equilibria

The model described by Figure 2 may account for temporary sales. Some stores offer the newly produced good at the high ("regular") price of market 2. Then if demand is low they accumulate inventories and offer the good for sale at the low price of market 1. We also note that the price and quantity in the first market may change over time. Prices are more volatile than cost. In the example illustrated by Figure 2B, the cost does not change but the price in the first market does.[8]

A 1% change in λ will change prices in both markets (and both states) by 1%. Sales may occur in response to temporary change in cost in addition to sales that occur in response to the accumulation of inventories. There is however a difference between the two types of sales: Sales that occur because of a change in technology will affect the

[8] Eichenbaum, Jaimovich, and Rebelo (EJR, 2011) found that most price changes are associated with a change in cost. Under the constant returns to scale assumption, changes in prices may occur as a result of changes in inventories and without changes in cost. This is not the case in the BE model. In their model, there is no distinction between the producer and the store (the retailer). Once we introduce this distinction, there is no puzzle. The producer set a price that changes in response to both the aggregate level of inventories and technology. Therefore, when we look at the cost from the store's point of view (as EJR did), changes in aggregate inventories are associated with changes in cost and most price changes are associated with cost changes.

price in both markets while sales that occur because of the accumulation of inventories affect the price in the first market only.

Accounting for the stylized facts.

We now examine the ability of our example to account for the stylized facts documented above. We assume that a sale occurs when the price drop for one period and the drop in the price is greater than 10%. We also assume that: $\frac{P_2}{P(1,I)} > 1.1$ so that the price drop in stores that accumulated inventories is large enough to satisfy our definition of sale. (That is, it is larger than 10%).

1. For the average good, the fraction of weeks in which there is no sale in any of the stores is not small.

This will occur in our example if the probability that demand is at its highest realization is not small.

2. Removing sale observations lowers the standard deviation of the average price.

This may occur in the case illustrated by Figure 2B. We start with the case in which $\frac{P(1,NI)}{P(1,I)} \leq 1.1$. In this case only the drop in the price for stores that accumulated inventories satisfies the definition of sale but the drop in the price for stores that do not have inventories is small and does not satisfy our definition of a sale.

Let,

$$P(NI) = \frac{x_2 P_2 + x(1,NI)P(1,NI)}{x_2 + x(1,NI)} \; ; \; P(I) = \frac{x_2 P_2 + x(1,I)P(1,I)}{x_2 + x(1,I)}$$

denote the average price in the no inventories state and the average price in the state with inventories. Let

$$P(I,R) = \frac{x_2 P_2 + x(1,NI)P(1,I)}{x_2 + x(1,NI)}$$

denote the average regular price in the inventories state. Note that after removing sale observations the number of units sold in the first market is: $x(1,NI) < x(1,I)$. Since $P(1,NI) > P(1,I)$, we get that $P(NI) > P(I,R)$. Since $x(1,NI) < x(1,I)$, we get that $P(I,R) > P(I)$. It follows that: $P(NI) > P(I,R) > P(I)$.

The average regular price fluctuates between $P(NI)$ and $P(I,R)$. The average price fluctuates between $P(NI)$ and $P(I)$. Since $P(NI) > P(I,R) > P(I)$, the average price fluctuates more than the average regular price.

We now consider the case in which $\frac{P(1,NI)}{P(1,I)} > 1.1$ and the drop in price for stores with no inventories is large and satisfies our definition of a sale. In this case only stores in market 2 post a regular price and $P(I,R) = P_2$. It follows that: $P(I,R) > P(NI) > P(I)$. The average regular price fluctuates between $P(I,R)$ and $P(NI)$. The average price fluctuates between $P(NI)$ and $P(I)$. The standard deviation of the average price will be larger if: $P(NI) - P(I) > P(I,R) - P(NI)$.

3. There is a positive correlation between the frequency of sale and the standard deviation of the average regular price.

Sales occur with frequency of $1-q$ in our model and UPCs with higher sale frequencies have a lower q. The variance of the average regular price is:

$$VAR(q) = q[P(NI)]^2 + (1-q)[P(I,R)]^2 - q[P(NI)] - (1-q)[P(I,R)]$$

The derivative is:

$$VAR'(q) = \{[P(NI)]^2 - [P(NI)]\} - \{[P(I,R)]^2 - [P(I,R)]\}$$

When $P(I,R) > P(NI) > \frac{1}{2}$, this derivative is less than zero and the correlation between the frequency of sale ($1-q$) and the variance of the regular price is positive.

Stepping out of the example, we may assume that some changes in demand conditions are known in advance and some are not. Changes that are known in advance are typically more permanent and they typically lead to regular price changes. Negative demand shocks that are not known in advance are typically more transitory and lead to the accumulation of inventories and to sales. Goods that face more changes that are known in advance may also face more negative demand shocks and this leads to a correlation between the standard deviation of the average regular price and the frequency of sales.

We now turn to examine additional implications of the model.

4. THE BEHAVIOR OF THE CROSS-SECTIONAL PRICE DISTRIBUTION

In our model, there are more changes in the lower end of the price distribution than in the upper end. In the case illustrated by Figure 2B, the price in the second market changes only in response to changes in cost while the price in the first market changes also in response to the level of "unwanted inventories" that may occur as a result of a negative demand shock.[9]

The behavior of temporary sales is also not symmetric. A temporary cost reduction affect all stores: If unit cost went down by 20% than all stores reduce their price by 20%. But sales in response to the accumulation of inventories affect the low end of the price distribution.

To formulate testable hypotheses, we split the stores in each UPC-Week cell into bins of approximately equal size. For example, in the two bins case, we have high and low-price stores, where the price of the stores in the high price bin is greater than or equal to the median. In terms of this division into bins our mode suggests the following hypotheses:

[9] In the BE model the accumulation of inventories leads to a drop in all prices. Intuition suggests that if we replace the exponential depreciation in the BE model with the one-hos-shay depreciation we will get that the accumulation of inventories affect mainly the low end of the price distribution. This is because inventories with an expiration date get a "priority" in low price markets.

(a) The average price charged by the stores in any given bin fluctuates over weeks, but the variations in the average price are larger for low price bins.

(b) There are "sale prices" in all bins, but the fraction of sale prices is larger in low price bins.

The average price fluctuates in all bins primarily because of supply shocks (changes in λ). Variations in the average price are larger for low price bins because demand shocks that leads to the accumulation of “unwanted inventories” affect prices in low price bins more than prices in high price bins. Similarly, sales occur in all bins because of temporary supply shocks but occur more in low price bins because of demand shocks that leads to the accumulation of inventories.

Table 6 is about bin size. As was said before, the bins are only approximately of the same size because of the discrete nature of the data. In the 2 bins division, 60% of the stores are in bin 1 (the highest price bin) and 40% in bin 2 (the low-price bin). Later, when we control for store effects, the sizes of the bins are more similar.

Table 7a is about the frequency of temporary sales by bins. This is calculated by dividing the number of "sale prices" in the bin (aggregating over all UPCs and weeks) by the number of prices in the bin. When using the 2005 sample and the 2 bins division, 10% of the prices in bin 1 are "sale prices". The number for bin 2 is 34%. Using the 2005 sample and the 5 bins division, 42% of the prices in the lowest price bin (bin 5) are sale prices. The number for the highest price bin (bin 1) is 5%. This says that being on sale does not guarantee low relative price. The fraction of prices on sale is increasing with the index of the bin suggesting that the probability that an item is cheap relative to other stores given that it is on "sale" is higher than the unconditional probability.

Table 7b estimates the conditional probabilities: The probability that a price is in bin i given that it is a "sale price". For example, when using the 2005 sample and a 2 bins division, the probability that a "sale price" is in bin 1 is 0.3. This conditional probability is calculated as follows. The unconditional probability that a price is in bin 1 is: $\Pr ob(bin1) = 0.6$. The unconditional probability that a price is a "sale price" is: $\Pr ob(sale) = 0.2$. The probability that a price in bin 1 is a "sale price" is: $\Pr ob(Sale \mid bin = 1) = 0.1$. The probability that a price is in bin 1 and it is a "sale price" is: $\Pr ob(bin1 \cap Sale) = \Pr ob(bin1)\Pr ob(Sale \mid bin = 1) = (0.6)(0.1) = 0.06$. The probability that a price is in bin 1 given that it is a sale price is: $\Pr ob(bin1 \mid price = "sale") = \frac{\Pr ob(bin1 \cap Sale)}{\Pr ob(Sale)} = \frac{0.06}{0.2} = 0.3$. There is a remarkable agreement about the estimates of the conditional probabilities across samples.

Table 6*: Bin size

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

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

Table 7a: Frequency of temporary sales by bins

	bin 1	bin 2	bin 3	bin 4	bin 5
2 bins					
2004	0.09	0.35			
2005	0.10	0.34			
04-05	0.10	0.37			
3 bins					
2004	0.06	0.22	0.38		
2005	0.07	0.24	0.37		
04-05	0.07	0.25	0.41		
5 bins					
2004	0.04	0.16	0.24	0.33	0.43
2005	0.05	0.18	0.27	0.32	0.42
04-05	0.05	0.18	0.27	0.35	0.45

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

Table 7b: The probability that the price is in bin i given that it is a "sale price"

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

Table 8 provides the averages of the main variables using the 2 bins division. Here and in the rest of the paper we use the larger samples described in Tables 1 -3 to estimate magnitudes labelled “All prices”. To estimate magnitudes labelled “Regular prices” we delete “sale observations” from the smaller samples described in Table 4. These smaller samples have at least 11 stores per UPC-week cell and therefore we can divide the cell into bins.

The difference in average log price between the high price stores and the low-price stores (P1-P2) is about 20%. (It is 21% for the 2004 sample, 18% for the 2005 sample and 21% for the combined 04-05 sample). For regular prices, the average price is about 15% higher in the high price bin. Thus, it seems that temporary sales contribute to cross sectional price dispersion.

Table 8*: Means

	All Prices		Regular Prices	
	P1	P2	P1	P2
2004	0.81	0.59	0.9	0.76
2005	0.86	0.68	1.08	0.93
2004-05	0.76	0.55	1.17	1.03

* The Table uses the 2 bins division. P1 is the average log price for high price stores and P2 is the average log price for low price stores (average across UPCs). The first two columns use the larger samples of all prices described in Tables 1-3. The last two columns use the sample of regular prices obtained by deleting observations that are labeled as "sale prices" from the smaller samples described in Table 4.

Table 9 computes the standard deviation of the average price over weeks. We first calculate the average (over stores) price for each UPC-week-bin cell. We then calculate the standard deviation of these averages for each UPC-bin across weeks. Table 9 reports the average of these standard deviations across UPCs. In the two bins case, the standard deviation of P2 (the average weekly log price in the low-price bin) is more than 30% larger than the standard deviation of P1. It is larger by 54% for the 2004 sample, by 30% for the 2005 sample and by 40% for the 04-05 sample.

The following 3 rows in Table 9 describe the standard deviations when dividing each UPC-Week cell into three bins: High, medium and low. Also here, the standard deviation of the price in the low price bin is higher than the standard deviation of the price in the high price bin. The last rows in Table 9 are the standard deviations when dividing each UPC-Week cell into 5 bins. The standard deviations in bin 5 (the lowest price bin) are higher than the standard deviations in bin 1 (the highest price bin). The ratio of the standard deviations of the average price in bin 5 to the standard deviation in bin 1 is 1.8 on average (2 for 2004, 1.6 for 2005 and 1.76 for 2004-05).

Table 9*: Standard deviations over weeks

	2004	2005	2004-2005
One bin			
P	0.08	0.09	0.08
Two bins			
P1	0.07	0.09	0.08
P2	0.11	0.11	0.11
Three bins			
P1	0.06	0.08	0.07
P2	0.09	0.11	0.10
P3	0.12	0.11	0.12
Five bins			
P1	0.06	0.07	0.07
P2	0.08	0.10	0.09
P3	0.10	0.11	0.10
P4	0.11	0.11	0.11
P5	0.12	0.11	0.13
Regular prices			
	2004	2005	2004-2005
One bin			
P	0.02	0.04	0.03
Two Bins			
P1	0.02	0.04	0.03
P2	0.04	0.05	0.04
Three Bins			
P1	0.03	0.04	0.03
P2	0.04	0.05	0.05
P3	0.04	0.06	0.05
Five Bin			
P1	0.03	0.04	0.03
P2	0.04	0.05	0.05
P3	0.04	0.06	0.05
P4	0.05	0.06	0.05
P5	0.04	0.06	0.05

* This Table reports standard deviations over weeks. We first calculate the average price for each UPC-week-bin cell. We then calculate the standard deviation of these averages for each UPC-bin across weeks. The Table reports the average of these standard deviations over UPCs. The first rows report the standard deviation for the 2 bins case. The next rows report the standard deviation for the 3 bins case and the rows in the bottom report the standard deviation for the 5 bins case. The second half of the table repeats the calculations after eliminating all "temporary sale" observations from the smaller samples described in Table 4.

4.1. Store effect

Stores that are similar in price may be similar in other ways. For example, stores in rich neighborhoods may charge on average a price that is higher than the price charged by stores in poor neighborhoods. In an attempt to address this problem, we remove the store effect by running the following regressions.

$$\ln(P_{ijt}) = a_i + b_j(store - dummy) + e^P_{ijt} \tag{7}$$

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

Tables 6' are comparable Tables 6. The bins are more equal in size because the residuals are different across stores and the problem of lack of price dispersion is less common. The conditional probabilities in Table 7b' are not very different from the conditional probabilities in Table 7b.

Table 6': Bin size

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

Table 7a': Frequency of temporary sales by bins

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

Table 7b': The probability that the price is in bin i given that it is a "sale price"

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

Table 9' is comparable to Tables 9. The results are qualitatively the same suggesting that store effects do not drive our findings about the standard deviations by bins.

Table 9': Standard deviations over weeks

	2004	2005	2004-2005
One bin			
P	0.08	0.09	0.08
Two bins			
P1	0.06	0.08	0.07
P2	0.10	0.11	0.11
Three bins			
P1	0.06	0.08	0.07
P2	0.09	0.10	0.09
P3	0.12	0.12	0.12
Five bins			
P1	0.06	0.07	0.07
P2	0.07	0.09	0.08
P3	0.08	0.11	0.09
P4	0.10	0.12	0.11
P5	0.13	0.12	0.13
Regular prices			
	2004	2005	2004-2005
One bin			
P	0.02	0.04	0.03
Two Bins			
P1	0.02	0.04	0.03
P2	0.03	0.05	0.04
Three Bins			
P1	0.02	0.04	0.03
P2	0.03	0.04	0.03
P3	0.03	0.05	0.04
Five Bin			
P1	0.02	0.04	0.03
P2	0.03	0.04	0.03
P3	0.03	0.04	0.03
P4	0.03	0.05	0.04
P5	0.03	0.05	0.05

4.2. UPC specific store effect

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

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

As before, we repeat the Tables after replacing ln(P) with the residuals e^P_{iit}.

Tables 7" are comparable to Tables 7 and Table 7'. The bin sizes are similar to the one reported in Table 7' and so are the unconditional frequency of sales.

Table 7a": Frequency of temporary sales by bins

	bin 1	bin 2	bin 3	bin 4	bin 5
2 bins					
2004	0.07	0.32			
2005	0.09	0.31			
2004-2005	0.08	0.35			
3 bins					
2004	0.05	0.15	0.38		
2005	0.06	0.18	0.35		
2004-2005	0.05	0.18	0.41		
5 bins					
2004	0.03	0.08	0.15	0.27	0.42
2005	0.05	0.10	0.17	0.27	0.39
2004-2005	0.04	0.09	0.17	0.31	0.44

Table 7b'': The probability that a price is in bin i given that it is a "sale price"

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

Table 9'' is comparable to Tables 9 and 9'. It shows the same pattern: The standard deviation across weeks is increasing with the index of the bin. This is not the case in the sample of regular prices.

Table 9'': Standard deviations over weeks

	2004	2005	2004-2005
One bin			
P	0.08	0.09	0.08
Two bins			
P1	0.06	0.09	0.07
P2	0.11	0.11	0.11
Three bins			
P1	0.06	0.08	0.07
P2	0.08	0.10	0.09
P3	0.12	0.12	0.13
Five bins			
P1	0.06	0.07	0.07
P2	0.07	0.09	0.08
P3	0.09	0.11	0.09
P4	0.10	0.12	0.11
P5	0.13	0.12	0.13
Regular prices			
	2004	2005	2004-2005
One bin			
P	0.02	0.04	0.03
Two Bins			
P1	0.02	0.04	0.03
P2	0.03	0.04	0.04
Three Bins			
P1	0.02	0.04	0.03
P2	0.02	0.04	0.03
P3	0.03	0.05	0.04
Five Bin			
P1	0.02	0.04	0.04
P2	0.02	0.04	0.03
P3	0.02	0.04	0.03
P4	0.02	0.04	0.03
P5	0.04	0.05	0.05

Variations over weeks by bins.

Table 10 computes the ratio of the average standard deviation in the lowest price bin to the average standard deviation in the highest price bin (averaged across samples). The first column (All) reports the ratio of the standard deviations of prices when using the sample of all prices. When using the 2 bins division, the standard deviation in the low-price bin is 42% larger than the standard deviation in the high price bin. This difference is 52% when controlling for a store effect and 53% when controlling for a UPC specific store effect. When using the 3 and 5 bins divisions the differences are larger. The percentage differences in the standard deviations are lower when using the sample of regular prices (Regular in the second row).

Table 10*: Ratio of the average standard deviation in the lowest price bin to the average standard deviation in the highest price bin.

	Original prices			Store effect			UPC specific		
	2 bins	3 bins	5 bins	2 bins	3 bins	5 bins	2 bins	3 bins	5 bins
All	1.421	1.65	1.8	1.52	1.74	1.91	1.53	1.81	2.01
Regular	1.420	1.57	1.62	1.26	1.37	1.44	1.22	1.3	1.36

* The Table reports the ratio of the average standard deviation in the lowest price bin to the average standard deviation in the highest price bin. Averages are over samples. The first row (All) is the ratio of the standard deviations of prices in the samples of all prices. The second row (Regular) is this ratio in the samples of regular prices.

Table 10 shows that the average price in the low-price bin fluctuates more than the average price in the high price bin. It supports the hypothesis that high prices fluctuate less than low prices even after removing "sale" observations.

This observation is consistent with the UST example in section 3.2. In this example the price in the second market fluctuate only as a result of cost shocks while the price in the first market fluctuate also in response to the accumulation of "unwanted inventories" which occur as a result of negative demand shocks.

5. CONCLUDING REMARKS

We have established five stylized facts.

1. The fraction of weeks in which there are no sales in any of the stores is much larger than the fraction predicted by the hypothesis that stores use a mix strategy to choose temporary sales. For example, in the 2005 sample the fraction of weeks in which there is no sale in any of the stores is 45% while the mixed strategy hypothesis predicts 0.5%.

2. Goods with more fluctuations in regular prices have also more temporary sales. For example, the standard deviation of the average regular price in UPCs with sale frequencies between 20 to 30 percent is more than twice the standard deviation of the average regular price in UPCs with sale frequencies between 0 to 10 percent. This suggests that temporary sales and regular prices react to shocks that are related to each other. It is possible for example, that some demand shocks lead to regular price changes and other (more transitory) demand shocks lead to temporary sales. UPCs that are subject to relatively more demand shocks will typically have more of both types of shocks.
3. Temporary sales contribute substantially to the weekly variation of the average cross-sectional price of the typical good. In the larger sample of 2005 the standard deviation of the average price is 20% higher than the standard deviation of the average regular price. Since the frequency of sales is 20% in this sample, the contribution of a 1% temporary sale prices is on average a 1% increase in the standard deviation. In the smaller sample, the frequency of sale is 5% and the standard deviation of the average price is 10% higher than the standard deviation of the average regular price. In this smaller sample, a 1% temporary sale prices increases the standard deviation by 2%.
4. High prices appear to be more rigid than low prices. In the 2 bins division, the standard deviation of the average price in the high-price bin is 40% higher than the standard deviation of the average price in the low-price bin. When controlling for store effect and UPC specific store effect it is 50% higher.
5. A temporary sale price may not necessarily be cheap relative to the price in other stores. But a sale price is more likely to be relatively cheap: The probability that a sale price is in the bottom third of the distribution is around 60%.

We argue that these stylized facts are consistent with a model in which prices are completely flexible and temporary sales play an important role in reacting to demand and supply shocks.

Our findings are not consistent with the hypothesis that stores use a mixed strategy to determine temporary sales but are consistent with menu cost models of the type explored by Kehoe and Midrigan (2015). We argue however that these findings by themselves do not show that menu costs are important and that “prices are sticky after all”. They can be explained by a UST model that assumes no menu costs.

Some may argue that in the absence of menu costs there will be no effect of money on output. This is true from the point of view of sticky price models. It is not true from the point of view of the UST model in which money affect output even when prices are completely flexible. See Eden (1994).

From the point of view of the UST model the behavior of the entire price distribution is important for the question of efficiency, while the behavior of prices in individual stores is not. The findings here suggest that the price distribution is flexible and temporary sale contributes to the flexibility of the price distribution.

REFERENCES

Anderson Eric & Benjamin A. Malin & Emi Nakamura & Duncan Simester & Jón Steinsson, 2013. "**Informational Rigidities and the Stickiness of Temporary Sales**," NBER Working Papers 19350, National Bureau of Economic Research, Inc.

Aguirregabiria, Victor, 1999. "**The Dynamics of Markups and Inventories in Retailing Firms**," Review of Economic Studies, Wiley Blackwell, vol. 66(2), pages 275-308, April.

Bental, Benjamin and Benjamin Eden (1993). "**Inventories in a Competitive Environment**," Journal of Political Economy, University of Chicago Press, vol. 101(5), pages 863-86, October.

Coibion Oliver, Yuri Gorodnichenko and Gee Hee Hong., The Cyclicality of Sales, Regular and Effective Prices: Business Cycle and Policy Implications". American Economic Review 2015, 105(3):993-1029.

Dana James D. Jr. "Advance-Purchase Discounts and Price Discrimination in Competitive Markets" Journal of Political Economy, Vol.106, Number 2, April 1998, 395-422.

_______ "Equilibrium Price Dispersion under Demand Uncertainty: The Roles of Costly Capacity and Market Structure" The RAND Journal of Economics, Vol. 30, No. 4 (Winter, 1999), pp. 632-660.

Deneckere Raymond and James Peck., "Dynamic Competition with Random Demand and Costless Search: A Theory of Price Posting". Econometrica, Vol. 80, No. 3 (May, 2012), 1185–1247.

Eden, Benjamin. "Marginal Cost Pricing When Spot Markets are Complete" Journal of Political Economy, Vol. 98, No.6,1293-1306, Dec. 1990.

________ "**The Adjustment of Prices to Monetary Shocks When Trade Is Uncertain and Sequential**," Journal of Political Economy, University of Chicago Press, vol. 102(3), pages 493-509, June 1994.

_______ "**Price Dispersion And Demand Uncertainty: Evidence From U.S. Scanner Data**," International Economic Review, Department of Economics, University of Pennsylvania and Osaka University Institute of Social and Economic Research Association, vol. 59(3), pages 1035-1075, August 2018.

Eichenbaum Martin & Nir Jaimovich & Sergio Rebelo, 2011. "**Reference Prices, Costs, and Nominal Rigidities**," American Economic Review, American Economic Association, vol. 101(1), pages 234-62, February.

Glandon, Philip John, Sales and the (Mis) Measurement of Price Level Fluctuations (July 20, 2015). Available at SSRN: http://ssrn.com/abstract=2047127 or http://dx.doi.org/10.2139/ssrn.2047127 .

Guimaraes, Bernardo, and Kevin D. Sheedy. *2011.* "Sales and Monetary Policy." American Economic Review*, 101 (2): 844-76.*

Kaplan Greg & Guido Menzio, 2015. "**The Morphology Of Price Dispersion**," International Economic Review, Department of Economics, University of Pennsylvania and Osaka University Institute of Social and Economic Research Association, vol. 56, pages 1165-1206, November.

Kehoe Patrick J. & Virgiliu Midrigan, 2015. "**Prices are Sticky After All"**, Journal of Monetary Economics, Volume 75, October 2015, pages 35-53.

Lach Saul., "Existence and Persistence of Price Dispersion: An Empirical Analysis" The Review of Economics and Statistics, August 2002, 84(3): 433–444.

Nakamura, Emi & Jón Steinsson, 2008. "**Five Facts about Prices: A Reevaluation of Menu Cost Models**," The Quarterly Journal of Economics, MIT Press, vol. 123(4), pages 1415-1464, November.

Prescott, Edward. C., "Efficiency of the Natural Rate" Journal of Political Economy, 83 (Dec. 1975): 1229-1236.

Salop S., and J. Stiglitz, "Bargains and Ripoffs: A Model of Monopolistically Competitive Price Dispersion," Rev. Econ. Stud., Oct. 1977, 44, 493-510.

Shilony, Yuval., "Mixed Pricing in Oligopoly," J. Econ. Theory, Apr. 1977, 14, 373-88.

Sorensen, Alan T. "Equilibrium Price Dispersion in Retail Markets for Prescription Drugs" Journal of Political Economy, Vol. 108, No. 4 (August 2000), pp. 833-850.

Varian, H., "A Model of Sales," American Economic Review 70:4 (1980), 651–659.