Small Price Changes, Sales Volume, and Menu Cost*

Doron Sayag
Department of Economics, Bar-Ilan University
Ramat-Gan 5290002, Israel, and
DoronSayag2@gmail.com

Avichai Snir
Department of Banking and Finance, Netanya Academic College
Netanya 4223587, Israel
Avichai.Snir@gmail.com

Daniel Levy**
Department of Economics, Bar-Ilan University
Ramat-Gan 5290002, ISRAEL,
Department of Economics, Emory University
Atlanta, GA 30322, USA, and
RCEA
Daniel.Levy@biu.ac.il

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** Corresponding author: Daniel Levy, Daniel.Levy@biu.ac.il

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Abstract

In many retail price datasets, small price changes account for 20%–44% of price changes, which much of the literature interprets as evidence against the menu cost model. To reconcile, we consider a prediction of the menu cost model—an inverse relationship between sales volume and the width of the (S, s) band, which implies that if sales volume is high, small price changes will be more frequent. Analyzing scanner price dataset that contains information on both prices and sales-volume, we find evidence consistent with this prediction: small price changes are more frequent for products with higher sales volume.

1. Introduction

Extensive empirical analyses of price-setting behavior using various micro-level price datasets, show that individual prices tend to change at a significantly lower frequency than the corresponding market conditions.[1] A leading theory offered to explain the sluggish response of prices to underlying shocks is the menu cost theory, which posits that each time a firm changes a price, it incurs a lump sum cost ("menu cost") that is independent of the size or the direction of the price change.[2]

A key prediction of the menu cost theory is that firms will make infrequent but relatively large price changes because making small price changes are less profitable. However, empirical studies find that between 20%–44% of the observed price changes are small.[3] This inconsistency is often cited as evidence against the menu cost theory.

To reconcile small price changes with menu costs, Dotsey et al. (1999) hypothesize stochastic menu costs which lead to small price changes if the realized menu cost is small. Lach and Tsiddon (2007), Klenow and Malin, Midrigan (2011), Alvarez and Lippi (2014), and Chakraborty et al. (2015) offer evidence that is consistent with economies of scope in price setting with high average price change, allowing both small and large individual price changes.[4] Rotemberg (1982b) and Chen et al. (2008) suggest that consumer inattention or fairness considerations can make small price changes profitable.

We argue that small price changes do not necessarily contradict the menu cost model. The intuition of this argument is straightforward. In the menu cost model, a firm changes the price if the increase in profits expected from the price change exceeds the menu cost. Ceteris paribus, the expected profit from a price change will be greater the greater is the sales volume. In other words, the likelihood that a small price change is profitable

[1] See, for example, Liebermann and Zilberfarb (1985), Carlton (1986), Cecchetti (1986), Lach and Tsiddon (1992, 1996), Blinder et al. (1998), Levy et al. (1998), Eden (2001, 2018), Dutta et al. (2002), Levy et al. (2002), Owen and Trzepacz (2002), Baharad and Eden (2004), Bils and Klenow (2004), Álvarez, et al. (2006), Dhyne et al. (2006), Nakamura and Steinsson (2008), Kehoe and Midrigan (2015), Gorodnichenko et al. (2017), Anderson et al. (2015, 2017), and studies cited therein. For older surveys, see Romer (1993), Weiss (1993), Taylor (1999), Willis (2003), and Wolman (2007). More recent surveys include Klenow and Malin (2011), Leahy (2011), and Nakamuara and Steinsson (2013).

[2] See, for example, Barro (1972), Sheshinski and Weiss (1977, 1979, and 1982), Rotemberg (1982a,b), Akerlof and Yellen (1985), and Mankiw (1985).

[3] See, for example, Bils and Klenow (2004), Nakamura and Steinsson (2008), Chen et al. (2008), Klenow and Kryvtsov (2008), Midrigan (2011), Bhattarai and Schoenle (2014), and Klenow and Malin (2011).

[4] Eichenbaum et al. (2014) and Cavallo and Rigobon (2012) suggest that many of the reported small price changes are due to mesurment errors. Even these studies, however, find a non-negligible share of small price changes that cannot be explained by measurement errors.

increases with the sales volume.[5]

To demonstrate this argument formally, we extend Barro's (1972) menu cost model by deriving the relationship between the width of the (*S*, *s*) band and the sales volume. We show that the greater is the sales volume, the narrower is the optimal (*S*, *s*) band, which in turn implies that smaller price changes become more profitable.

We test this prediction using Dominick's scanner price data, which is particularly useful for our purpose because the data contain weekly information on both the prices and the sales volume for 18,035 different products in 29 product categories.

We proceed as follows. In section 2, we derive analytically the relationship between the sales volume and the (*S*, *s*) band. In section 3, we discuss the data. In section 4, we present the empirical results. In section 5, we discuss robustness. We conclude in section 6. In the Appendix, we report the details of some additional tests and analyses.

2. Sales volume and the width of the optimal (*S*, *s*) band

Following Barro (1972), consider a profit maximizing monopolist producing a homogenous good. The linear demand and the quadratic cost functions are given by $Y = \alpha - \beta P + u$ and $C(Y) = a + bY + cY^2$, where u is a symmetric demand disturbance/shifter, $C'(Y) > 0$, and $a, b, c, \alpha, \beta > 0$. The producer's maximization problem is thus given by:

$$\begin{cases} \max\left[PY - \left(a + bY + cY^2\right)\right] \\ \text{s.t. } Y = \alpha - \beta P + u \end{cases} \tag{1}$$

Setting $MR = MC$, and solving for P and Y, we obtain

$$P^* = \left[\frac{\alpha + \beta\left(2c\alpha + b\right)}{2\beta\left(1 + c\beta\right)}\right] + \left[\frac{1 + 2c\beta}{2\beta\left(1 + c\beta\right)}\right]u \tag{2}$$

and

$$Y^* = \left[\frac{\alpha - \beta b}{2\left(1 + c\beta\right)}\right] + \left[\frac{1}{2\left(1 + c\beta\right)}\right]u \tag{3}$$

The second order condition for a maximum is given by $1 + c\beta > 0$.

[5] Bhattarai and Schoenle (2014) use micro-data underlying the US PPI to show that firms selling more products adjust prices more frequently.

In the absence of a disturbance $u=0$, the profit maximizing output is given by

$$Y^*\big|_{u=0} = \frac{\alpha-\beta b}{2\left(1+c\beta\right)} \tag{4}$$

where $\alpha-\beta b>0$, which is required for the output to be positive in the disturbance-free equilibrium. We can think of $Y^*\big|_{u=0}$ as the expected output.

Following Barro (1972, p. 19), suppose that the value of the disturbance changes from 0 to *u*. Assuming that the firm continuously adjusts its price and output to the change in *u*, the resulting change in the firm's profit, as Barro shows, is given by

$$\begin{aligned}\Delta\pi_{(0,u)} &= \int_0^u \left(\frac{d\pi}{du}\right) du \\ &= \int_0^u \left[P - C'(Y)\right] du \\ &= \left[\frac{\alpha-\beta b}{2\beta\left(1+c\beta\right)}\right] u + \left[\frac{1}{4\beta\left(1+c\beta\right)}\right] u^2\end{aligned} \tag{5}$$

Next, assume that the firm's price is sticky at $\hat{P}$, the optimal price in the disturbance-free equilibrium, with $\frac{d\hat{P}}{du}=0$. According to (2),

$$\hat{P} = \frac{\alpha+\beta\left(2c\alpha+b\right)}{2\beta\left(1+c\beta\right)} \tag{6}$$

We follow Barro (1972, p. 20) to assume that the disturbance is not "too small" or "too large", i.e., $u_{\min} \le u \le u_{\max}$. This is necessary to avoid the situations of no production, which will be the case if $u < u_{\min}$, or a shortage, which will be the case if $u > u_{\max}$. Then,

$$\begin{aligned}\Delta\hat{\pi}_{(0,u)} &= \int_0^u \left(\frac{d\hat{\pi}}{du}\right) du \\ &= \int_0^u \left[\hat{P} - C'(\hat{Y})\right] du \\ &= \left[\frac{\alpha-\beta b}{2\beta\left(1+c\beta\right)}\right] u - cu^2\end{aligned} \tag{7}$$

The expression in (7) is the change in the profit when the disturbance value changes from

0 to u, but the firm does not adjust its price, i.e., when the price is stuck at $\hat{P}$.

The firm's profit gain, if it adjusts its price to the demand shock, is therefore given by

$$\Delta\pi_{(0,u)} - \Delta\hat{\pi}_{(0,u)} = \theta u^2 \tag{8}$$

where

$$\theta = \frac{(1+2c\beta)^2}{4\beta(1+c\beta)} > 0 \tag{9}$$

The expression in (9) can be interpreted as the loss the firm incurs for not adjusting its price in response to the demand shock. As Barro (1972, p. 20) notes, the symmetry of this loss means that what matters is the size of the demand shock, not its sign. It follows that the optimal price adjustment rule (S, s), is symmetric. Also, for a given disturbance u, the loss from not adjusting the price decreases with the price sensitivity of demand β, and increases with the slope of the marginal cost curve $C''(Y) = 2c$.

If u follows a symmetric random walk, then the optimal (S, s) band is symmetric, given by $\left(\hat{h}, -\hat{h}\right)$, where

$$\hat{h} = \sqrt{\sigma}\left(\frac{6\gamma}{\theta}\right)^{\frac{1}{4}} \tag{10}$$

where γ is a fixed, lump-sum menu cost, σ^2 is the variance of the Bernoulli process driving the symmetric random walk, and θ is given by (9).

According to (10), the higher is the menu cost, the wider is the band of inaction. On the other hand, a high θ implies a narrow band of inaction. That is because a high θ, according to (8)–(9), means a greater profit loss from not adjusting the price.

We can take advantage of the linear-quadratic structure of the optimization problem, to derive the relationship between the output and the optimal (S, s) band. Rewrite (9) as

$$\begin{aligned} \theta &= \frac{(1+2c\beta)^2}{4\beta(1+c\beta)} \\ &= \left[\frac{\alpha-\beta b}{2(1+c\beta)}\right]\left[\frac{(1+2c\beta)^2}{2\beta(\alpha-\beta b)}\right] \end{aligned} \tag{11}$$

By (4), the term in the first brackets is the optimal level of output in the disturbance-free equilibrium $Y^*|_{u=0}$. Therefore, (11) can be written as a function of $Y^*|_{u=0}$,

$$\theta\left(Y^*|_{u=0}\right)=\left(Y^*|_{u=0}\right)\left[\frac{\left(1+2c\beta\right)^2}{2\beta\left(\alpha-\beta b\right)}\right] \tag{12}$$

with the derivative

$$\theta'\left(Y^*|_{u=0}\right)=\left[\frac{\left(1+2c\beta\right)^2}{2\beta\left(\alpha-\beta b\right)}\right]>0 \tag{13}$$

In other words, the greater is the monopolist's expected output level, the greater is θ, which means that the greater is the loss the firm incurs from not adjusting the price. Combining (10) and (12), we have θ

$$\hat{h}=\sqrt{\sigma}\left\{6\gamma\left(Y^*|_{u=0}\right)^{-1}\left[\frac{\left(1+2c\beta\right)^2}{2\beta\left(\alpha-\beta b\right)}\right]^{-1}\right\}^{\frac{1}{4}} \tag{14}$$

with a partial derivative

$$\frac{\partial\hat{h}}{\partial\left(Y^*|_{u=0}\right)}<0 \tag{15}$$

The expression in (15) is the main result: the greater is the monopolist's output level, the smaller is $\hat{h}$, and thus the narrower is the optimal (*S*, *s*) band. In other words, there is an inverse relationship between the level of output and the width of the (*S*, *s*) band. If the output of the monopolist is high (low), then the (*S*, *s*) band will be narrower (wider), which means that we will see more (less) frequent smaller price changes.

This prediction can be tested with a dataset that contains both retail prices and quantities. The model predicts that if the average quantity sold is high, then we will see more frequent small price changes.

3. Data

We use the dataset of Dominick's, a large US retail food chain, operating 93 stores in the greater Chicago area with a market share of 25%. The dataset contains 98+ million weekly observations over an 8-year period, from September 14, 1989 to May 8, 1997, for

18,035 products (UPCs) in 29 product categories, including food, cleaning products, pharmaceutical products, and hygienic products. Each weekly observation includes the retail price, the number of units sold, the revenue, the retailer's markup and some product attributes. These features make the Dominick's dataset especially well-suited for our analysis. In the data, there is a large variability in both prices and sales volumes, both across goods and across stores. The latter is important, because it allows us to test the effect of variation in the sales volumes across stores, holding the product constant.[6]

4. Empirical findings

4a. Results of cross-category analyses

Table 1 shows by product category the number of all price changes and the number of small price changes $(\Delta P \leq 10¢)$, both conditional on observing the prices in consecutive weeks (t and $t + 1$), the percentage of small price changes out of all price changes, and the average sales volume. The latter is calculated by first finding the average weekly sales volume for each product in each store (*product-store*) in the category, and then averaging over all products. There is a large cross-category variation in the share of small price changes, ranging from 5.4% for the beer category to 56.6% for the canned tuna category.

Figure 1 shows a scatterplot of the category-level average sales volume and the percentage of small price changes, along with a linear regression line (red solid line). We find a positive correlation between sales volume and the percentage of small price changes. The correlation is even stronger (green dashed line) if we exclude the categories of paper towels and bathroom tissues, which have particularly high values of both average sales volumes and percentage of small price changes.

To test this more formally, we run cross-category OLS regressions which we report in Table 2. The dependent variable in all regressions is the category level percentage of small price changes. In column 1, the independent variable is the average weekly sales volume. We find that the coefficient is 0.89. Thus, at the category level, 1-unit increase in the average weekly sales volume is associated with an increase of 0.89% in the percentage of small price changes.

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[6] Dominick's prices are calculated as a ratio of revenue to quantity-sold. This is unlikely to pose a problem, as the Dominick's prices are set on a weekly basis. If shoppers use manufacturer coupons, we cannot account for these. However, during the sample period, the use of such coupons was limited. See Barksy et al. (2003), Chen et al. (2008), and Levy et al. (2010, 2011), for more details about the data.

A possible explanation for this correlation could be that categories with low average price level have higher share of small price changes and higher sales volumes. The regression in column 2 shows that there is indeed a negative correlation between the average price in a category and the percentage of small price changes. However, in column 3, which reports the results of a regression that includes both the average prices and the average sales volumes as independent variables, we find that the coefficient of the average sales volumes is 0.69 and statistically significant. Thus, we find that sales volume is correlated with small price changes even after controlling for the price level.

A possible alternative explanation is competition. It could be that products in categories with high sales volume face stronger competition, and their producers may want to avoid large price changes that could alienate consumers. To tests this, in column 4 we look at the correlation between the percentage of small price changes and category level estimates of absolute own price elasticity, which is taken from Hoch et al. (1995). We find that the correlation is negative. I.e., small price changes are more common in product categories with low rather than high (in absolute values) price elasticities, which is inconsistent with the hypothesis that small price changes are a response to competition.

It is consistent, however, with our model, because a low price elasticity means a small response to price changes and, consequently, as an approximation, the retailer's benefit from a small price change can be assessed based on the sales volume before the price change. Furthermore, in column 5, where we report the results of a regression with both the sales volumes and the price elasticity as independent variables, we find that adding the price elasticity as a control does not change the effect of the sales volume substantially. The coefficient of the sales volume is 0.73, and statistically significant.

As another test of the correlation between sales volume and the % of small price changes, we merged the observations in all 29 categories and then divided product-stores into deciles according to their sales volume. Figure 2 shows the frequency of small price changes by sales volume deciles. As the figure indicates, an increase in the sales volume is associated with a significant increase in the percentage of small price changes. The percentage of small price changes in the 10th decile of sales volumes is 31.7%, 3.2 times higher than the percentage of price changes in the 1st decile of sales volumes, 10.0%.

4b. Results of category-level analyses

To further study the correlation between small price changes and sales volume, we compare high sales volume products to low sales volume products in each category. For each product in each store, we compute the average sales volume over the entire sample period. By taking the average over a long period, we obtain an estimate of the expected sales volume that does not depend on transitory shocks or sales. We then group the products into high, medium and low sales volume products. Low sales volume products are products with average sales volume in the lower third of the distribution, high sales volume products have sales volumes in the higher third of the distribution, and medium sales volume products have sales volumes in between.

Figure 4 shows, for every category, the frequency of price changes for each size of price change from 1¢ to 50¢. The red dashed line depicts the frequency of price changes among high sales volume products, while the blue solid line depicts the frequency of price changes among low sales volume products. The green shaded area shows the range of small price changes, $\Delta P \leq 10¢$.

The figure shows that the most common price changes are multiples of 10¢. It can also be observed that consistent with the prediction of Barro's (1972) model, in all categories except beers, which is highly regulated, price changes are significantly more common among high sales volume products than among low sales volume products.

Focusing on the shaded area, we see that the frequency of small price changes is far greater among the high sales volume products than low sales volume products. Indeed, for high sales volume products, in most product categories, the frequency of small price changes exceeds the frequency of large price changes. This is far less common, and less dramatic, among low sales volume products.

As a formal test, we estimate a series of fixed effect regressions:

$$\begin{aligned} small\ \ price\ change_{i,s,t} &= \alpha + \beta \log(average\ sales\ volume_{i,s}) + \gamma \mathbf{X}_{i,s,t} \\ &+ month_t + year_t + \delta_s + \mu_i + u_{i,s,t} \end{aligned} \qquad (16)$$

where small price change is a dummy that equals 1 if a price change of product *i* in store *s* at time *t* is less or equal to 10¢, and 0 otherwise. The average sales volume is the average sales volume of product *i* in store *s* over the sample period. **X** is a matrix of other control variables. Month and year are fixed effects for the month and the year of the price change. δ and μ are fixed effects for stores and for products. *u* is an iid error term. We estimate separate regressions for each product category, clustering the errors by product.

Table 3 reports the coefficients of the key variable, the average sales volume, for each product category. Column 1 reports the results of baseline regressions that include only the average sales volume and the fixed effects for months, years, stores, and products.

We find that in all 29 product categories, the coefficients are positive and statistically significant. In other words, in all 29 product categories, there is a positive correlation between the likelihood that a price change is small and the average sales volume. The effect is economically significant. The average coefficient is 0.035, suggesting that an increase of 1% in the sales volume is associated with an increase of 3.5% in the likelihood that a price change will be small.

In column 2, we add the following controls: the log of the average price to control for the price level effect on the size of price changes, the log of the absolute change in the wholesale price, and a control for sale- and bounce back prices. The latter is important as price changes associated with sales tend to be large (Nakamura and Steinsson 2008).[7]

The results are similar to column 1. The coefficient of the average sales volume is positive and statistically significant in all categories, averaging 0.03. Thus, even after including the controls, we still find that increasing the average sales volume by 1% is associated with an increase of 3% in the likelihood of a small price change.

In column 3, we add a dummy for 9-ending prices as an additional control because when the pre-change price is 9-ending, price changes tend to be larger than when the pre-change price ends in other digits (Levy et al. 2020). Thus, if products with high sales volume tend to have non 9-ending prices, then it might lead to high sales volume product prices changing by small amounts.

However, adding this dummy does not change the main result appreciably. All 29 coefficients remain positive and statistically significant. On average, once we control for 9-ending prices, increasing the average sales volume by 1% is associated with an increase of 2.6% in the likelihood of a small price change.

In column 4, we focus on regular prices by excluding sale- and bounce back prices. We do this for two reasons. First, sale- and bounce back prices tend to be large and therefore, we need to account for them properly. Second, changes in sale prices have smaller effect on inflation than changes in regular prices (Nakamura and Steinsson 2008,

[7] To identify sale prices, we do not use the sales' flag included in the Dominick's data because it was not set on a consistent basis (Peltzman 2000). We therefore use the sales spotter algorithm of Fox and Syed (2016) to identify sales. This algorithm has the advantage that it was calibrated using the Dominick's data and, consequently, it is particularly useful for identifying sales in the Dominick's data.

Midrigan 2011, Anderson et al. 2017). It is therefore of interest to look at regular prices when studying the correlation between small price changes and sales volume.

We find that excluding sale prices strengthens the correlation between sales volume and small price changes. All coefficients are again positive and statistically significant, averaging 0.045, implying that for regular prices, an increase of 1% in the average sales volume is associated with an increase of 4.5% in the likelihood of a small price change.

4c. Results of product-level analyses

A possible explanation for the correlation between sales volume and small price changes is that products with high sales volume have some unobserved attributes that makes them prone to small price changes. We explore this possibility by estimating for each product a separate regression. If the correlation between sales volume and small price changes is found also at the level of individual products, then it cannot be explained by unobserved attributes, since in each regression we have data on only one product.

Before presenting the full regression results, consider as an example the crackers category. In Figure 5, we show a scatter plot for each of the 22 cracker products that has data for all 93 stores of Dominick's. In each of the 22 figures, there are 93 dots, one for each store. In each figure, the x-axis in the figures gives the average weekly sales volume of the product in a store, and the y-axis gives the share of small price changes of the product in a store. The straight lines are regression lines.

According to the plots, the correlation between sales volume and the share of small price changes is positive for all 22 individual products. For 20 of them (marked with solid black regression lines), the correlations are statistically significant. The two regression lines that are not statistically significant are marked with red dotted lines.

For a more formal analyses, we calculate for each product in each of the 29 product categories the average weekly sales volume and the share of small price changes in each of the stores it was offered. Many products in the sample were offered for only short periods or only in a small number of stores. To avoid biases, we drop products for which we do not have information for at least 30 stores.

Using these data, we estimate for each product in each category an OLS regression with robust standard errors. The dependent variable is the share of small price changes for the product in each store. The independent variable is the average sales volume of the product in each store. The estimation results are summarized in Table 4.

Column 1 gives, for each product category, the average of the estimated coefficients. Columns 2–5 give information on the sign of the estimated coefficients: the number of positive coefficients, the number of negative coefficients, the percentage of the positive coefficients, and the percentage of negative coefficients, respectively. Columns 6 and 7 report the number of coefficients that are both positive and statistically significant, and negative and statistically significant, respectively, at the 5% level.

According to the figures in the table, the average coefficients are positive in 28 of the 29 product categories. The only exception is the cigarettes category, which is highly regulated and, consequently, it is often excluded from the analyses (Chen et al. 2008, p. 729, footnote 2). The number of positive coefficients far exceeds the number of negative coefficients. On average, the former is 4.6 times larger than the latter. Ignoring the cigarettes category, in all 28 categories more than 71% of the coefficients are positive.

Focusing on statistically significant coefficients, we find a far greater number of positive coefficients that are significant than negative coefficients that are significant. In fact, in 16 product categories we do not have a single case of statistically significant negative coefficient. In the remaining categories there are only 1–4 products with statistically significant negative coefficient. In other words, for the overwhelming majority of the individual products in our sample, we find a positive relationship between their sales volume and the share of small price changes.

To summarize, we find that the correlation between sales volume and the share of small price changes is positive whether we look across categories, within categories, and for individual products across stores. It seems unlikely, therefore, that the correlation is due to unobserved characteristics of the products or the product categories.

5. Robustness

We conducted several robustness checks. To minimize the possibility of mistakes, we repeat the analyses (1) by excluding all 1¢ price changes (Eichenbaum et al. 2014), and (2) by excluding observations if the price, after it changes, does not last for at least two weeks (Strulov-Shlain 2019). In addition, we repeated the analyses by defining a small price change as a price change of (3) smaller or equal to 5¢, (4) smaller or equal to 15¢, (5) smaller or equal to 2%, and (6) smaller or equal to 5%. (7) We used the average sales volume in each year instead of the average sales volume in the entire sample period. (8) We augment the data with demographic information about consumers living in the neighborhood of each store, including their median income, the share of minorities, and the share of unemployed. To control for local competition, we also add a control for the pricing zone of each store. We re-estimate the product-level regressions using these variables as controls. Our main results remain unchanged. Online Web Appendix contains the details of these analysis.

6. Conclusion

The finding of frequent small price changes in many retail price datasets has been interpreted by many authors as a prima facie evidence against the menu cost model. We, however, argue that the finding of frequent small price changes is not necessarily inconsistent with the menu cost model. It depends on the sales volume of the product in question. If the retailer expects to sell many units of the product, then small price changes might be profitable even in a world with fixed menu cost.

We extend Barro's (1972) theoretical menu cost model to demonstrate analytically that there is a negative relationship between the sales volume and the width of the (S, s) band. It follows that if the sales volume is high, then we are more likely to see more frequent small price changes.

To test this prediction, we analyze Dominick's scanner price dataset, which has the advantage that it contains information on both prices and sales volume. Consistent with the predictions of the theoretical model, we find that there are more frequent small price changes for products with higher sales volume.

This finding is quite robust. It holds across product categories, within product categories, and for individual products. The finding is also robust to a variety of sensitivity analyses such as the definition of "small" price changes, measurement errors, inclusion of various control variables, etc.

We should note two caveats, however. On the theoretical front, we show that this result holds in the simple menu costs model of Barro (1972).[8] We do not know whether it will hold in a more complex menu cost model. On the empirical front, the dataset we use is somewhat old. Future work should therefore explore the relationship between sales volume and the width of the (S, s) band in more complex menu cost models, and test their predictions using more recent datasets.

[8] The result also holds in Mankiw (1985) model.

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Table 1. Proportion of small price changes and the average sales volume by product categories

Product Category	All price changes (1)	Small price changes (2)	% of small price changes (3)	Average sales volume (4)
Analgesics	276,225	35,378	12.8	1.25
Bath soap	35,572	5,125	14.4	0.73
Bathroom tissues	325,837	136,493	41.9	39.21
Beer	45,9405	24,859	5.4	3.61
Bottled juices	962,368	358,443	37.3	8.12
Canned soups	950,357	488,159	51.4	12.4
Canned tuna	379,680	214,923	56.6	9.66
Cereals	724,013	226,449	31.3	14.98
Cheese	1,811,753	813,305	44.9	11.44
Cigarettes	56,000	16,327	29.2	2.37
Cookies	1,353,330	374,027	27.6	5.19
Crackers	476,008	164,529	34.6	4.81
Dish detergents	374,058	138,909	37.1	8.50
Fabric softeners	348,422	116,134	33.3	5.57
Front end candies	487,886	249,939	51.2	11.26
Frozen dinners	502,830	115,471	23.0	5.57
Frozen entrees	1,846,911	314,441	17.0	6.56
Frozen juices	658,225	235,246	35.7	16.32
Grooming products	659,842	82,759	12.5	1.21
Laundry detergents	559,576	107,931	19.3	7.29
Oatmeal	169,093	68,971	40.8	7.20
Paper towels	248,289	135,462	54.6	35.00
Refrigerated juices	800,280	259,263	32.4	19.82
Shampoos	701,813	54,068	7.7	0.87
Snack crackers	800,253	220,178	27.5	6.74
Soaps	324,724	145,984	45.0	4.69
Soft drinks	4,532,158	743,243	16.4	13.46
Toothbrushes	295,021	33,386	11.3	1.80
Toothpastes	588,261	100,141	17.0	3.07
Total	21,708,190	5,979,543	27.6	9.27

Notes: Column 1 presents the total number of price changes in each category. Column 2 presents the number of small price changes $(\Delta P \leq 10¢)$. Column 3 presents the % of small price changes out of all price changes. Column 4 presents the average number of units sold per product, per week, per store.

Table 2. Cross-category regression of the % of small price changes and sales volume

	(1)	(2)	(3)	(4)	(5)
Average sales volume	0.89***		0.69**		0.73***
	(0.020)		(0.264)		(0.209)
Average price		–4.83***	–3.28*		
		(1.651)	(1.610)		
Absolute elasticity				–12.82**	–15.70**
				(5.282)	(4.139)
R^2	0.30	0.24	0.40	0.27	0.60
Number of categories	29	29	29	18	18

Notes: The table presents the results of OLS regressions. The dependent variable is the % of small price changes out of all price changes, in each of the 29 categories. Small price changes are defined as price changes of $\Delta P \leq 10¢$. The average price is the average price in the product category. The absolute elasticity is the absolute value of the demand price elasticity estimates as reported by Hoch et al. (1995). Columns (4) and (5) contain only 18 observations because Hoch et al. (1995) provide elasticity estimates only for 18 of the 29 product categories. * p < 10%, ** p < 5%, *** p < 1%

Table 3. Category-level regressions of small price changes and sales volume

		(1)	(2)	(3)	(4)
Analgesics	Coefficient	0.0381***	0.031***	0.0253***	0.047***
	(Std.)	(0.0032)	(0.0027)	(0.0025)	(0.0052)
	Observations	276,225	276,225	276,225	77,653
Bath soap	Coefficient	0.043***	0.0471***	0.0438***	0.0885***
	(Std.)	(0.0087)	(0.0094)	(0.0091)	(0.0157)
	Observations	35,572	35,572	35,572	6,540
Bathroom tissues	Coefficient	0.0321***	0.0163***	0.0136***	0.0332***
	(Std.)	(0.0057)	(0.0046)	(0.0043)	(0.0067)
	Observations	32,5837	32,5837	32,5837	82,602
Beer	Coefficient	0.0235***	0.0252***	0.0209***	0.0679***
	(Std.)	(0.0015)	(0.0012)	(0.0012)	(0.005)
	Observations	459,405	459,405	459,405	56,829
Bottled juice	Coefficient	0.0474***	0.0377***	0.0332***	0.033***
	(Std.)	(0.0037)	(0.0031)	(0.0031)	(0.0044)
	Observations	962,368	962,368	962,368	243,787
Canned soup	Coefficient	0.0239***	0.0161***	0.0167***	0.0182***
	(Std.)	(0.004)	(0.0034)	(0.0033)	(0.0038)
	Observations	950,357	950,357	950,357	278,543
Canned tuna	Coefficient	0.0367***	0.0269***	0.0228***	0.0295***
	(Std.)	(0.0046)	(0.0039)	(0.0036)	(0.0043)
	Observations	379,680	379,680	379,680	116,890
Cereals	Coefficient	0.0238***	0.0184***	0.0172***	0.027***
	(Std.)	(0.0026)	(0.0023)	(0.0024)	(0.0034)
	Observations	724,013	724,013	724,013	260,460
Cheese	Coefficient	0.0374***	0.0219***	0.018***	0.0127***
	(Std.)	(0.0027)	(0.0021)	(0.0021)	(0.0032)
	Observations	1,811,753	1,811,753	1,811,753	521,244
Cigarettes	Coefficient	0.0196***	0.0191***	0.0185***	0.0186***
	(Std.)	(0.0031)	(0.0031)	(0.0031)	(0.0037)
	Observations	56,000	56,000	56,000	44,322
Cookies	Coefficient	0.0436***	0.0382***	0.0323***	0.0532***
	(Std.)	(0.0016)	(0.0016)	(0.0014)	(0.003)
	Observations	1,353,330	1,353,330	1,353,330	228,976
Crackers	Coefficient	0.0548***	0.0435***	0.0392***	0.0581***
	(Std.)	(0.0033)	(0.0031)	(0.0029)	(0.0063)
	Observations	476,008	476,008	476,008	88,768
Dish detergent	Coefficient	0.0513***	0.0388***	0.0337***	0.0419***
	(Std.)	(0.0034)	(0.0028)	(0.0028)	(0.004)
	Observations	374,058	374,058	374,058	93,657
Fabric softener	Coefficient	0.0434***	0.0316***	0.028***	0.0473***
	(Std.)	(0.0038)	(0.0036)	(0.0036)	(0.0047)
	Observations	348,422	348,422	348,422	100,472
Front-end-candies	Coefficient	0.0043***	0.008***	0.0069***	0.0087***
	(Std.)	(0.0035)	(0.0027)	(0.0027)	(0.0029)
	Observations	487,886	487,886	487,886	157,539

Table 3. (Cont.)

		(1)	(2)	(3)	(4)
Frozen dinners	Coefficient	0.0513***	0.0406***	0.0392***	0.0874***
	(Std.)	(0.0025)	(0.0022)	(0.0022)	(0.0056)
	Observations	502,830	502,830	502,830	72,865
Frozen entrees	Coefficient	0.033***	0.0328***	0.0319***	0.0635***
	(Std.)	(0.0019)	(0.0016)	(0.0016)	(0.0034)
	Observations	1,846,911	1,846,911	1,846,911	352,717
Frozen juices	Coefficient	0.0326***	0.0261***	0.0235***	0.0295***
	(Std.)	(0.0037)	(0.0032)	(0.0031)	(0.0048)
	Observations	658,225	658,225	658,225	150,064
Grooming products	Coefficient	0.0398***	0.0448***	0.0388***	0.0624***
	(Std.)	(0.0022)	(0.002)	(0.0019)	(0.005)
	Observations	659,842	659,842	659,842	107,669
Laundry detergents	Coefficient	0.032***	0.0227***	0.0185***	0.0366***
	(Std.)	(0.0027)	(0.0024)	(0.0024)	(0.0041)
	Observations.	559,576	559,576	559,576	148,548
Oatmeal	Coefficient	0.0295***	0.0175***	0.0156***	0.0314***
	(Std.)	(0.0073)	(0.0052)	(0.0052)	(0.0093)
	Observations	169,093	169,093	169,093	63,705
Paper towels	Coefficient	0.0347***	0.0275***	0.0263***	0.0285***
	Std.	(0.0095)	(0.0102)	(0.0103)	(0.0085)
	Observations	248,289	248,289	248,289	53,732
Refrigerated juices	Coefficient	0.0307***	0.0208***	0.0181***	0.0302***
	(Std.)	(0.0032)	(0.0027)	(0.0026)	(0.0041)
	Observations	800,280	800,280	800,280	161,098
Shampoos	Coefficient	0.0305***	0.0377***	0.0329***	0.0581***
	(Std.)	(0.0013)	(0.0013)	(0.0012)	(0.0035)
	Observations	701,813	701,813	701,813	96,389
Snack crackers	Coefficient	0.044***	0.0388****	0.0343***	0.0641***
	(Std.)	(0.0032)	(0.003)	(0.0026)	(0.004)
	Observations	800,253	800,253	800,253	143,143
Soap	Coefficient	0.0238***	0.0266***	0.0223***	0.0606***
	(Std.)	(0.0013)	(0.001)	(0.0009)	(0.0027)
	Observations	4,532,158	4,532,158	4,532,158	350,167
Soft drinks	Coefficient	0.0567***	0.0404***	0.0333***	0.0515***
	(Std.)	(0.0043)	(0.0042)	(0.0041)	(0.0054)
	Observations	324,724	324,724	324,724	96,574
Toothbrushes	Coefficient	0.0293***	0.0321***	0.0263***	0.0583***
	(Std.)	(0.0028)	(0.0028)	(0.0025)	(0.0063)
	Observations	295,021	295,021	295,021	45,457
Toothpastes	Coefficient	0.0293***	0.0292***	0.0255***	0.0593***
	(Std.)	(0.0027)	(0.0021)	(0.002)	(0.0053)
	Observations	588,261	588,261	588,261	96,728

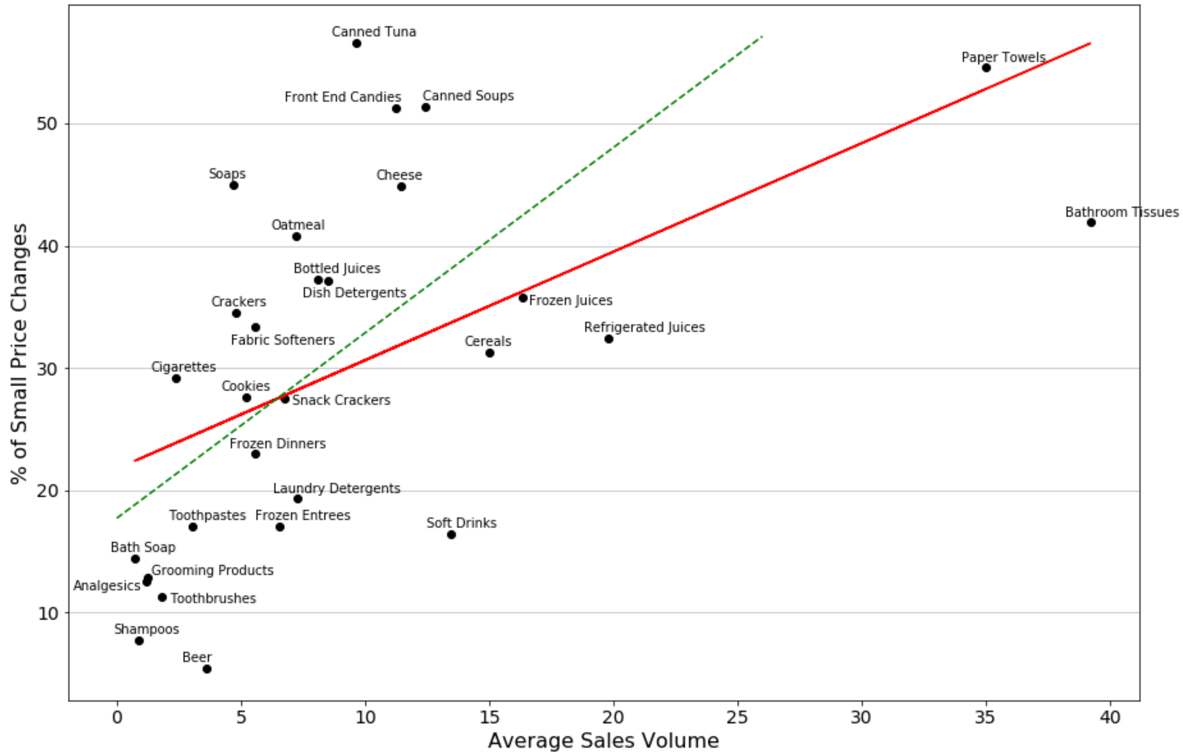
Notes: The table reports the results of category-level fixed effect regressions of the probability of a small price change. The dependent variable is "small price change," which equals 1 if a price change of product *i* in store *s* at time *t* is less or equal to 10¢, and 0 otherwise. The main independent variable is the average sales volume of product *i* in store *s* over the sample period. Column 1 reports the results of baseline regression that includes only the average sales volume and the fixed effects for months, years, stores, and products. In column 2, we add the following controls: the log of the average price, the log of the absolute change in the wholesale price, and a control for sale- and bounce back prices, which we identify using a sales filter algorithm. In column 3, we add a dummy for 9-ending prices as an additional control. In column 4, we focus on regular prices by excluding the sale- and bounce back prices. We estimate separate regressions for each product category, clustering the errors by product. *** $p < 1\%$

Table 4. Product-level regressions of the % of small price changes and sales volume by categories

Product Category	Average coefficient (1)	No. of positive coefficients (2)	No. of negative coefficients (3)	% positive coefficients (4)	% Negative coefficients (5)	No. of positive & significant (6)	No. of negative & significant (7)
Analgesics	4.04	230	47	83.0	17.0	43	0
Bath Soaps	4.67	31	11	73.8	26.2	7	0
Bathroom tissues	4.75	83	20	80.6	19.4	16	0
Beers	2.35	253	23	91.7	8.3	84	0
Bottled juices	6.97	316	69	82.1	7.9	102	4
Canned soups	4.13	268	85	75.9	24.1	70	0
Canned tuna	4.94	137	47	74.5	25.5	30	1
Cereals	4.06	286	74	79.4	20.6	43	0
Cheese	4.50	399	95	80.8	19.2	133	1
Cigarettes	-0.06	84	45	65.1	34.9	1	1
Cookies	5.17	588	126	82.4	17.6	178	1
Crackers	5.96	193	25	88.5	11.5	71	0
Dish detergents	5.12	176	35	83.4	16.3	47	0
Fabric softeners	5.86	195	43	81.9	18.1	42	2
Front end candies	4.37	210	84	71.4	28.6	26	0
Frozen dinners	6.02	206	18	92.0	8.0	67	0
Frozen entrees	5.00	612	80	88.4	11.6	194	0
Frozen juices	3.87	108	35	75.5	24.5	31	0
Grooming products	2.89	565	145	79.6	20.4	119	3
Laundry detergents	3.50	334	100	77.0	23.0	48	2
Oatmeal	4.85	55	16	77.5	22.5	9	0
Paper towels	3.89	69	23	75.0	25.0	13	0
Refrigerated juices	3.54	133	49	73.1	26.9	33	3
Shampoos	3.05	757	177	81.0	19.0	116	0
Snack crackers	5.60	256	38	87.1	12.9	90	3
Soaps	5.89	185	46	80.1	19.9	29	0
Soft drinks	3.08	837	187	81.7	18.3	266	4
Toothbrushes	2.98	202	53	79.2	20.8	45	1
Toothpastes	2.32	275	103	72.8	27.2	46	1

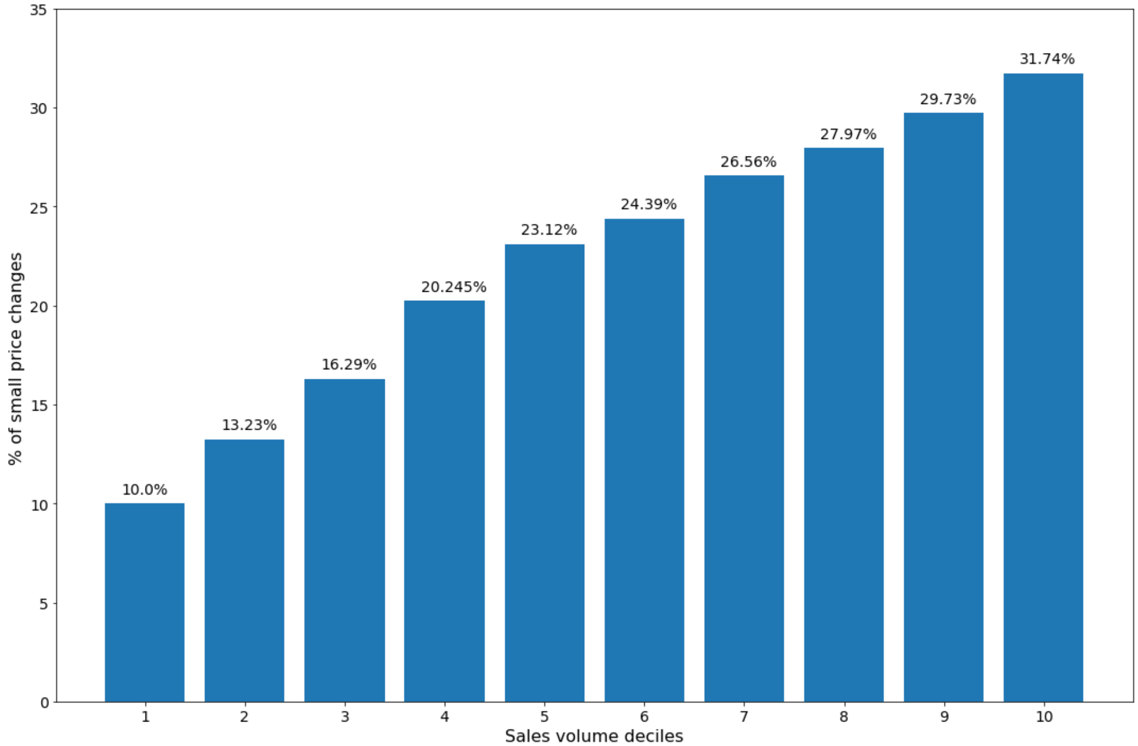
Notes: For each product category, column 1 presents the average estimated coefficients. Column 2 presents the number of positive coefficients. Column 3 presents the number of negative coefficients. Column 4 presents the % of positive coefficients. Column 5 presents the % of negative coefficients. Last two columns present the number of coefficients that are both positive (negative) and statistically significant, at the 5% level.

Figure 1. Cross-category correlation between small price changes and sales volume



Notes: The red solid line is a linear regression line when all 29 product categories are included. The dotted green line is the linear regression line if the two RHS categories (paper towels and bathroom tissues) are excluded.

Figure 2. Frequency of small price changes by sales volume deciles



Notes: The chart was obtained by merging all 29 product categories and dividing it into deciles according to the products' sales volume. The % of small price changes was calculated for each decile as a ratio of the number of small price changes to the number of total price changes in each decile.

Figure 3. Frequency of price changes by size for high and low sales volume products

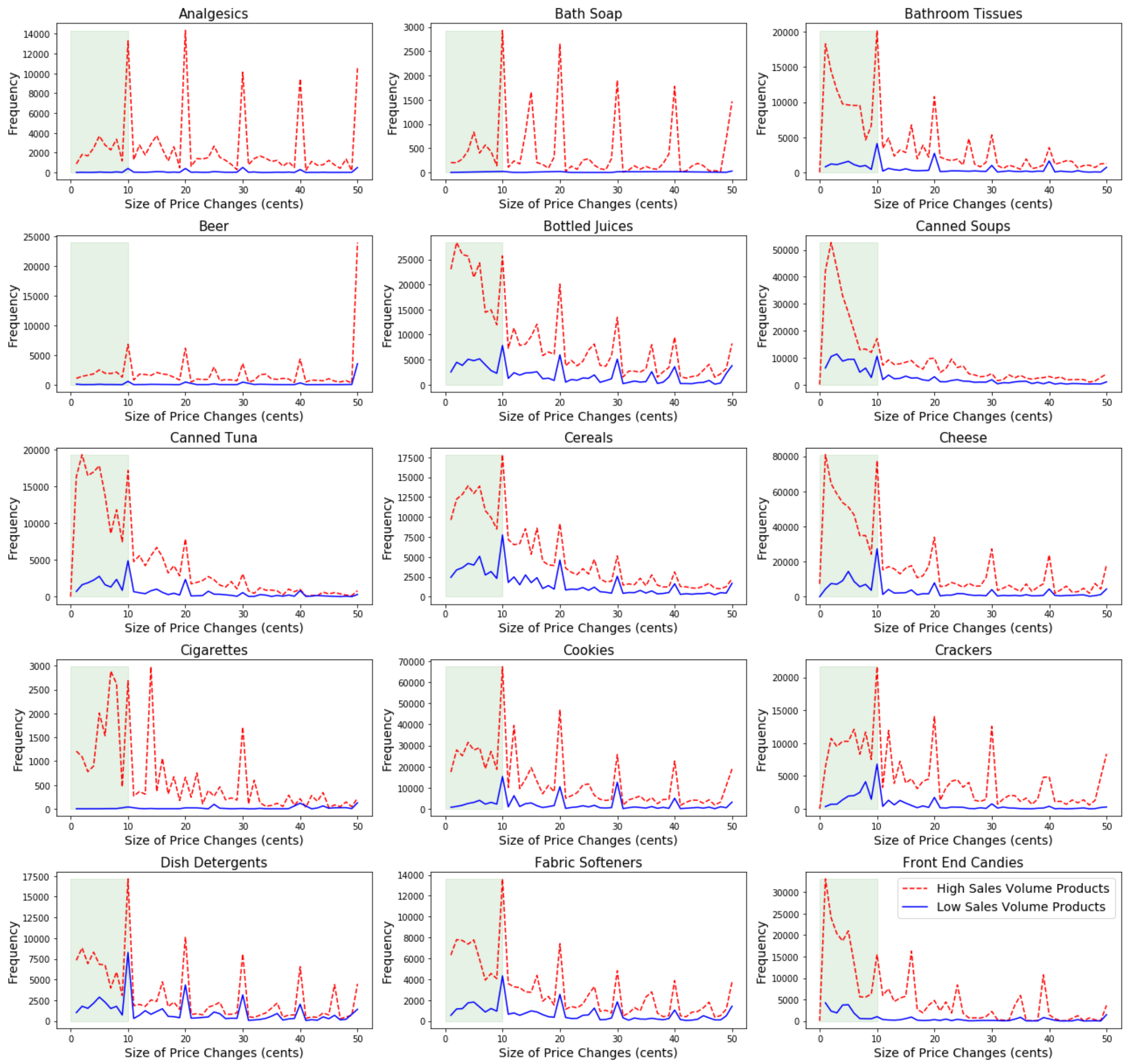
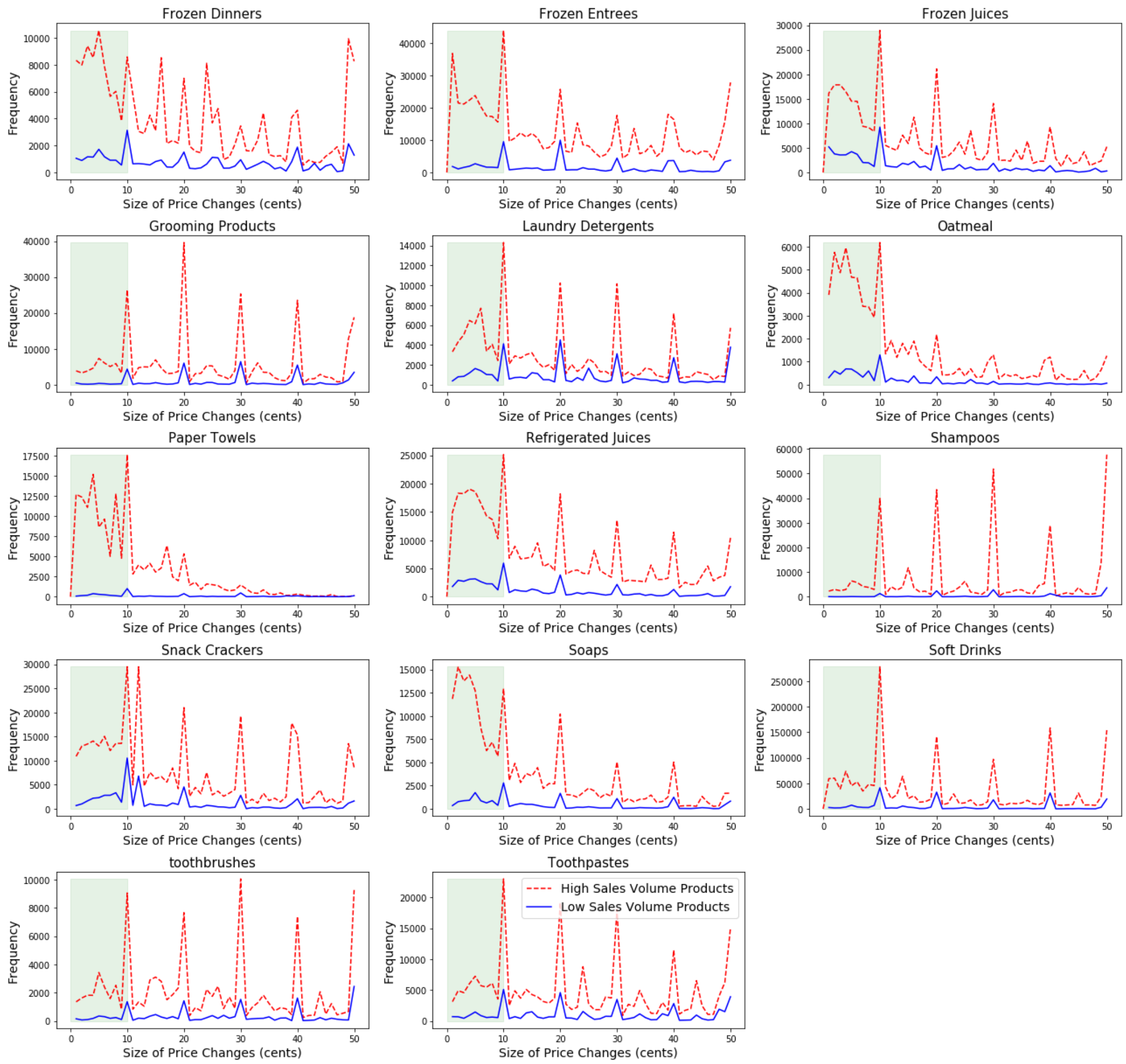
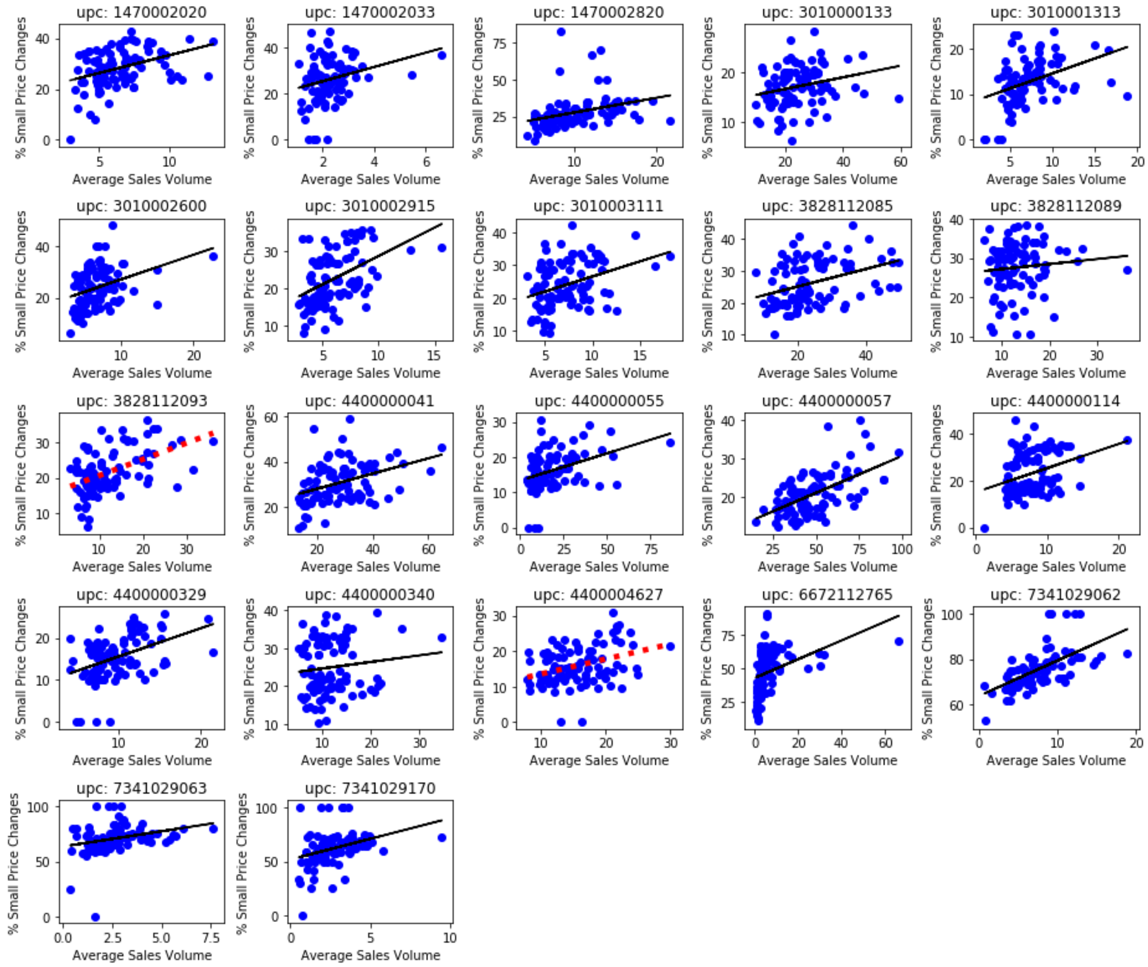


Figure 3. (Continues)



Notes: For each category, the figure shows the frequency of price changes for each size of price change from 1¢ to 50¢, comparing high sales volume products to low sales volume products. To obtain the figures, we compute the average sales volume over the entire sample period for each product, in each store. We then group the products into high, medium and low sales volume products. High (low) sales volume products are products in the high (low) third of the distribution. The y-axis shows the frequency of price changes. The red dashed line depicts the frequency of price changes for the high sales volume products, and the blue solid line depicts the frequency of price changes for the low sales volume products. The green shaded area shows the range of small price changes, $\Delta P \leq 10¢$.

Figure 4. Product-level correlations between sales volume and small price changes in the Crackers Category



Note: The figure depicts the correlation between average sales volumes (x-axis) and the percentage of small price changes for various products in the crackers' category. Each dot in the figures represents the data for the product in a specific store. There are 93 dots in each figure, one for each store. Straight lines in the figures are the regression lines. Black solid regression lines indicate that the regression coefficient is significant at the 5% significance level, which is the case for 20 of the 22 products. The two regression lines that are not statistically significant, are red dotted lines.