Appendices for "Menu Costs, Multi-Product Firms, and Aggregate Fluctuations"

Virgiliu Midrigan, NYU, May 2009

Appendix 1: Data Description

A. Description of Price Series

AC Nielsen

I use the household-level data to construct weekly price series according to the following algorithm[1]. For each store/good in the sample, I calculate the number (if any) of units sold at a particular price during the course of the week. If the store sells the product at a single price during the week, I assign this value to the weekly price series. If more than one price is available, the weekly price is the price at which the store sold the largest number of units. In case of a tie in the number of units sold at a particular price, the weekly price is the highest price at which the store sells in a given week[2].

Given that I use scanner price data, price observations for a particular store/good is only available when a customer purchases the product in a particular week. The original prices series are therefore frequently interrupted by gaps. I ignore the gaps if these last for four weeks or less, and use the first available price after the gap to fill in the price series. Unlike in an earlier version of this paper, [3] I do not exclude any time-series of prices, however short, from the data.

[1] This algorithm is very similar to the first few steps discussed in the pf_creation file that accompanies the AC Nielsen data.

[2] Intuitively, if the number of units sold at two prices is equal, the highest price is likely to have been in effect for a longer time-period as consumers are more likely to buy at the lowest price.

[3] Midrigan (2006).

Dominick's

The Kilts Center for Marketing makes available weekly price quotes for 86 of Dominick's stores. As noted above, this dataset is a by-product of a series of randomized pricing experiments conducted by Dominick's from 1992 to 1993[4].

Dominick's stores are divided into three groups: high, low and medium-price stores, depending on the extent of local competition. Prices within, but also across groups, are strongly correlated, as Dominick's sets prices on a chain-wide basis[5]. I choose thus to work with the price of one single store, # 122, the store with the largest number of price observations that was part of the control zone and thus not subject to the pricing experiment.

B. Sales algorithm

Retail prices are characterized by a large number of temporary discounts (sales). Kackmeister (2005) reports that 40% of price changes arise due to sales in a dataset of forty-eight products sold in retail stores during 1997-1999. Hosken and Reiffen (2004) find that 60% of the price decreases in their sample of twenty products sold in 30 locations during 1988-1997 are followed by a price increase in the following month. Several hypothesis have been advanced to explain this pattern of retail price variation, stressing informational frictions on consumer's side of the market (Varian 1980), demand uncertainty (Lazear 1986), or thick-market explanations (Warren and Barsky, 1995), to name a few. In the paper I report all statistics for two sets of price changes: all price changes, as well as for those price changes that are not associated with sales. This subsection describes the algorithm used to identify sales in the data[6]. This algorithm was used in Kehoe and Midrigan (2007) and is a

[4]Hoch, Dreze and Purk (1994) discuss Dominick's experiment in detail.

[5]See Peltzman (2000) for a discussion of Dominick's pricing practices. He notes that the retail price at Dominick's stores is set by the chain's head office and the correlation between price changes within a particular pricing zone are in the neighborhood of .8 to .9.

[6]Dominick's dataset includes a "sales" variable that we could in principle use to eliminate temporary markdowns from our price series. This variable is however coded inconsistently and leaves

variation of the algorithm described in the pf_creation file that accompanies the AC Nielsen data. I apply this filter to the weekly data first, and then time-aggregate the data to monthly (4-week) frequency, by selecting the price in effect at the beginning of each month[7].

Step 1: return above or to the same level

For each price cut (defined as a period in which $p_t < p_{t-1}$ & p_t, p_{t-1} are non-missing), check if $p_{t+j} \geqslant p_{t-1}$ for $j \leqslant 3$. Let $\bar{j}$ be the minimum j for which this condition is satisfied (if at all). Replace $p_t, p_{t+1,..}, p_{t+\bar{j}-1}$ etc. with p_{t-1} for those js between p_t and $p_{t+\bar{j}}$ for which the original price is available.Notice that we impose no restrictions on what the old price does prior to the period it returns to a level equal to or above to the pre-sale price. It can fall gradually, stay fixed, gradually increase etc.

Step 2: return below the original level.

For each price cut (defined as a period in which $p_t < p_{t-1}$ & p_t, p_{t-1} are non-missing), check if $p_{t+j} \geqslant p_t$ for $j \leqslant 3$. Let $\bar{j}$ be the minimum j for which this condition is satisfied (if at all). Replace $p_t, p_{t+1,..}, p_{t+\bar{j}-1}$ etc. with p_{t-1} for those js between p_t and $p_{t+\bar{j}}$ for which there are no gaps in the original price series. I apply this second procedure 3 times in order to eliminate temporary price cuts in the newly created regular price series.

Note a final issue that will play an important role in our discussion of the size and frequency of price changes. By eliminating temporary price cuts, I have introduced artificial price changes in the regular price series (by artificial I mean price changes that are not observed in the raw data). Any time temporary price reductions are not completely reversed, or followed by price changes larger than the original price cut, setting the regular price equal to the price prior to the sale will

out many temporary price cuts. I therefore choose to eliminate sales manually.

[7] The alternative choice (of time-aggregating the data first and then eliminating sales) can produce spurious price changes if stores periodically put their prices on sale, at regular intervals.

artificially introduce a number of price changes that are otherwise absent in the actual price data. When reporting statistics for price changes excluding sales, I only use the regular price series created above to define a sale (a price that is below the regular price) and not for other purposes. The statistics reported under the non-sale Δp in Tables 1, 3 and 4 are thus computed for those price changes observed in the original price data. The only exception to this are the statistics in Table 2 in which I model the price adjustment decision. Given that here the focus is on the adjustment decision (rather than the size), and that artificial price changes are associated with changes in the raw data, I treat these as any other price change.

Finally, given that most quantitative studies of sticky price models calibrates them to the monthly or quarterly frequency, I assume a period of one month in the model presented in text. I therefore time-aggregate weekly observations into monthly data, by constructing the monthly series using price data collected in the first week of the month.

Appendix 2: Evidence of economies of scope

In this section I establish that (i) stores tend to adjust prices in narrow product categories simultaneously; (ii) price changes tend to be of the same sign; (iii) the size of individual price changes is larger than the size of the average product category's price change; and (iv) present direct evidence of economies of scope in price adjustment.

A. Price changes are synchronized

I establish that prices within a store adjust in tandem using a reduced-form discrete-choice specification in which I model each product's price adjustment decision as a function of observables that are a priori relevant for each good's desired price change, as well as variables that capture the price adjustment decisions of other products sold by a store. To be clear, no attempt is made to identify causality or the source of synchronization here: the exercise below is simply a statistical description of the extent to which price changes within a store are synchronized[8].

In particular, I estimate probit regressions[9] in which the dependent variable $y_{it} = \{0, 1\}$ is good $i's$ price adjustment decision and the independent variables are proxies for the good's desired price change[10]. In the AC Nielsen data I construct the absolute value of the deviation of a good's last period price (i.e. the price the store would charge were it not to adjust) from the current price of its competitors: $x_{it} = |\log(P_t/p_{it-1})|$. P_t here is the average price of the same upc in all stores within a city, excluding the prices of the stores that belong to the same chain[11]. In the Dominick's data an (albeit imperfect) measure of replacement cost is available[12]. I

[8] See also Lach and Tsiddon (1996) and Fisher and Konieczny (2000) for additional evidence of synchronization within multi-product firms.

[9] Cecchetti (1986) employs a similar approach to study the adjustment of magazine prices.

[10] As earlier, any nominal price change (i.e., greater or equal to 1 cent) is counted as a price change.

[11] I only compute this for observations for which at least 5 competitor's prices are available.

[12] The measure reported is average acquistion cost of items currently in inventory. Although this measure may spuriously co-move with prices, Peltzman (2000) argues that the problem is much less severe at monthly frequencies as inventories turn over more frequently than once a month in retail stores.

use the absolute value of the change in this cost measure since the good's last price change, $x_{it} = |\Delta \log c_{it}|$. For both datasets I only use observations for which the date of the last price change is observed. That is, I are allow no gaps from the month of the last change to the month in question. In addition to these two proxies for good-specific desired price changes, I include three measures of within-store and across store synchronization: (i) the fraction of all remaining goods within a store whose prices change in a given month; (ii) the proportion of price changes in a particular good-category (data on 29 product categories, ranging from analgesics to toothpastes is available for Dominick's and 6 categories for AC Nielsen); (iii) the proportion of prices for goods produced by the same manufacturer that experience a price change[13], as well as (iv) the proportion of prices of this particular product that are changed in all remaining stores in the same city that are not part of the same chain[14]. All these measures of synchronization are computed based on the adjustment decision of all goods other than i in a given group, and I exclude those observations for which any of these statistics are calculated based on fewer than five observations in a given period. When modeling the decision to adjust the regular price, I compute these fractions for regular price changes only. I weigh each observation by its revenue share when computing the fraction of adjusting prices.

Finally, I allow the adjustment probability to depend on the duration of the current price spell (to account for the negative adjustment hazard documented in the data) as well as the revenue share of a given good (more important goods experience price changes/discounts more frequently). In addition, I have experimented with allowing for good, store, and time-specific fixed/random effects, as well as changes in aggregate wages, CPI, food and energy prices, but these in most cases are small and imprecisely estimated and do not have much impact on the estimates of the variables

[13]Identified based on the first 5 digits of the upc code. I include this variable only for Dominick's data, as too few goods per manufacturer are available in case of the AC Nielsen data.

[14]Only available in the AC Nielsen data, as I use the price of a single store for Dominick's.

I am interested in. Table A1 thus reports only the most parsimonious specifications that exclude these additional controls.

As Table A1 illustrates, the probability that a particular product experiences a price change does indeed depend on the fraction of other prices within that store that experience adjustment, especially those in a particular product category. In the AC Nielsen data, an increase in the fraction of adjusting prices in a given product category from 0 to 1 increases the probability that a given product adjusts by 52%. This is true for all price changes, as well as for regular price changes (the corresponding increase in probability is 51%). Similarly, there is evidence of within-store synchronization across all items sold in a particular store (26% and 30% for regular price changes). Finally, there is also some, albeit weaker, synchronization across stores in a particular city. If all other stores change the price of a particular good, the store in question is also more likely to adjust: the marginal effect is 19% and 17%, respectively. A similar pattern holds in case of Dominick's data. Here the evidence for storewide synchronization is weaker, especially for regular price changes, but prices within a manufacturer or product category do change simultaneously. The marginal effect in one good's adjustment probability of an increase in the fraction of adjusting prices for goods produced by the same manufacturer is 0.74 (0.58 for regular price changes), whereas for the fraction of goods adjusted in one of the 29 product categories is 0.34 (0.41 for regular price changes. Finally, notice that my measure of goodness of fit (the average model predicted probability for observations that do experience a price change, minus the predicted probability for observations that do not) is typically more than double when I add measures of synchronization, suggesting that what happens to other products within the store matters more than idiosyncratic fluctuations in a good's costs or competitor's prices.

B. Price changes tend to be of the same sign

To see this, I now model separately the probability of a good's price increase/decrease as a function of the fraction of price increases/decreases within the store. Specifically, the dependent variable is now $y_{it}^{increaase} = \{0, 1\}$ that is equal to 1 if the price increases, or $y_{it}^{decrease} = \{0, 1\}$ that is equal to 1 if the price decreases. The dependent variables now include the deviation of a store's price from that of its competitors (AC Nielsen) and the cumulative change in costs since the previous price adjustment (Dominick's), as well as the fraction of price decreases in narrow product categories within a store (as well as for the same good across stores in the AC Nielsen data), and the fraction of price increases in these same categories.

Table A2 reports the results of these probit regressions. Clearly, the probability of a price decrease (increase) is strongly correlated with the fraction of price decreases (increases) within narrow product categories within a store. For example, in the AC Nielsen data an increase in the fraction of other good's price decreases (increase) from 0 to 1 raises the probability that the good in question will also experience a price decrease (increase) by 44% (34%). In contrast, the marginal effects of the fraction of price changes in the opposite direction is, although in most cases positive and statistically significant, an order of magnitude smaller. For example in the AC Nielsen data an increase in the fraction of price increases (decreases) from 0 to 1 raises the probability that the good in question will experience a price decrease (increases) by 5% (4%). These results are robust across the two datasets and when I model regular price changes only.

Note finally that the fact that price changes within a narrow product category tend to be of the same sign is not necessarily evidence against economies of scope in price adjustment. Rather, this is evidence that unobservable shocks to stores' desired prices tend to be correlated across goods, although it does suggest that evidence of within-store synchronization is not necessarily evidence of economies of scope. I next attempt to measure the size of this correlation.

C. Correlation of price changes

I next ask, How large is the correlation in the unobserved shocks that account for the synchronized price changes in the same direction documented above? If this correlation were perfect, economies of scope in price adjustment would be irrelevant as price changes would be of the same magnitude/sign: the size of a price change for a good would be equal to the average price change for a bundle of goods that share the same technology of price adjustment. To answer this question, I compute the average size of a good's price change, conditional on adjustment: $\underset{ict}{mean}\left(|\Delta p_{ict}| \text{ given } |\Delta p_{ict}| > 0\right)$ where i is the good, c the product category it belongs to. This is the same statistics as that reported in Table 1. In addition, I compute the average size of the mean price change for all prices within a store that experience a change in a given period: $\underset{ct}{mean}\left|\left(\underset{i\in ct}{mean}\left(\Delta p_{ict} \text{ given } |\Delta p_{ict}| > 0\right)\right)\right|$. In other words, the first statistic is the average size of a non-zero price change for individual products, whereas the second is the average size of the mean price change for the bundle of goods in a product category that experience adjustment.

If price changes were perfectly correlated, the two statistics would be identical. If they are not, the mean size of a bundle's price change would be smaller, because of the presence of a few price changes of the opposite sign than the rest. Indeed, as Table A3 reports, the mean size of a bundle's price change is typically smaller than the mean size of an individual price change. The ratio of the latter to the first ranges from 0.4 to 0.7. For example, in the AC Nielsen data, the mean size of price changes is 19.4% and 15.0% for all and regular price changes, respectively. In contrast, the mean size of a product category's price change is only 13.5% and 8.5%, respectively.

D. Direct evidence of economies of scope

Small price changes and synchronization alone are not necessarily evidence of economies of scope in price adjustment. For example, models with time-varying product-specific menu costs (together with correlated cost shocks) can generate both of these features of the data, just like models with economies of scope. What distinguishes models in which the menu cost varies over time from those with economies of scope in price adjustment is that in the latter a good's probability of adjustment depends not only on the good's individual desired price change, but also on the desired price change of other goods among which the economies of scope are shared.

To fix ideas, consider the following simple example. Suppose that a retailer sells $N+1$ goods, and that the losses from charging its existing prices p_i for each of the goods indexed by $i = 1...N+1$ are $L = \sum_{i=1}^{N+1} (p_i - p_i^*)^2$ where p_i^* is the optimal desired (log) price for each product. Suppose that the menu cost, K, applies to the entire bundle of goods the producer sells. In a static environment the retailer would adjust all prices whenever the losses from not doing so exceed the menu cost. The hazard of price changes for any good j is thus the probability that $\sum_{i=1}^{N+1} (p_i - p_i^*)^2 > K$ and is thus proportional to the desired price change for that good, $(p_j - p_j^*)^2$ as well as to the mean desired price change for all other goods, $N\mu_{-j}$, where $\mu_{-j} = \frac{1}{N} \sum_{i=1, i \neq j}^{N+1} (p_i - p_i^*)^2$. I next ask whether there is indeed evidence that a good's adjustment probability also depends on the desired price change for the other goods the store sells[15].

To do so I need a measure of desired price changes for individual products. For the Dominick's data, I construct a proxy by asumming that $p_{it}^* = \gamma c_{it}$ where c_{it} is the (log) wholesale price of the good. The desired price change can be constructed then as $p_{it-1} - p_{it}^* = -\gamma \Delta c_{it}$ where Δc_{it} is the change since the time of the last price change (i.e, the last date τ at which $p_{it-1} = p_{i\tau}$[16]). I then relate the hazard

[15] This argument extends to alternative, more flexible specifications of the technology of price changes. What matters is that a good's individual price adjustment cost is decreasing in the number of other prices that adjust.

[16] As above, I compute these measures only for uninterrupted price spells. The above equality

that good i experiences a price change, to the squared of the good's own desired price change, $\gamma^2 (\Delta c_{it})^2$, as well as to the mean square of the desired price changes of all other goods in a given product/manufacturer category. These deviations are constructed in a similar fashion (the squared of each good's change in costs since its own previous price change), and only for those observations for which at least 5 products are available within a group. Thus each good's adjustment probability is modeled as

$$\Pr(\text{i adjusts}) \sim \gamma^2 \left[(\Delta c_{it})^2 + N \times \underset{j \neq i}{\text{mean}} \left((\Delta c_{jt})^2 \right) \right]$$

In case of the AC Nielsen data I assume that the deviation from the optimal price $p_{it-1} - p_{it}^*$ is proportional to $\gamma (p_{it-1} - P_{-it})$ [17], where P_{-it} is the (log) average price of the same upc in all stores within a pricing zone (city), excluding the prices of the stores that belong to the same chain. The adjustment probability of good i is modelled as

$$\Pr(\text{i adjusts}) \sim \gamma^2 \left[(p_{it} - P_{-it})^2 + N \times \underset{j \neq i}{\text{mean}} \left((p_{jt} - P_{-jt})^2 \right) \right]$$

Table A4 (columns titled I) reports estimates of probit regressions similar to those used above. The hazard of a good's price change increases in the mean desired price change for all other goods in a given product category (N is estimated in the neighborhood of 1), as well as for the goods produced by the same manufacturer in the Dominick's data (N is equal to 0.63). A literal interpretation of the size of these coefficients suggests that the menu cost is shared among two of the goods the retailer sells. Measurement error associated with imperfect observability of a good's immediate neighbours, inclusion of irrelevant goods, missing observations etc., is likely

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follows from the assumption that $p_{i\tau} = p_{i\tau}^*$, i.e., that firms charge the optimal desired price every time they adjust.

[17] Imposing here $\gamma = 1$ does not affect the coefficient estimate of N much as the estimate of γ is close 1.

however to bias this coefficient downwards.

Note that in these regressions, by using observables directly as proxies for desired price changes, I account for the possibility that unobserved correlated cost or preference shocks are entirely responsible for the synchronization in the timing of price changes documented above. The desired price change for good i is indeed strongly correlated with the mean desired price change for all other goods within the store, but both are controlled for in these regressions. Evidence of a positive coefficient on the mean desired price change of other goods suggests that a particular good i is more likely to experience a price change even if its own desired price change is small, as long as other products within the store need larger price changes.

I next ask whether the relationship between good $i's$ adjustment probability and the mean desired price change of its neighbours is stronger for goods that need smaller price changes. Intuitively, if good i is in need of a large price change, it is likely to do so regardless of what happens to its neigbors. In contrast, a good that needs a smaller price change may be more sensitive to the desired price change of its neigbors. In particular, I now relate the probability of adjustment for good i to:

$$\Pr(\text{i adjusts}) \sim \left[(p_{it} - p^*_{it})^2 + N_0 \times \underset{j \neq i}{\text{mean}} \left((p_{jt} - p^*_{jt})^2\right) + N_1 \times (p_{it} - p^*_{it})^2 \times \underset{j \neq i}{\text{mean}} \left((p_{jt} - p^*_{jt})^2\right)\right]$$

Columns II in Table A2 show that indeed the coefficient estimate of this interaction term is negative and range from -1.8 to -3.7. Thus if good i needs a larger price change $(p_{it} - p^*_{it})^2$, its adjustment probability is less sensitive to the mean desired price change of its neighbors.

Appendix 3: Computational Algorithm

I discuss here the solution method used to compute optimal decision rules given a guess for how aggregate variables evolve with the state as well as the law of motion for the mean deviation of past prices from their frictionless optima, ϕ_1:

$$\log(p) = \varsigma_0 + \varsigma_1 \log \mu + \varsigma_2 \phi$$

$$\phi_1' = \xi_0 + \xi_1 \log \mu + \xi_2 \phi_1 - \eta'$$

I use a projection-based (global) approximation method[18]. Specifically, I approximate the two value function (of adjustment and inaction), as well as the expected continuation value, $\hat{V}(\mathbf{p}_{-1}, \mathbf{a}; \mu, \boldsymbol{\phi}) = \int \frac{U_c\prime}{U_c} V(\mathbf{p}_{-1}', \mathbf{a}'; \mu\prime, \boldsymbol{\phi}\prime) dF(\varepsilon^1, \varepsilon^2, \eta)$, using splines (a combination of linear and cubic). This approximation reduces the problem to that of finding a set of coefficients of the basis function (I compute multi-variate basis function from univariate ones using tensor products) that solves the system of functional equations at a finite grid of nodes in the state-space. I have increased the number of nodes (and thus basis functions) along each dimension to the point at which further increases produce no significant effect on optimal price rules and also render the distance between the two sides of each functional equation at points other than the collocation nodes (at which this distance is zero by construction) insignificant (the maximum relative errors are of the order of 10^{-4}, average relative errors are of the order of 10^{-5}). Depending on the problem, I use up to 15-20 basis functions in the price space, 7-11 in the productivity space, and a smaller number of nodes in the aggregate state space. I approximate intergrals using Gaussian quadrature, again with more nodes used in the idiosyncratic (productivity shock) space (9-11) and fewer in the

[18] See Miranda and Fackler (2002) for a detailed description of these methods as well as a toolkit that facilitates their implementation.

money shock space. Finally, I solve the optimization problem on the right hand side of the adjustment Bellman equation using a simplex-based (Nelder-mead) method as derivative-based methods are somewhat less stable when I search over the parameter values that best match the moments in the data. The calibration exercise is also conducted using a simplex-based method.

Table A1: Synchronization in price changes, AC Nielsen

	All price changes		Regular price changes	
	I	**II**	**I**	**II**
$\lvert \log(P/p_{-1}) \rvert$	0.63**	0.44**	0.38**	0.22**
Fraction of price changes:				
same category within store	-	0.52**	-	0.51**
same store	-	0.26**	-	0.30**
same upc across stores	-	0.19**	-	0.17**
goodness-of-fit	0.07	0.14	0.03	0.12
# obs.	27645	27645	25802	25802

Notes:

1. Marginal effect on probability of price changes reported
2. Observations are weighted (by each upc's revenues in all periods)
3. The fraction of price changes is computed for all upcs other than the upc in question, weighting incidences of price changes using each upcs revenue-based weight
   Observations excluded if less than 5 products are available in a category within store or given upc across stores in a particular month.
   Deviation from competitor's price and fraction of stores adjusting a particular upc computed only for stores within a city.
4. Also included are the upc's revenue share and time since last change (not reported)
5. A ** denotes rejection of 0 null at 1%, * at 10%
6. My measure of goodness of fit is the model's predicted probability for observations that do adjust minus the predicted probability for observations that do not

Table A1: Synchronization in price changes, Dominick's

	All price changes		Regular price changes	
	I	II	I	II
$\|\Delta \log c\|$	0.94**	0.77**	0.08***	0.14***
Fraction of price changes:				
same manufacturer	-	0.74**	-	0.58**
same category	-	0.34**	-	0.41**
storewide	-	0.13**	-	-0.03
goodness-of-fit	0.12	0.28	0.05	0.26
# obs.	239751	239751	209008	209008

Notes:

1. Marginal effect on probability of price changes reported
2. Observations are weighted (by each upc's revenues in all periods)
3. The fraction of price changes is computed for all upcs other than the upc in question, weighting incidences of price changes using each upcs revenue-based weight. Observations excluded if less than 5 products are available in a given manufacturer/category group in a particular period.
4. Also included are the upc's revenue share and time since last change (not reported)
5. A ** denotes rejection of 0 null at 1%, * at 10%
6. My measure of goodness of fit is the model's predicted probability for observations that do adjust minus the predicted probability for observations that do not

Table A2: Synchronization and correlation in price changes, AC Nielsen

	All price changes		Regular price changes	
	decreases	increases	decreases	increases
$\log(P/p_{-1})$	-0.48**	0.35**	-0.49***	0.53***
Fraction of price decreases:				
same category within store	0.44**	0.04*	0.47**	-0.00
same upc across stores	0.18**	0.00	0.08**	0.05**
Fraction of price increases				
same category within store	0.05*	0.34**	0.03	0.29**
same upc across stores	0.03	0.10**	0.02	0.11**
# obs.	34345	34345	32019	32019

Notes:

1. Observations are weighted (by each upc's revenues in all periods)
2. The fraction of price changes is computed for all upcs other than the upc in question,
   weighting incidences of price changes using each upcs revenue-based weight
   Observations excluded if less than 5 products are available in a category within store or for a given upc across stores in a particular period
   Deviation from competitor's price and fraction of stores adjusting a particular upc computed only for stores within a city
3. Also included are the upc's revenue share and time since last change (not reported)
4. A ** denotes rejection of 0 null at 1%, * at 10%
5. Marginal effect on probability of price change reported

Table A2: Synchronization and correlation in price changes, Dominick's

	All price changes		Regular price changes	
	decreases	increases	decreases	increases
Δ log c	-0.67**	0.69**	-0.13***	0.18***
Fraction of price decreases:				
same manufacturer	0.56**	0.01	0.35**	0.01
same category	0.26**	0.05**	0.26**	0.06**
Fraction of price increases				
same manufacturer	0.04**	0.56**	0.02**	0.40**
same category	0.05**	0.30**	0.02*	0.26**
# obs.	239751	239751	209008	209008

Notes:

1. Observations are weighted (by each upc's revenues in all periods)
2. The fraction of price changes is computed for all upcs other than the upc in question, weighting incidences of price changes using each upcs revenue-based weight
   Observations excluded if less than 5 products are available in a given manufacturer/category group in a particular period
3. Also included are the upc's revenue share and time since last change (not reported)
4. A ** denotes rejection of 0 null at 1%, * at 10%
5. Marginal effect on probability of price change reported

Table A3: Mean size of price changes

AC Nielsen

	all Δp	non-sale Δp
mean $\lvert \Delta p_{upc} \rvert$	0.194	0.150
mean $\lvert \Delta p_{cat} \rvert$	0.135	0.085

Dominick's

	all Δp	non-sale Δp
mean $\lvert \Delta p_{upc} \rvert$	0.168	0.086
mean $\lvert \Delta p_{man} \rvert$	0.093	0.058
mean $\lvert \Delta p_{cat} \rvert$	0.064	0.055

Notes:
1. Observations are weighted (by each upc's share in the store's revenues)
2. The mean price change for goods within a manufacturer/product category reported if at least 5 price changes available in a given period

Table A4: Economies of scope in price adjustment, AC Nielsen

	I	II
$mean(p_{-i} - p^*_{-i})^2$	0.82	0.97
	(0.21)	(0.17)
$(p-p^*)^2 \times mean(p_{-i} - p^*_{-i})^2$		-1.80
		(0.34)
# obs.	34674	34674

Notes:

1. Observations are weighted (by each upc's revenues)
2. The mean squared deviation is computed for all upcs other than the upc in question,
   weighting each product by its revenue-based weight
   Observations excluded if less than 5 products are available in a given manufacturer/category group in a particular period
3. Also included are the upc's revenue share and time since last change (not reported)
4. Standard errors in parantheses

Table A4: Economies of scope in price adjustment, Dominick's

	Product category		Manufacturer	
	I	**II**	**I**	**II**
$mean(p_{-i}-p^*_{-i})^2$	1.19	1.02	0.63	0.75
	(0.13)	(0.08)	(0.09)	(0.07)
$(p-p^*)^2 \times mean(p_{-i}-p^*_{-i})^2$		-3.71		-1.95
		(0.27)		(0.17)
# obs.	251528	251528	228407	228407

Notes:

1. Observations are weighted (by each upc's revenues)
2. The mean squared deviation is computed for all upcs other than the upc in question, weighting each product by its revenue-based weight
   Observations excluded if less than 5 products are available in a given manufacturer/category group in a particular period
3. Also included are the upc's revenue share and time since last change (not reported)
4. Standard errors in parantheses

Table A5.I: Calibration targets, iid money growth

	Data	Model	
		Scope economies Fat-tailed shocks Benchmark	No scope economies Gaussian shocks (GL 2007)
Micro			
frequency of price changes	0.24	0.25	0.25
mean(Δp)	0.001	0.001	0.001
mean ($\|\Delta p\|$)	0.12	0.12	0.12
ser. corr. p	0.65	0.65	0.68
std ($\|\Delta p\|$)	0.09	0.10	0.03
fraction changes < 1/2 mean	0.28	0.29	0.00
fraction changes < 1/4 mean	0.12	0.10	0.00
kurtosis(Δp)	4	4.08	1.41
Macro			
std. dev. Inflation, %	0.26	0.26	0.35
serial correlation inflation	0.31	0.36	0.30

Table A5.II: Calibration targets, economy with sales

	Data	Model	
		No scope economies Fat-tailed shocks	No scope economies Gaussian shocks (GL 2007)
frequency of price changes	0.40	0.40	0.41
frequency of price changes, excluding sales	0.24	0.22	0.24
proportion returns to pre-existing price	0.64	0.63	0.84
probability a sale ends	0.75	0.78	0.85
mean(Δp)	-0.002	-0.002	-0.002
mean (|Δp|)	0.18	0.20	0.18
ser. corr. p	0.45	0.51	0.50
std (|Δp|)	0.14	0.15	<u>0.03</u>
fraction changes < 1/2 mean	0.29	0.36	<u>0.00</u>
fraction changes < 1/4 mean	0.14	0.13	<u>0.00</u>
kurtosis(Δp)	3.5	3.12	<u>1.41</u>

Table A5.III: Calibration targets, economy with Poisson shocks

	Data	Model
frequency of price changes	0.24	0.24
mean(Δp)	0.001	0.001
mean (|Δp|)	0.12	0.12
ser. corr. p	0.65	0.70
std (|Δp|)	0.09	0.09
fraction changes < 1/2 mean	0.28	0.31
fraction changes < 1/4 mean	0.12	0.00
kurtosis(Δp)	4	3.11

Table A5.IV: Calibration targets, economy with random menu costs

	Data	Model
frequency of price changes	0.24	0.24
mean(Δp)	0.001	0.001
mean (|Δp|)	0.12	0.12
ser. corr. p	0.65	0.67
std (|Δp|)	0.09	0.10
fraction changes < 1/2 mean	0.28	0.31
fraction changes < 1/4 mean	0.12	0.11
kurtosis(Δp)	4	3.98

Table A6.I: Parameter values, iid money growth

		Scope economies Fat-tailed shocks Benchmark	No scope economies Gaussian shocks (GL 2007)
Assigned parameters			
β	discount factor	0.997	0.997
ψ	marginal disutility from work	2.0	2.0
θ	elasticity of substitution across stores	3	3
γ	elasticity of substitution across goods within store	11.5	-
Calibrated parameters			
σ_η	std. dev. of money shocks	0.0052	0.0052
ρ_μ	persistence of money shocks	0.000	0.000
μ	mean growth rate of money, %	0.069	0.069
κ	menu cost, % of SS revenue	1.109	0.980
ρ_a	persistence of technology shocks	0.553	0.553
χ	correlation of techn. shocks within store	1.119	-
α_1	Beta(α_1,α_2)	0.042	-
α_2	Beta(α_1,α_2)	1.058	-
σ_ε	volatility of technology shocks	0.340	0.065

Table A6.II: Parameter Values, economy with sales

		No scope economies Fat-tailed shocks	No scope economies Gaussian shocks
Assigned parameters			
β	discount factor	0.997	0.997
ψ	marginal disutility from work	2.0	2.0
θ	elasticity of substitution across stores	3	3
σ_η	std. dev. of money shocks	0.0018	0.0018
ρ_μ	persistence of money shocks	0.61	0.61
Calibrated parameters			
μ	mean growth rate of money, %	-0.018	-0.011
κ^R	menu cost of regular p change, % of SS revenue	0.252	1.380
κ^T	menu cost of temporary p change, % of SS revenue	0.131	1.640
ρ_a	persistence of technology shocks	0.097	0.067
α_1	Beta(α_1,α_2)	0.090	-
α_2	Beta(α_1,α_2)	1.091	-
σ_ε	volatility of technology shocks	0.590	0.107

Table A6.III: Parameter Values, economy with Poisson shocks

Assigned parameters

β	discount factor	0.997
ψ	marginal disutility from work	2.0
θ	elasticity of substitution across stores	3
σ_η	std. dev. of money shocks	0.0018
ρ_μ	persistence of money shocks	0.61

Calibrated parameters

μ	mean growth rate of money, %	0.023
κ	menu cost, % of SS revenue	0.240
ρ_a	persistence of technology shocks	0.550
τ	probability of no idiosyncratic shock	0.905
σ_ε	volatility of technology shocks	0.368

Table A6.IV: Parameter Values, economy with random menu cost

Assigned parameters

β	discount factor	0.997
ψ	marginal disutility from work	2.0
θ	elasticity of substitution across stores	3
σ_η	std. dev. of money shocks	0.0018
ρ_μ	persistence of money shocks	0.61

Calibrated parameters

μ	mean growth rate of money, %	0.024
κ	menu cost, % of SS revenue	0.313
ρ_a	persistence of technology shocks	0.420
λ	probability of free price change	0.045
α_1	Beta(α_1,α_2)	0.040
α_2	Beta(α_1,α_2)	1.0424
σ_ε	volatility of technology shocks	0.470