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Appendix
Prices Are Sticky After All*

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ABSTRACT

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1. The Algorithm to Construct the Regular Price

Here we describe, first intuitively and then precisely, our algorithm for constructing a regular price series for each product in the data. We have applied this algorithm ourselves to the Dominick's data set. Nakamura and Steinsson (2010) apply this algorithm to compute statistics for the BLS data set.

Our algorithm is based on the idea that a price is a *regular price* if the store charges it frequently in a window of time adjacent to that observation. We start by computing for each period the mode of prices p_t^M that occur in a window which includes prices in the previous five periods, the current period, and the next five periods.[1] Then, based on the modal price in this window, we construct the regular price recursively as follows. For the initial period, set the regular price equal to the modal price.[2] For each subsequent period, if the store charges the modal price in that period, and at least one-third of prices in the window are equal to the modal price, then set the regular price equal to the modal price. Otherwise, set the regular price equal to the preceding period's regular price.

We want to eliminate regular price changes that occur when the store's posted price does not change, but only if the posted and regular prices coincide in the period before or after the regular price change. To do that, if the initial algorithm generates a path for regular prices in which a change in the regular price occurs without a corresponding change in the actual price, then we replace the last period's regular price with the current period's actual price for each period in which the regular and actual prices coincide. Similarly, we replace the current period's regular price with the last period's actual price if the two have coincided in the previous period.

Now we provide the precise algorithm we use to compute the regular price and describe how we apply it.

1. Choose parameters: $l = 2$ (= *lag*, or size of the window: the number of months before or after the current period used to compute the modal price. For the Dominick's data, we set $l = 5$ weeks), $c = 1/3$ (= *cutoff* used to determine whether a price is temporary),

[1] We do this calculation only if at least one-half of the prices in this window are available.

[2] If in the window around this price more than half of the data is missing, then we set the initial reference price equal to the actual price.

$a = .5$ (= the number of periods in the window with the *available* price required in order to compute a modal price).

We apply the algorithm below for each good separately:

Let p_t be the price in period t; T, the length of the price series.

2. For each time period $t \in (1 + l, T - l)$,

- If the number of periods with available data in $(t - l, ..., t + l)$ is $\geq 2al$, then

  Let $p_t^M = mode(p_{t-l}, ..., p_{t+l})$.

  Let f_t = the fraction of periods (with available data) in this window subject to $p_t = p_t^M$.

- Else, set $f_t, p_t^M = 0$ (missing data).

3. Define the regular price in period t, p_t^R, using the following recursive algorithm:

- If $p_{1+l}^M \neq 0$, then set $p_{1+l}^R = p_{1+l}^M$ (initial value).
- Else, set $p_{1+l}^R = p_{1+l}$ for $t = 2 + l, ..., T$.

  If $(p_t^M \neq 0$ & $f_t > c$ & $p_t = p_t^M)$, then set $p_t^R = p_t^M$.

  Else, set $p_t^R = p_{t-1}^R$.

4. Repeat the following algorithm five times:

- Let $\mathcal{R} = \{t : p_t^R \neq p_{t-1}^R \;\&\; p_{t-1}^R \neq 0 \;\&\; p_t^R \neq 0\}$ be the set of periods with regular price changes.
- Let $\mathcal{C} = \{t : p_t^R = p_t \;\&\; p_t^R \neq 0 \;\&\; p_t \neq 0\}$ be the set of periods in which a store charges the regular price.
- Let $\mathcal{P} = \{t : p_{t-1}^R = p_{t-1} \;\&\; p_{t-1}^R \neq 0 \;\&\; p_{t-1} \neq 0\}$ be the set of periods in which a store's last period price was the regular price.
- Set $p_{\{\mathcal{R}\cap\mathcal{C}\}-1}^R = p_{\{\mathcal{R}\cap\mathcal{C}\}}$. Set $p_{\{\mathcal{R}\cap\mathcal{P}\}}^R = p_{\{\mathcal{R}\cap\mathcal{P}\}-1}$.

2. Robustness Exercises for Benchmark Menu Cost Model

Here we provide some detail for the robustness exercises we conducted on our Benchmark menu cost model with temporary price changes. For simplicity, we have stripped down our original model of some of its ingredients. In particular, we eliminate the demand shocks from the firm's problem (by assuming one single aggregator of individual varieties) and have eliminated capital and intermediate inputs from the production technology as well as have replaced the money in the utility function specification with a simple cash in advance constraint in most of our analysis here. As we show below, none of these modifications affect our quantitative results.

Having stipped down the model, we then conduct a number of departures from the baseline model. These departures entail either alternative specifications of the price adjustment technology, or changes in the process for idiosyncratic and aggregate shocks. None of these modifications overturn our results. We also briefly provide more details about how the parameters in the menu cost model are identified from moments of the micro-price data.

A. Baseline Economy

The consumer's problem is now to choose consumption $c(s^t)$, nominal labor $l(s^t)$, nominal money balances $M(s^t)$, and a vector of bonds $\{B(s^t, s_{t+1})\}_{s_{t+1}}$ to maximize utility

$$\sum_{t=0}^{\infty} \sum_{s^t} \beta^t \pi\left(s^t\right) U\left(c\left(s^t\right), l\left(s^t\right)\right),$$

subject to a cash-in-advance constraint

$$P\left(s^t\right) c(s^t) = M\left(s^t\right),$$

and a budget constraint

$$M(s^t) + \sum_{s^{t+1}} Q\left(s^{t+1} | s^t\right) B\left(s^{t+1}\right) = W\left(s^t\right) l\left(s^t\right) + \Pi\left(s^t\right) + B\left(s^t\right).$$

The problem of a final good firm is to choose the amount of each intermediate good $y_i(s^t)$ to purchase in order to maximize

$$P\left(s^t\right) y\left(s^t\right) - \int_0^1 P_i\left(s^t\right) y_i\left(s^t\right) di$$

subject to the final good production function

$$y(s^t) = \left[\int y_i(s^t)^{\frac{\theta-1}{\theta}} di \right]^{\frac{\theta}{\theta-1}}.$$

We define $P(s^t) = \left(\int_0^1 P_i(s^t)^{1-\theta} di \right)^{\frac{1}{1-\theta}}$ as the price of the final good, $P_i(s^t)$ as the price of good i purchased from an intermediate good firm, and θ as the elasticity of substitution among intermediate inputs. The solution to this problem is, then,

$$y_i(s^t) = \left(P_i(s^t) / P(s^t) \right)^{-\theta} y(s^t),$$

which is the demand function faced by the producer of intermediate good i.

The producer of intermediate good i uses the technology $y_i(s^t) = a_i(s^t) z_i(s^t) l_i(s^t)$, where $y_i(s^t)$ is the output of good i and $l_i(s^t)$ is the labor input. The good-specific productivity has two components: a transitory one, $z_i(s^t)$, and a permanent one, $a_i(s^t)$.

The firm's period nominal profits, excluding fixed costs at price $P_i(s^t)$, are $D\big(P_i(s^t); s^t\big) = [(P_i(s^t) - W(s^t)/(a_i(s^t) z_i(s^t))] y_i(s^t)$, where $W(s^t)/(a_i(s^t) z_i(s^t))$ is the nominal cost of producing one unit of output. The present discounted value of profits of the firm, expressed in units of period 0 money, is given by

$$(1) \quad \sum_t \sum_{s^t} Q(s^t)(1-\rho_e)^t \big[D\big(P_i(s^t); s^t\big) - W(s^t)\big(\kappa \delta_{L,i}(s^t) + \phi \delta_{T,i}(s^t)\big)\big],$$

where $\delta_{L,i}(s^t)$ is an indicator variable that equals one when the firm changes its list price $(P_{L,i}(s^t) \neq P_{L,i}(s^{t-1}))$ and zero otherwise, and $\delta_{T,i}(s^t)$ is an indicator variable that equals one when the firm temporarily deviates from the list price $(P_i(s^t) \neq P_{L,i}(s^t))$ and zero otherwise. In expression (1), the term $W(s^t)\kappa\delta_{L,i}(s^t)$ is the labor cost of changing list prices, which we think of as the *menu cost*, and $W(s^t)\phi\delta_{T,i}(s^t)$ is the cost of deviating from the list price.

Quantification

We assume the same process for permanent productivity shocks as in the main text. To keep the model simple, we now assume that the transitory shocks follow a three-state Markov chain, with $z_t \in \{-\bar{z}, 0, \bar{z}\}$ referred to as the *low, medium*, and *high* productivity values, with transition probabilities

$$\begin{bmatrix} \rho_s & 1-\rho_s & 0 \\ \rho_l & 1-\rho_l-\rho_h & \rho_h \\ 0 & 1-\rho_s & \rho_s \end{bmatrix}.$$

Here, the subscripts l and h indicate the low and high productivity values. Hence, ρ_l is the probability of experiencing a decrease in productivity from 0 to $-\bar{z}$, and ρ_h is the probability of experiencing an increase in productivity from 0 to $\bar{z}$. Note that we do not impose symmetry in this matrix. Thus, we allow the probability of experiencing a productivity increase to differ from the probability of a decrease. Finally, ρ_s is the probability of staying in a non-medium state. Our parameterization of these shocks thus has four parameters $\{\bar{z}, \rho_s, \rho_l, \rho_h\}$. Here, ρ_l and ρ_h govern the probability of temporary price increases and decreases, while ρ_s determines the duration of temporary price changes.

We have a total of 8 parameters that describe the process for permanent and transitory productivity shocks, as well as the two costs of price changes, and we choose these to minimize the distance between the 13 moments in the data and the model listed in panel A of Table A1. As in the main text, the moments include the facts about temporary and regular price changes, as well as other measures of the degree of low- and high-frequency price variation in the BLS data we have discussed. The notes to Table A1 list the parameter values that allow the model to best match the moments in the data.

Aggregate Implications

Panel B. of Table A1 reports this model's degree of aggregate price stickiness given a 50 b.p. cumulative increase in the money supply. Recall that our measureof aggregate price stickiness is the average difference, over the first 24 months after the shock, between the impulse responses of the money supply and the price level divided by the average money supply impulse response over that period. The model's degree of aggregate price stickiness is about 20%, much lower than in our model of the main text, reflecting the absence of intermediate inputs as a factor of production.

The table also summarizes how the aggregate stickiness manifests itself in output. The money shock leads to an average output response of about 9.3 basis points in the first 24 months after the shock.

We have reported on one measure of the real effects of money, namely, the impulse response to a monetary shock. Another common measure of these effects is the volatility and persistence of output induced by such shocks at business cycle frequencies. In Table 2 we report that the standard deviation of HP-filtered output is equal to 0.33% while its serial correlation is 0.92.

Panel B of Table A1 also shows that for the standard menu cost model (a model with only permanent productivity shocks and no option to temporarily deviate from the list price) to reproduce the degree of aggregate price stickiness in our Benchmark menu cost model, the frequency of price changes needs to be 11.8 months, in line with our results in the much more complex model of the main text.

B. Identification of Key Parameters

Here we explain the method we used to pin down our parameters and we attempt to give some intuition about how the micro moments help identify the parameters.

Method to Pin Down Parameters

We begin with our method of pinning down the parameters. We choose the parameter vector θ to minimize the mean absolute error (MAE):

$$\frac{\sum_{i=1}^{13} \omega_i \left| \frac{m_i(\theta) - \bar{m}_i}{\bar{m}_i} \right|}{\sum_{i=1}^{13} \omega_i} \tag{2}$$

where $\theta = \{\kappa, \phi, \lambda_a, \bar{v}, \rho_s, \rho_l, \rho_h, \bar{z}\}$ is the vector of parameter values, $\bar{m}_i$ are the thirteen moments from the data listed in Table A1, $m_i(\theta)$ are the corresponding moments from the model. The weights ω_i, assigned to each moment, are listed in Table A2. Note we assign much higher weights to the frequency of all and regular price changes than we do to the other moments. We do so in order to ensure that the model reproduces exactly the frequency of price changes in the data. We note that, at the benchmark parametrization, the MAE is equal to 6%.

Intuition for Identification

To illustrate how the moments in the data pin down our key parameter values, we next perturb these parameters and show how the resulting micro moments change.

Consider first the fixed cost of a regular price change, κ. In Table A2 we see that when we double κ relative to its benchmark value, holding all other parameters fixed, the frequency of price changes falls from 6.9% to 5.7% and the fraction of temporary price changes increases from 76% to 81%. Briefly, regular prices become too sticky relative to the data. As a result, the MAE more than doubles, from 6% to 13.2%. Intuitively then, κ is identified by the frequency of regular price changes.

Consider next the fixed cost of temporary price change, ϕ. In Table A2 we see that when we double ϕ relative to its benchmark value, holding all other parameters fixed, four moments are most affected. The frequency of all price changes decreases relative to the data, the frequency of regular price changes increases, temporary prices never return to the pre-existing regular price, the fraction of periods with temporary prices is cut in half. Intuitively, as ϕ increases, firms use list price changes more often and temporary price deviations less often to respond to transitory productivity shocks. As a result, the MAE increases by a factor of 7 relative to the benchmark. Intuitively then, ϕ is identified by the relative frequency of temporary to regular price changes, as well as by how often a temporary price returns to the pre-existing regular price.

Consider next the probability of a permanent productivity shock, λ_a. In Table A2 we see that when we double λ_a relative to its benchmark value, holding all other parameters fixed, the frequency of regular price changes increases from 6.9% to 11% and thus the frequency of all price changes increases as well from 22% to 26%. The fraction of prices at the annual mode decreases from 75% to 64%. Briefly, regular prices become too flexible relative to the data. As a result, the MAE increases by a factor of 4 relative to the benchmark. Intuitively then, λ_a is identified by the frequency of regular price changes.

Since both κ and λ_a are identified by the frequency of price changes, we next show how we identify each one separately. To see this, consider doubling the value of λ_a and then recalibrating κ (as well as $\bar{v}$) to ensure the same frequency and size of regular price changes as in the baseline parametrization. Note in Table A2 that when we do so, the model produces an interquartile range of regular price changes of only 3%, much smaller than in the data. As a result the MAE increases by a factor of 5. Intuitively then, λ_a and κ are jointly pinned down by the frequency of regular price changes and the dispersion in the size of regular price changes.

Consider next the probability of exiting from the median transitory state, $z = 0$, to a non-median state, $z = \bar{z}$ or $z = -\bar{z}$. To see this, consider doubling the value of ρ_l and ρ_h. Note in Table A2 that when we do so, the model produces too many temporary price changes and the MAE increases by a factor of 5. Intuitively then, the frequency of transitory shocks is pinned down by the frequency of temporary price changes. Note also that, as in the case of regular price changes, the frequency of transitory shocks is separately identified from the fixed cost ϕ by the dispersion of the size of all price changes.

Finally, the parameter governing the persistence of transitory shocks, ρ_s, is identified by the probability with which temporary price spells end. To see this, consider the effect of halving ρ_s from its baseline value. Table A2 shows that when we do so the probability that a temporary price spell ends increases.

C. Alternative Pricing Technologies

We considered three alternative pricing technologies. Here we discuss each.

Sticky Temporary Price

This model is identical to the benchmark model except for the details of the costs to the intermediate good firm of temporary price changes. Here paying the fixed cost ϕ once gives the manager the right to continuously charge a given temporary price as long as that manager sees fit. Once the manager discontinues the spell of this particular price the manager can freely revert to the existing regular price, pay a fixed cost κ and charge a new regular price, or pay a fixed cost ϕ and start a new temporary price spell.

We focus on the recursive formulation of the problem of an intermediate good firm. Here a firm that charged a temporary price p_{T-1} in the previous period has the option of charging that price again at no cost. Hence, at any point in time, the firm can be one of two types: a firm that charged a temporary price in the previous period and, hence, has the option to do so again or a firm that charged the list price. We let V_T and V_L denote the value of the two types of firms.

Consider, first, a firm that has just charged a temporary price, $p_{T,-1}$, and has a list price $p_{L,-1}$. Such a firm has four options: charge the old list price at no cost; charge the old temporary price at no cost; charge a new temporary price and pay a fixed cost ϕ; or charge a new list price and pay a fixed cost κ.

For such a firm with state $(p_{L,-1}, p_{T,-1}, a, z; S)$, the value of charging the old list price is $V_T^{L_0}(p_{L,-1}, a, z; S)$

$$= d\left(p_{L,-1}, a, z, S\right) + \beta(1-\rho_e)E\left[\sum_{S'} Q(S', S)V_L(p_{L,-1}, a', z'; S')|a, z)\right];$$

the value of charging the old temporary price is $V_T^{T_0}(p_{L,-1}, p_{T,-1}, a, z; S)$

$$= d\left(p_{T,-1}, a, z, S\right) + \beta(1-\rho_e)E\left[\sum_{S'} Q(S', S)V_T(p_{L,-1}, p_{T,-1}, a', z'; S')|a, z)\right];$$

the value of charging a new list price is $V_T^{L_1}(a, z; S)$

$$= \max_{p_L} d\left(p_L, a, z, S\right) - \kappa + \beta(1-\rho_e)E\left[\sum_{S'} Q(S', S)V_L(p_L, a', z'; S')|a, z)\right];$$

and the value of charging a new temporary price is $V_T^{T_1}(p_{L,-1}, a, z; S)$

$$= \max_{p_T} d\left(p_T, a, z, S\right) - \phi + \beta(1-\rho_e)E\left[\sum_{S'} Q(S', S)V_T(p_{L,-1}, p_T, a', z'; S')|a, z)\right].$$

The value of this firm is the highest of these four values, so that $V_T = \max(V_T^{L_0}, V_T^{T_0}, V_T^{L_1}, V_T^{T_1})$, where we have suppressed the arguments of the value functions.

Consider, next, a firm that has just charged a list price, $p_{L,-1}$. Such a firm has only three options: charge the old list price at no cost; charge a new list price and pay a fixed cost κ; or charge a new temporary price and pay a fixed cost ϕ. For such a firm with state $(p_{L,-1}, a, z; S)$, the value of charging the old list price is $V_L^{L_0} = V_T^{L_0}$; the value of charging a new list price is $V_L^{L_1} = V_T^{L_1}$; and the value of charging a new temporary price is $V_L^{T_1} = V_T^{T_1}$. The value of such a firm is the highest of these three values, so that

$V_L(p_{L,-1}, a, z; S) = \max(V_L^{L_0}, V_L^{L_1}, V_L^{T_1})$.

Table A3 reports results from this model. Panel A shows that this model does nearly as well as matching the moments as the original model. Note that, at the parameter values in the baseline model, simply adding the option to charge the old temporary price at no extra cost would lead to a greater degree of micro price stickiness. This extra price stickiness arises because at these parameter values, firms find it optimal to have multi-period temporary price spells in which the price does not change. Because of this, reproducing the micro moments now requires somewhat smaller costs of both temporary and regular price changes, as well as more frequent arrival of transitory shocks.

As panel B of Table A3 shows, the benchmark model and the sticky temporary price model have nearly identical implications for the degree of aggregate price stickiness. To reproduce the aggregate price stickiness in the sticky temporary price model, a standard model (without temporary changes) needs a frequency of micro price changes of 11.6 months. This frequency is remarkably close to the 11.8 months that we found in our analogous experiment with the benchmark model.

Flexible Temporary Prices

Here we assume that paying this fixed cost ϕ once gives the manager the right to vary the temporary it charges freely for a period of $\bar{\tau} = 3$ months. After this three month spell of flexible prices, the manager can freely revert to the existing regular price, pay a fixed cost κ and charge a new regular price, or pay a fixed cost ϕ and start a new temporary price spell.

Let $V^{\tau}(p_L)$ be the value to the firm of having τ more periods in which it can flexibly change any price that it wants. Clearly, it does not pay to update the list price in the meanwhile due to discounting. So the firm will wait until $\tau = 0$ and then decide whether it wants to buy the option to set $\tau = \bar{\tau}$ (3 months) at a fixed cost ϕ.

The firm's options if it finds itself at node $\tau = 0$ (the period of flexibility has just ended) is to either reset its list price, charge the old list price, or buy the option of $\bar{\tau}$ more periods of temporary price changes. Consider each in turn

Reset the list price:

$$V^{0,L}(z,S) = \max_{p'_L} d\left(p'_L, z, S\right) - \kappa + \beta E \sum_{S'} Q(S',S) V^0\left(p'_L, z', S'\right)$$

Charge the old list price:

$$V^{0,N}(p_L,z,S) = d\left(p_L, z, S\right) + \beta E \sum_{S'} Q(S',S) V^0\left(p_L, z', S'\right)$$

Buy the option to freely choose a temporary price at the beginning of each of the next $\bar{\tau}$ periods.

$$V^{0,T}(p_L,z,S) = \max_{p_T} d\left(p_T, z, S\right) - \phi + \beta E \sum_{S'} Q(S',S) V^{\bar{\tau}-1}\left(p_L, z', S'\right)$$

If $\tau \geqslant 1$, the firm will just charge its temporary price, since that is free:

$$V^{\tau}(p_L,z,S) = \max_{p_T} d\left(p_T, z, S\right) + \beta E \sum_{S'} Q(S',S) V^{\bar{\tau}-1}\left(p_L, z', S'\right)$$

We set $\bar{\tau} = 3$ (3 months) We also note

$$V^0 = \max\left(V^{0,L}, V^{0,N}, V^{0,T}\right)$$

Table A4 reports the moments and parameter values we have used in this experiment. Once again, this model does a good job at reproducing the key features of the micro price data. Table A5 reports this model's aggregate predictions. Now that the temporary price is flexible, the model generates a slightly smaller degree of aggregate price stickiness. This is not enough, however, to overturn our baseline model's predictions: a standard menu cost models still needs a large degree of micro price stickiness (10.8 months) to reproduce the degree of aggregate price stickiness in this model with flexible temporary prices.

Free Switching to Temporary Price

Here we assume that paying this fixed cost ϕ once gives the manager the right to choose one temporary price and to freely switch between that one price and the regular price for a fixed amount of time, here three months. After this three month spell, the manager can freely revert to the existing regular price, pay a fixed cost κ and charge a new regular price, or pay a fixed cost ϕ and start a new temporary price spell.

Let (p_L, p_T, τ, z) be the state of the firm, its list price, its old temporary price, the number of periods it can keep charging the given temporary price p_T, and the idiosyncratic productivity.

Let $\bar{\tau}$ be the number of months a temporary price can last from the moment the fixed cost ϕ is paid. Consider the value of a firm whose temporary price p_T can last for τ more periods. It has 4 options:

Reset list price at cost κ

$$V^{L_{new}}\left(p_L, p_T, \tau, z, S\right) = \max_{p'_L} d\left(p'_L, z, S\right) - \kappa + \beta E \sum_{S'} Q(S', S) V\left(p'_L, p_T, \max\left(\tau - 1, 0\right), z', S'\right)$$

Start a new temporary price spell at cost ϕ

$$V^{T_{new}}\left(p_L, p_T, \tau, z, S\right) = \max_{p'_T} d\left(p'_T, z, S\right) - \phi + \beta E \sum_{S'} Q(S', S) V\left(p_L, p'_T, \bar{\tau} - 1, z', S'\right)$$

Charge the old temporary price for free. If $\tau > 0$, then

$$V^{T_{old}}\left(p_L, p_T, \tau, z, S\right) = d\left(p_T, z, S\right) + \beta E \sum_{S'} Q(S', S) V\left(p_L, p_T, \max\left(\tau - 1, 0\right), z', S'\right)$$

Charge old list price for free

$$V^{L_{old}}\left(p_L, p_T, \tau, z\right) = d\left(p_L, z, S\right) + \beta E \sum_{S'} Q(S', S) V\left(p_L, p_T, \max\left(\tau - 1, 0\right), z', S'\right)$$

The continuation value is

$$V\left(p_L, p_T, \tau, z\right) = \max\left(V^{L_{new}}, V^{T_{new}}, V^{T_{old}}, V^{L_{old}}\right)$$

Table A6 reports the moments and parameters we have used in this experiment. This version of the model accounts for the micro price data somewhat worse than our baseline model as it generates too little dispersion in the size of price changes (the IQR is only 0.02 compared to 0.09 in the data). Table A7 shows that this model generates a somewhat greater degree of aggregate price stickiness. A standard menu cost model need a 17.5 month degree of micro price stickiness to reproduce these impulse responses.

D. The Nature of Shocks and Menu Costs

Here we explain the details of our robustness checks about the nature of the shocks and menu costs.

Random Menu Costs

We have purposefully kept our benchmark model very simple in order to illustrate our main point. We have shown that even though it has few parameters, the model can match well thirteen moments of the micro-price data. Our model, however, clearly misses on one feature of the data: it cannot generate the large number of small price changes found in this data. Here we discuss this discrepancy and then modify our model to match these additional facts.

To see the discrepancy between our model and the data, we report in Table A8 that the 25th percentile of the distribution of all and of regular price changes is equal to 3% (that is 25% of both all price changes and regular price changes are less than 3% in absolute value). Our model, in contrast, predicts that the 25th percentile of the distribution of all price changes is 5.4%, while that of regular price changes is 7.4%. Thus, our model generates too few small price changes.

A parsimonious way of modifying our model so that it can generate small price changes is to make the menu cost random. In particular, we assume that with probability α_L the firm is allowed to change its regular price once without paying a cost. Similarly, we assume that with probability α_T the firm is allowed to charge a temporary price at no extra cost.

Conditional on not being able to change its price at no extra cost, the firm's value of a list price change, V^L, a temporary price change, V^T, and of inaction, V^N, are the same as earlier. The only modification is that the value of the firm V is now

$$\begin{aligned} V\left(p_{L,-1}, a, z, S\right) &= (1-\alpha_R-\alpha_T)\max\left(V^N, V^T, V^L\right) + \ldots \\ &\quad \alpha_R \max\left(V^L+\kappa, V^T, V^N\right) + \alpha_T\left(V^T+\phi\right) \end{aligned}$$

Note that, given the option of a regular price change at no cost (with probability α_R), the firm may still choose to undertake any of the other options (say it may choose to have a temporary change to respond to a transitory shock). Hence, when there is a free regular price change add back the fixed cost κ to the value V^L but still give the firm 3 options. In contrast, whenever it is given an option to change its temporary price for free the firm will take it. Thus, under this option we just add back the fixed cost ϕ to V^T.

We report the results of the model with random menu cost in Tables A8 and A9. We choose the probabilities of a free price change, α_R and α_T, in addition to all other parameters, to match the 13 original moments together with two other moments: the 25th percentile of the size of both all and of regular price changes. Notice the model now reproduces the fact that 25% of all and regular price changes are less than 3% in absolute value.

Table A9 shows that the aggregate predictions of our model are essentially unchanged. The model now produces a 18.5% degree of aggregate price stickiness, which is just a bit smaller than the 19.9% we found in the benchmark model. For the standard model to reproduce this amount of aggregate price stickiness, the frequency of micro-price changes must be once every 11.5 months. Note that in making this comparison we have also modified the standard model to also include a random menu cost the size of which is chosen to allow the model to reproduce the 25th percentile of price changes.

We thus conclude that our results are robust to a modification that allows the model to reproduce the large number of small price changes in the micro-price data.

Gaussian Shocks

In the benchmark model, we have assumed a fat-tailed distribution of both permanent and transitory shocks. We did so in order to allow the model to reproduce the dispersion of the size of price changes in the data. We next ask whether our results are robust to assuming Gaussian, rather than fat-tailed productivity shocks.

We assume now that permanent productivity evolves according to

$$a_{it} = a_{it-1} + \varepsilon_{it}^{a}$$

where the permanent productivity shocks ε_{it}^{a} are normally distribution with mean 0 and variance σ_a^2, while transitory productivity evolves according to

$$z_{it} = \rho z_{it-1} + \varepsilon_{it}^{z}$$

where ρ is the persistence and ε_{it}^{z} is normally distributed with mean 0 and variance σ_z^2.

We choose again all parameter values in order to minimize the mean absolute error between the moments in the model and the data. Table A10 shows that the model can reproduce most of the moments in the data, with the exception of those describing the dispersion of the size of price changes in the data, such as the interquartile range of all and regular price changes. Briefly, the menu cost is much larger now (5.6% of firm's profits vs. 0.81% in the benchmark model) in order to prevent firms from responding to continuously-arriving productivity shocks. As a result the inaction region is much wider and firms always change prices by large amounts so that the dispersion in the size of price changes is too low relative to the data. See Midrigan (2010) for a more detailed discussion.

In Table A11 we show that this version of the model produces much less aggregate price stickiness than our benchmark model. For example, the degree of aggregate price stickiness is only 3.1%, thus 1/6th of the level in the benchmark model (19.9%). This difference is due to a much stronger selection effect in the model with Gaussian shocks, as discussed in Midrigan (2010).

The selection effect is equally strong, however, in the standard model as it is in our model with temporary price changes. Hence, when we ask what is the degree of micro-price stickiness that the model without temporary changes and Gaussian shocks needs to reproduce the same impulse responses as our model with temporary changes, we find the answer is 11.4 months. Note that this number is very similar to the one we found using the model with fat-tailed shocks.

E. Dominick's Data

Recall that we have so far used the BLS data set with our benchmark model because this data set has a comprehensive coverage of goods. But the BLS data are available only monthly, so the dataset might miss high-frequency movements in prices. And the BLS data include no quantities, so they leave open the possibility that almost all purchases are made when goods are on sale, making regular prices irrelevant. To investigate these possibilities, we here switch to the Dominick's data set, which is less comprehensive, but has both prices and quantities available and on a much more frequent basis (weekly). The results with this data set are consistent with those from the original exercise.

The Regularities in Dominick's Data

The Dominick's data set includes nine years (1989–97) of weekly store-level reports from 86 grocery stores in the Chicago area on the prices of more than 4,500 individual products, organized into 29 product categories. For a detailed description of the data and Dominick's pricing practices, see the work of Chevalier, Kashyap, and Rossi (2003).

Many of the patterns that we documented in the BLS data are the same — and stronger— in the Dominick's weekly data. As Table A12 shows, nearly all price changes are temporary (94%), and after such changes, 80% of these prices come back to the pre-existing price. As a result, even though prices change relatively frequently, once every 3 weeks, the regular price changes occur much less often, once every 8 months. Unlike the BLS data, the Dominick's data also contain information on quantities sold. Using those data, we find that a disproportionate fraction of goods are sold during periods of temporary prices: even though temporary price changes occur only about a quarter of the time, almost 40% of goods are sold during these periods.

We calibrate the model's parameters to match all the moments listed in Panel A of Table A12. Notice that this version of the benchmark model does a good job of reproducing the price facts in the data. In addition, the model accounts well for the quantity facts as well. In both the data and the model, periods with temporary price changes account for a disproportionate amount of goods sold.[3] Even though prices are temporary 24% of the weeks in the data and 22% of the time in the model, these periods account for 39% of the goods sold in the data and 34% in the model. Periods in which prices are temporarily below the regular price account for the bulk of these sales: 32% of goods are sold during such episodes in the data and 35% in the model. The reason the Dominick's model does so well at reproducing these quantity facts is that its demand elasticity ($\theta = 3$) is consistent with the price elasticities of demand in the data.

The Degree of Aggregate Price Stickiness

Finally, we study the degree of aggregate price stickiness in our Dominick's model to see whether our earlier results using BLS data are supported. We find that they are.

We first shock money growth in the model in the same way as in the benchmark model based on the BLS data: this innovation leads to an eventual increase of 50 basis points in the money supply. We then calculate the degree of aggregate price stickiness in our (re-parameterized) model. Panel B of Table A12 shows that a standard model requires a frequency of price changes of 6.6 months in order to produce the same degree of aggregate price stickiness as in our Dominick's model.

These results are consistent with our earlier results using the BLS data. Since the frequency of price changes is much higher in the Dominick's data than in the BLS data (3 weeks vs. 4.5 months), we view the 6.6 months as a very conservative lower bound on the degree of price stickiness in the economy as a whole. Here, as with the BLS data, we conclude that aggregate prices are sticky after all.

Dominick's Economy with Demand Shocks

We have also studied a version of the Dominick's economy with the demand shocks that we have introduced in the main text. Tables A13 and A14 show that allowing for such demand shocks does not change the model's predictions. The model accounts well for both

[3] See Chevalier and Kashyap (2011), who provide some additional evidence on how quantities purchased vary with prices during periods with temporary price changes.

price and quantity facts in the Dominick's data. A standard model now requires a frequency of price changes of 6.1 months in order to produce the same degree of aggregate price stickiness as in our Dominick's model with demand shocks.

F. The Nature of Idiosyncratic Shocks

Dependent Shocks

In the benchmark model we have assumed that the transitory and permanent shocks are independent. This independence shows up in two ways. In the benchmark model the arrival of the permanent shock is independent of the arrival of a transitory shock. Moreover, the two shocks are also uncorrelated. Here we ask whether our results are robust to allowing dependence between the two types of shocks.

We introduce two types of dependence between these shocks. We allow the arrival dates of the shocks to be correlated and, conditional on arrival, we allow the shocks to be correlated.

We do so by keeping the permanent productivity shock process unchanged but allowing the transition probability for transitory shocks to depend on the realization of the permanent shock. Recall that the permanent productivity process evolves according to:

$$\log a_i\left(s^t\right) = \log a_i\left(s^{t-1}\right) + \varepsilon_i\left(s^t\right)$$

where $\varepsilon_i\left(s^t\right)$ arrive at rate λ_a and follow

$$\varepsilon_i\left(s^t\right) = \begin{cases} U\left[-\bar{v},\bar{v}\right] \text{ with prob. } \lambda_a \\ 0 \text{ with prob. } 1-\lambda_a \end{cases}.$$

The transition probability for transitory shocks, $z_i\left(s^t\right)$, depends on the realization of the permanent shock $\varepsilon_i\left(s^t\right)$. If $\varepsilon_i\left(s^t\right) = 0$, then

$$P_{z|z_{-1}} = \begin{bmatrix} \rho_s & 1-\rho_s & 0 \\ \rho_l & 1-\rho_l-\rho_h & \rho_h \\ 0 & 1-\rho_s & \rho_s \end{bmatrix},$$

if $\varepsilon_i(s^t) > 0$, then

$$P_{z|z_{-1}} = \begin{bmatrix} \rho_s & 1-\rho_s & 0 \\ \rho_l & 1-\rho_l-(1+\tau)\rho_h & (1+\tau)\rho_h \\ 0 & 1-\rho_s & \rho_s \end{bmatrix},$$

while if $\varepsilon_i(s^t) < 0$, then

$$P_{z|z_{-1}} = \begin{bmatrix} \rho_s & 1-\rho_s & 0 \\ (1+\tau)\rho_l & 1-(1+\tau)\rho_l-\rho_h & \rho_h \\ 0 & 1-\rho_s & \rho_s \end{bmatrix},$$

where $\tau > 0$. Thus when a permanent productivity shock arrives (either positive or negative) two features differ from our benchmark process. First, the probability of transiting from the median transitory shock state $z = 0$ increases (by $\tau\rho_h$ if this shock is positive and by $\tau\rho_l$ is this shock is negative). Second, conditional on this shock arriving the relative probabilities of transiting to the high and low transitory shock are altered. When a positive permanent shock arrives ($\varepsilon_i(s^t) > 0$) the conditional probability of transiting to a high transitory shock relative to a low one increases by a factor of $1+\tau$. In contrast, when a negative permanent shock arrives ($\varepsilon_i(s^t) < 0$) the conditional probability of transiting to a low transitory shock relative to a high one increases by a factor of $1+\tau$. Note that in the limit $\tau = 0$ and the two shocks are independent.

We report our results for the model with dependent shocks in Table A15 and A16. We set $1+\tau = 5$ so that conditional on, say, a positive permanent shock arriving, the relative probability of transiting to a high transitory state is 5 times larger than it is in the benchmark model. We also choose the rest of the parameters to match our 13 moments of the micro-price data. Notice we do as almost as well as in the benchmark model (the MAE is 6.2% vs. 6% earlier).

Table A16 shows that the aggregate predictions of our model are essentially unchanged. The model now produces a 21.8% degree of aggregate price stickiness, which is just a bit larger than the 19.9% we found in the benchmark model. For the standard model to reproduce this amount of aggregate price stickiness, the frequency of micro-price changes must be once every 13.6 months.

We thus conclude that our results are robust to the assumed independence of transitory and permanent idiosyncratic shocks.

Permanent versus Transitory Shocks

We computed our measure of aggregate price stickiness in the benchmark model by asking, what degree of micro-price stickiness in a model without temporary changes would reproduce the same impulse responses to a monetary shock in our model. To answer this question, we have studied a model in which we have eliminated the option of a temporary price change, as well as eliminating the idiosyncratic transitory shocks.

Our idea was to ask what would the literature have found if they faced the same data we did and approached the data as they did in their papers. For example, Golosov and Lucas (2007), Nakamura and Steinsson (2008), and Midrigan (forthcoming) all posited a menu cost with one shock and chose the parameters of the model, including those of the shock process, to match moments of the distribution of price changes. In the body of the paper we focused on the procedure of Midrigan who posited a random walk process for productivity and choose the parameters of the process to reproduce the frequency, mean, and dispersion of the size of price changes. Here we ask if our results are robust to varying the degree of persistence of the productivity shock process.

We now eliminate the permanent shocks, $a_i\left(s^t\right)$ and assume that the transitory shocks, $z_i\left(s^t\right)$ evolves according to an AR(1) process:

$$\log z_i\left(s^t\right)=\rho_z \log z_i\left(s^{t-1}\right)+\varepsilon_i^z\left(s^t\right)$$

where

$$\varepsilon_i^z\left(s^t\right)=\begin{cases} U\left(-\bar{z},\bar{z}\right) \text{ with prob. } \lambda_z \\ 0 \text{ otherwise}\end{cases}$$

We assign several different values to ρ_z and then choose the rest of the parameters governing this process to reproduce the mean and dispersion of price changes as well the impulse response in the benchmark model.

We report our results for the standard model with transitory shocks in Table A17. We varied the level of persistence of the transitory shocks from a rather low level $\rho_z = 0.5$, to a rather high level, $\rho_z = 0.9$. In Table A17 we choose the menu cost, κ, the upper bound on shocks, $\bar{z}$, and the arrival rate of shocks, λ_z, to match the mean and dispersion (IQR) of the size of regular price changes in the data, as well as the degree of aggregate price stickiness in our benchmark model with temporary changes (19.9%). When we do so, we see that the model without temporary price changes needs a frequency of price changes of once every 11.3 months for $\rho_z = 0.5$, and once every 12.8 months for $\rho_z = 0.9$, in order to match the degree of aggregate price stickiness in our benchmark model.

We thus conclude that our results are robust to the assumed persistence of idiosyncratic shocks in the model without temporary price changes.

G. Nature of Monetary Shocks

The Response to Large Monetary Shocks

Here we show how prices and output respond to a very large monetary shock. We choose the shock to be a one-time, unanticipated 5% increase in the money supply. In Figure A1 we show that in response to this shock the aggregate price level immediately increases, almost one-for-one with the money supply. As a result the response of output is negligible. The reason for this result is that almost all firms find it optimal to change prices in response to a large shock.

Trend Stationary Money Supply

Even though there is very little empirical support for such a specification, we have also studied an economy in which the level of money supply is trend stationary. We now assume that the log of the money supply follows

$$\ln m_{t+1} = \rho_m \ln m_t + \varepsilon_{t+1}$$

Since the data is most consistent with a value of ρ_m close to unity, we have set $\rho_m = 0.9$ which implies a great deal of mean reversion. Since our time period is monthly, this implies that within a year a shock of size ■ has reverted to 0.9^{12}■ or 73% of the way back to the mean.

In Table A18 we find that changing the process for monetary shocks and keep the old parameter values from the economy with non-stationary money shocks, does not change the model's micro implications. The reason is that prices in our model respond mainly to idiosyncratic shocks and not the money shocks, since the former ar emuch more volatile.

In Table A19 we find that our original results are robust to this modification. A standard model without temporary changes (and trend stationary money supply) needs a degree of micro price stickiness of about 10 months to match the degree of aggregate price stickiness of our model with this money supply process and temporary changes.

Table A1: Economy with Temporary Price Changes
BLS Data

A. Moments

	BLS Data	Model
Frequency of all price changes	0.22	0.22
Frequency of regular price changes	0.069	0.069
Fraction of price changes that are temporary	0.72	0.76
Proportion of returns to regular price	0.50	0.70
Probability that temporary price spell ends	0.53	0.54
Fraction of periods with temp. prices	0.10	0.11
Fraction of periods with price temp. down	0.06	0.06
Fraction of prices at annual mode	0.75	0.73
Fraction of prices below annual mode	0.13	0.17
Mean size of price changes	0.11	0.11
Mean size of regular price changes	0.11	0.11
IQR of all price changes	0.09	0.09
IQR of regular price changes	0.08	0.07

B. Aggregate Implications

	Benchmark Model. With temporary changes	Standard Model. Without temporary changes
Micro-price stickiness, months	4.5	11.8
Impulse Response to a 50 b.p. monetary shock		
Aggregate price stickiness, %	19.9	19.9
Average output response, b.p.	9.3	9.3
Maximum output response, b.p.	19.0	20.8
Business Cycle Statistics		
Std. dev output, %	0.33	0.35
Autocorr. output	0.92	0.93

The costs of list and temporary price changes are κ = 0.81 and ϕ = 0.68 (% of SS profits).
The permanent shock parameters are λ_a = 7.6% (arrival rate) and *v_bar* = 18.4% (upper bound).
The transitory shock parameters are *z_bar* = 14.3% (size), ρ_l = 0.0264, ρ_h = 0.038, ρ_s = 0.52 (Markov transition probability).

Table A2: Identification of key parameters
BLS Data

A. Moments

	BLS Data	Weight	Benchmark	Double κ	Double ϕ	Double λ_a	Double $\lambda_{a,}$ Change v_{bar}, k_R	Double ρ_l, ρ_h	Halve ρ_s
Frequency of all price changes	0.22	5	0.22	0.23	**0.17**	**0.26**	0.33	**0.34**	0.20
Frequency of regular price changes	0.069	5	0.069	**0.057**	**0.121**	**0.110**	0.069	0.073	0.062
Fraction of price changes that are temporary	0.72	1	0.76	0.81	0.56	0.70	0.87	0.87	0.76
Proportion of returns to regular price	0.50	1	0.70	0.78	**0.00**	0.53	0.64	0.73	0.79
Probability that temporary price spell ends	0.53	1	0.54	0.49	0.73	0.56	0.35	0.51	**0.73**
Fraction of periods with temp. prices	0.10	1	0.11	0.12	0.06	0.12	0.22	**0.20**	0.09
Fraction of periods with price temp. down	0.06	1	0.06	0.07	0.03	0.06	0.11	**0.11**	0.06
Fraction of prices at annual mode	0.75	1	0.73	0.74	**0.67**	**0.64**	0.64	0.65	0.76
Fraction of prices below annual mode	0.13	1	0.17	0.17	0.19	0.20	0.19	0.20	0.15
Mean size of price changes	0.11	1	0.11	0.10	0.13	0.11	0.08	0.11	0.12
Mean size of regular price changes	0.11	1	0.11	0.11	0.13	0.12	0.10	0.12	0.11
IQR of all price changes	0.09	1	0.09	0.10	0.02	0.08	0.14	0.03	0.10
IQR of regular price changes	0.08	1	0.07	0.07	0.05	0.07	**0.03**	0.09	0.07
Objective: Mean Absolute Error, %			6.0	13.2	44.8	26.1	33.8	30.7	14.2

Note: The weight column reports the weights assigned to each moment in computing the root mean square error.
We have underlined the moments that alternative parametrizations fail to account for.

Table A3: Economy with Sticky Temporary Prices
BLS Data

A. Moments

	BLS Data	Model
Frequency of all price changes	0.22	0.22
Frequency of regular price changes	0.069	0.069
Fraction of price changes that are temporary	0.72	0.76
Proportion of returns to regular price	0.50	0.76
Probability that temporary price spell ends	0.53	0.66
Fraction of periods with temp. prices	0.10	0.10
Fraction of periods with price temp. down	0.06	0.06
Fraction of prices at annual mode	0.75	0.74
Fraction of prices below annual mode	0.13	0.16
Mean size of price changes	0.11	0.11
Mean size of regular price changes	0.11	0.11
IQR of all price changes	0.09	0.03
IQR of regular price changes	0.08	0.08

B. Aggregate Implications

	Our model	Standard Model. Without temporary changes
Micro-price stickiness, months	4.5	11.6
Impulse Response to a 50 b.p. monetary shock		
Aggregate price stickiness, %	19.7	19.7
Average output response, b.p.	9.2	9.2
Maximum output response, b.p.	19.5	20.7
Business Cycle Statistics		
Std. dev output, %	0.33	0.35
Autocorr. output	0.93	0.93

The costs of list and temporary price changes are κ = 0.45 and ϕ = 0.45 (% of SS profits).
The permanent shock parameters are λ_a = 6.2% (arrival rate) and *v_bar* = 21% (upper bound).
The transitory shock parameters are *z_bar* = 13% (size), ρ_l = 0.031, ρ_h = 0.05, ρ_s = 0.40 (Markov transition probability).

Table A4: Parameterization of economy with flexibilite temporary price
BLS Data

A. Moments

	BLS Data	Model
Frequency of all price changes	0.22	0.21
Frequency of regular price changes	0.069	0.070
Fraction of price changes that are temporary	0.72	0.77
Proportion of returns to regular price	0.50	0.50
Probability that temporary price spell ends	0.53	0.36
Fraction of periods with temp. prices	0.10	0.12
Fraction of periods with price temp. down	0.06	0.06
Fraction of prices at annual mode	0.75	0.72
Mean size of price changes	0.11	0.11
Mean size of regular price changes	0.11	0.11
IQR of all price changes	0.09	0.18
IQR of regular price changes	0.08	0.08

B. Parameter Values

Calibrated	
Menu cost of list price change, κ, % SS profits	0.66
Cost of temp. price deviation, ϕ, % SS profits	1.25
Arrival rate of permanent shock, λ_a	0.069
Upper bound of permanent productivity shock, *ν_bar*	0.149
Size of transitory productivity shock, *z_bar*	0.186
Probability of negative productivity shock, ρ_l	0.016
Probability of positive productivity shock, ρ_h	0.0341
Probability of staying in non-medium state, ρ_s	0.415
Assigned	
Period length	1 month
Probability of exit	0.018
Annual discount factor	0.96
AR(1) growth rate of M	0.61
S.D. of shocks to growth rate of M, %	0.18

Table A5: Aggregate Implications
Economy with flexible temporary price. BLS Data

Statistic	Our model. With temporary changes	Standard model. Without temporary changes
Micro-price stickiness, months	4.5	10.8
	Impulse Response to a 50 b.p. monetary shock	
Aggregate price stickiness, %	18.6	18.6
Average output response, b.p.	8.7	8.7
Maximum output response, b.p.	18.2	20.2
	Business Cycle Statistics	
Std. dev output, %	0.31	0.34
Autocorr. output	0.92	0.92

Notes:

Aggregate price stickiness is measured as the average difference between M and P responses, relative to the M response.
Responses are computed for the first 2 years after the shock.
Business cycle statistics reported for HP(14400) filtered data

Table A6: Parameterization of economy with free switching
BLS Data

A. Moments

	BLS Data	Model
Frequency of all price changes	0.22	0.22
Frequency of regular price changes	0.069	0.071
Fraction of price changes that are temporary	0.72	0.75
Proportion of returns to regular price	0.50	0.79
Probability that temporary price spell ends	0.53	0.79
Fraction of periods with temp. prices	0.10	0.10
Fraction of periods with price temp. down	0.06	0.06
Fraction of prices at annual mode	0.75	0.75
Mean size of price changes	0.11	0.11
Mean size of regular price changes	0.11	0.11
IQR of all price changes	0.09	0.02
IQR of regular price changes	0.08	0.07

B. Parameter Values

Calibrated	
Menu cost of list price change, κ, % SS profits	0.75
Cost of temp. price deviation, ϕ, % SS profits	0.72
Arrival rate of permanent shock, λ_a	0.057
Upper bound of permanent productivity shock, *ν_bar*	0.229
Size of transitory productivity shock, *z_bar*	0.105
Probability of negative productivity shock, ρ_l	0.035
Probability of positive productivity shock, ρ_h	0.059
Probability of staying in non-medium state, ρ_s	0.307
Assigned	
Period length	1 month
Probability of exit	0.018
Annual discount factor	0.96
AR(1) growth rate of M	0.61
S.D. of shocks to growth rate of M, %	0.18

Table A7: Aggregate Implications
Economy with option to switch between regular and temporary for 3 periods. BLS Data

Statistic	Our model. With temporary changes	Standard model. Without temporary changes
Micro-price stickiness, months	4.5	17.5
	Impulse Response to a 50 b.p. monetary shock	
Aggregate price stickiness, %	26.4	26.4
Average output response, b.p.	12.3	12.3
Maximum output response, b.p.	23.3	23.9
	Business Cycle Statistics	
Std. dev output, %	0.40	0.41
Autocorr. output	0.93	0.93

Notes:

Aggregate price stickiness is measured as the average difference between M and P responses, relative to the M response.
Responses are computed for the first 2 years after the shock.
Business cycle statistics reported for HP(14400) filtered data

Table A8: Parameterization of Economy with Temporary Price Changes
Economy with random menu cost. BLS Data

A. Moments

	BLS Data	Model
Frequency of all price changes	0.22	0.22
Frequency of regular price changes	0.069	0.069
Fraction of price changes that are temporary	0.72	0.76
Proportion of returns to regular price	0.50	0.81
Probability that temporary price spell ends	0.53	0.84
Fraction of periods with temp. prices	0.10	0.09
Fraction of periods with price temp. down	0.06	0.05
Fraction of prices at annual mode	0.75	0.74
Fraction of prices below annual mode	0.13	0.16
Mean size of price changes	0.11	0.09
Mean size of regular price changes	0.11	0.10
IQR of all price changes	0.09	0.08
IQR of regular price changes	0.08	0.12
25th percentile all price changes	0.03	0.03
25th percentile regular price changes	0.03	0.03
Objective: Mean Absolute Error, %		10.2

B. Parameter Values

Calibrated	
Menu cost of list price change, κ, % SS profits	5.40
Probability free list price change, α_L	0.029
Cost of temp. price deviation, ϕ, % SS profits	2.70
Probability free temporary price change, α_T	0.035
Arrival rate of permanent shock, λ_a	0.060
Upper bound of permanent productivity shock, ν_bar	0.225
Standard deviation transitory shocks, σ^z	0.044
Persistence transitory shocks, ρ	0.25
Assigned	
Period length	1 month
Probability of exit	0.018
Annual discount factor	0.96
AR(1) growth rate of M	0.61
S.D. of shocks to growth rate of M, %	0.18
Relative frequency of transitory shocks, τ	0.50

We assign the last 2 moments a weight of 5 to compute the Mean Absolute Error

Table A9: Aggregate Implications
Economy with random menu costs. BLS Data

Statistic	Our model. With temporary changes	Standard model. Without temporary changes
Micro-price stickiness, months	4.5	11.5
	Impulse Response to a 50 b.p. monetary shock	
Aggregate price stickiness, %	18.5	18.5
Average output response, b.p.	8.7	8.7
Maximum output response, b.p.	18.7	18.4
	Business Cycle Statistics	
Std. dev output, %	0.32	0.31
Autocorr. output	0.91	0.93

Notes:

Aggregate price stickiness is measured as the average difference between M and P responses, relative to the M response.
Responses are computed for the first 2 years after the shock.
Business cycle statistics reported for HP(14400) filtered data

Table A10: Parameterization of Economy with Temporary Price Changes
Gaussian Shocks. BLS Data

A. Moments

	BLS Data	Model
Frequency of all price changes	0.22	0.22
Frequency of regular price changes	0.069	0.069
Fraction of price changes that are temporary	0.72	0.74
Proportion of returns to regular price	0.50	0.79
Probability that temporary price spell ends	0.53	0.66
Fraction of periods with temp. prices	0.10	0.10
Fraction of periods with price temp. down	0.06	0.05
Fraction of prices at annual mode	0.75	0.73
Fraction of prices below annual mode	0.13	0.16
Mean size of price changes	0.11	0.11
Mean size of regular price changes	0.11	0.12
IQR of all price changes	0.09	0.03
IQR of regular price changes	0.08	0.03
Objective: Mean Absolute Error, %		13.4

B. Parameter Values

Calibrated	
Menu cost of list price change, κ, % SS profits	5.58
Cost of temp. price deviation, ϕ, % SS profits	3.24
Standard deviation permanent shocks, σ^a	0.023
Standard deviation transitory shocks, σ^z	0.049
Persistence transitory shocks, ρ	0.66
Assigned	
Period length	1 month
Probability of exit	0.018
Annual discount factor	0.96
AR(1) growth rate of M	0.61
S.D. of shocks to growth rate of M, %	0.18

Table A11: Aggregate Implications
Gaussian Shocks, BLS Data

Statistic	Our model. With temporary changes	Standard model. Without temporary changes
Micro-price stickiness, months	4.5	11.4
	Impulse Response to a 50 b.p. monetary shock	
Aggregate price stickiness, %	3.1	3.1
Average output response, b.p.	1.5	1.5
Maximum output response, b.p.	7.4	6.6
	Business Cycle Statistics	
Std. dev output, %	0.10	0.10
Autocorr. output	0.76	0.84

Notes:

Aggregate price stickiness is measured as the average difference between M and P responses, relative to the M response.
Responses are computed for the first 2 years after the shock.
Business cycle statistics reported for HP(14400) filtered data

Table A12: Economy with Temporary Price Changes
Dominick's Data

A. Moments

	BLS Data	Model
Frequency of all price changes	0.33	0.33
Frequency of regular price changes	0.029	0.029
Fraction of price changes that are temporary	0.94	0.95
Proportion of returns to regular price	0.80	0.87
Probability that temporary price spell ends	0.46	0.46
Fraction of periods with temp. prices	0.24	0.22
Fraction of periods with price temp. down	0.20	0.19
Fraction of prices at annual mode	0.58	0.55
Fraction of prices below annual mode	0.30	0.30
Mean size of price changes	0.17	0.16
Mean size of regular price changes	0.11	0.11
IQR of all price changes	0.15	0.24
IQR of regular price changes	0.08	0.07
Fraction of output sold when temp. prices	0.39	0.34
Fraction of output sold when price temp. down	0.35	0.32

B. Aggregate Implications

	Our model	Standard Model. Without temporary changes
Micro-price stickiness, months	0.7	6.6
Impulse Response to a 50 b.p. monetary shock		
Aggregate price stickiness, %	12.2	12.2
Average output response, b.p.	5.7	5.7
Maximum output response, b.p.	17.3	17.3
Business Cycle Statistics		
Std. dev output, %	0.30	0.29
Autocorr. output	0.92	0.93

The costs of list and temporary price changes are κ = 1.95 and ϕ = 1.2 (% of SS profits).
The permanent shock parameters are λ_a = 3.8% (arrival rate) and *v_bar* = 16% (upper bound).
The transitory shock parameters are *z_bar* = 24% (size), ρ_l = 0.018, ρ_h = 0.111, ρ_s = 0.52 (Markov transition probability).

Table A11: Parameterization of Economy with Temporary Price Changes
Economy with demand shocks. Dominick's Data

A. Moments

	BLS Data	Model
Frequency of all price changes	0.33	0.33
Frequency of regular price changes	0.029	0.029
Fraction of price changes that are temporary	0.94	0.97
Proportion of returns to regular price	0.80	0.82
Probability that temporary price spell ends	0.46	0.46
Fraction of periods with temp. prices	0.24	0.23
Fraction of periods with price temp. down	0.20	0.19
Fraction of prices at annual mode	0.58	0.56
Fraction of prices below annual mode	0.30	0.30
Mean size of price changes	0.17	0.16
Mean size of regular price changes	0.11	0.12
IQR of all price changes	0.15	0.22
IQR of regular price changes	0.08	0.07
Output ratio periods with temp prices down	2.2	2.3
Fraction of output sold when temp. prices	0.39	0.37
Fraction of output sold when price temp. down	0.35	0.35
Objective: Mean Absolute Error, %		5.0

B. Parameter Values

Calibrated	
Menu cost of regular price change, κ, % SS profits	3.77
Cost of temp. price deviation, ϕ, % SS profits	1.76
Arrival rate of permanent shock, λ_a	0.027
Upper bound of permanent productivity shock, *ν_bar*	0.106
Share of type *A* consumers, χ	0.931
Elasticity of substitution of type *A* consumers	2.30
Probability of staying in $\omega = 0$ state, δ_0	0.893
Probability of staying in $\omega = 1$ state, δ_1	0.50
Size of transitory productivity shock, *z_bar*	0.24
Probability of leaving to non-medium productivity state, ρ_h	0.039
Probability of staying non-medium demand state, ρ_s	0.49
Assigned	
Period length	1 week
Probability of exit	0.0045
Annual discount factor	0.96
AR(1) growth rate of *M*	0.88
S.D. of shocks to growth rate of *M*, %	0.032
Elasticity of substitution of type *B* consumers	6

Table A12: Aggregate Implications
Economy with demand shocks. Dominick's Data

Statistic	Our model. With temporary changes	Standard model. Without temporary changes
Micro-price stickiness, months	0.7	6.1
	Impulse Response to a 50 b.p. monetary shock	
Aggregate price stickiness, %	11.2	11.2
Average output response, b.p.	5.2	5.2
Maximum output response, b.p.	15.4	15.9
	Business Cycle Statistics	
Std. dev output, %	0.31	0.28
Autocorr. output	0.92	0.92

Notes:

Aggregate price stickiness is measured as the average difference between M and P responses, relative to the M response.
Responses are computed for the first 2 years after the shock.
Business cycle statistics reported for HP(14400) filtered (monthly) data

Table A15: Parameterization of Economy with Temporary Price Changes
Dependent Shocks. BLS Data

A. Moments

	BLS Data	Model
Frequency of all price changes	0.22	0.22
Frequency of regular price changes	0.069	0.069
Fraction of price changes that are temporary	0.72	0.79
Proportion of returns to regular price	0.50	0.60
Probability that temporary price spell ends	0.53	0.54
Fraction of periods with temp. prices	0.10	0.11
Fraction of periods with price temp. down	0.06	0.06
Fraction of prices at annual mode	0.75	0.73
Fraction of prices below annual mode	0.13	0.18
Mean size of price changes	0.11	0.11
Mean size of regular price changes	0.11	0.11
IQR of all price changes	0.09	0.10
IQR of regular price changes	0.08	0.08
Objective: Mean Absolute Error, %		6.2

B. Parameter Values

Calibrated	
Menu cost of list price change, κ, % SS profits	1.05
Cost of temp. price deviation, ϕ, % SS profits	0.84
Arrival rate of permanent shock, λ_a	0.056
Upper bound of permanent productivity shock, ν_bar	0.13
Size of transitory productivity shock, z_bar	0.14
Probability of negative productivity shock, ρ_l	0.026
Probability of positive productivity shock, ρ_h	0.042
Probability of staying in non-medium state, ρ_s	0.55
Assigned	
Period length	1 month
Probability of exit	0.018
Annual discount factor	0.96
AR(1) growth rate of M	0.61
S.D. of shocks to growth rate of M, %	0.18
Correlation parameter, τ	5

Table A16: Aggregate Implications
Dependent Shocks. BLS Data

Statistic	Our model. With temporary changes	Standard model. Without temporary changes
Micro-price stickiness, months	4.5	13.6
	Impulse Response to a 50 b.p. monetary shock	
Aggregate price stickiness, %	21.8	21.8
Average output response, b.p.	10.2	10.2
Maximum output response, b.p.	21.3	21.7
	Business Cycle Statistics	
Std. dev output, %	0.36	0.37
Autocorr. output	0.92	0.93

Notes:

Aggregate price stickiness is measured as the average difference between M and P responses, relative to the M response.
Responses are computed for the first 2 years after the shock.
Business cycle statistics reported for HP(14400) filtered data

Table A17: Parameterization of Economy without Temporary Price Changes
BLS Data

I. Moments

	BLS Data	Only Permanent Shocks	Only transitory shocks, $\rho_z = 0.5$	Only transitory shocks, $\rho_z = 0.9$
Frequency of all price changes	0.22	0.084	0.089	0.078
Mean size of price changes	0.11	0.11	0.11	0.11
IQR of all price changes	0.08	0.08	0.08	0.08

II. Parameters

	Original without Transitory Shocks	Only transitory shocks, $\rho_z = 0.5$	Only transitory shocks, $\rho_z = 0.9$
Menu cost of list price changes, % SS profits	1.05	1.92	2.55
Upper bound of uniform distribution of shocks	0.19	0.24	0.31
Frequency of shocks	0.099	0.058	0.043

III. Aggregate Implications

	Original without Transitory Shocks	Only transitory shocks, $\rho_z = 0.5$	Only transitory shocks, $\rho_z = 0.9$
Micro-price stickiness, months	11.8	11.3	12.8
Aggregate price stickiness, %	19.9	19.9	19.9
Average output response, b.p.	9.3	9.3	9.3

Table A18: Parameterization of economy with trend stationary money
BLS Data

A. Moments

	BLS Data	Model
Frequency of all price changes	0.22	0.22
Frequency of regular price changes	0.069	0.068
Fraction of price changes that are temporary	0.72	0.76
Proportion of returns to regular price	0.50	0.72
Probability that temporary price spell ends	0.53	0.53
Fraction of periods with temp. prices	0.10	0.11
Fraction of periods with price temp. down	0.06	0.06
Fraction of prices at annual mode	0.75	0.73
Mean size of price changes	0.11	0.11
Mean size of regular price changes	0.11	0.11
IQR of all price changes	0.09	0.09
IQR of regular price changes	0.08	0.07

B. Parameter Values

Calibrated	
Menu cost of list price change, κ, % SS profits	0.81
Cost of temp. price deviation, ϕ, % SS profits	0.70
Arrival rate of permanent shock, λ_a	0.084
Upper bound of permanent productivity shock, *ν_bar*	0.180
Size of transitory productivity shock, *z_bar*	0.143
Probability of negative productivity shock, ρ_l	0.026
Probability of positive productivity shock, ρ_h	0.037
Probability of staying in non-medium state, ρ_s	0.520
Assigned	
Period length	1 month
Probability of exit	0.018
Annual discount factor	0.96
AR(1) of M	0.90
S.D. of shocks to M, %	0.22

Table A19: Aggregate Implications
Economy with trend-stationary money. BLS Data

Statistic	Our model. With temporary changes	Standard model. Without temporary changes
Micro-price stickiness, months	4.5	9.7
	Impulse Response to a 50 b.p. monetary shock	
Aggregate price stickiness, %	42.8	42.8
Average output response, b.p.	8.2	8.2
Maximum output response, b.p.	38.6	43.8
	Business Cycle Statistics	
Std. dev output, %	0.25	0.27
Autocorr. output	0.74	0.71

Notes:

Aggregate price stickiness is measured as the average difference between M and P responses, relative to the M response.
Responses are computed for the first 2 years after the shock.
Business cycle statistics reported for HP(14400) filtered data

Figure A1: Impulse responses to a monetary shock of 5 % in our model