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Why Are Prices Sticky? The Dynamics of Wholesale Gasoline Prices

The menu-cost interpretation of sticky prices implies that the probability of a price change should depend on the past history of prices and fundamentals only through the gap between the current price and the frictionless price. We find that this prediction is broadly consistent with the behavior of nine Philadelphia gasoline wholesalers. Nevertheless, we reject the menu-cost model as a literal description of these firms' behavior, arguing instead that price stickiness arises from strategic considerations of how customers and competitors will react to price changes.

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THE FAILURE of prices to adjust immediately to changes in fundamentals is central to many of the key issues in economics. Why don't prices change every day? This paper investigates nine individual gasoline wholesalers, and tries to predict on which days a given firm will change its price. We use the regularities uncovered to draw conclusions about the forces that may prevent prices from changing.

Our starting point is Dixit's (1991) model of price determination with a fixed cost of changing prices. According to this framework, the past history of the firm's prices and fundamentals should help predict a price change only through the current gap between price and fundamentals. The model further implies a particular functional form, and allows interpretation of the coefficients in terms of parameters

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of the optimization problem facing the firm. We compare these predictions with those from more flexible, atheoretical forecasting models.

We find that in many respects, the Dixit framework serves quite well. The gap between price and fundamentals indeed appears to be the most important factor influencing the probability of a price change, and the Dixit functional form seems reasonably appropriate as well. We do find statistically significant departures from the predictions of the model for almost all the firms we study, though there is a surprising heterogeneity across the firms in the form that this departure takes. The most common finding contrary to the model's predictions is an asymmetric response to positive and negative price gaps. If the gap between the target and actual price is small in absolute value, a typical firm is more likely to raise its price when the current price is a little below its target than it is to lower the price when it is an equivalent amount above the target. On the other hand, if the gap between target and actual price has become large in absolute value, firms are quicker to change the price when their price is too high compared to when it is too low.

Another implication of the Dixit model that appears to be inconsistent with our data is the structural interpretation of the estimated coefficients. In order to fit the observed infrequency of price changes, one would need to assume that both the firm's uncertainty about future fundamentals and the amount by which it changes the price, when it does change, are quite large. Both parameters can be inferred directly using data other than the frequency of price adjustment, and these inferred values are an order of magnitude smaller than the structural estimates.

We conclude that although a cost of changing prices is probably an important factor in accounting for sticky prices, a typical firm's calculation is not accurately described as a trade-off between an administrative cost of changing price and loss of current profits, as presumed in the Dixit framework. Instead, the cost of changing prices seems more likely to be due to how the firm expects its customers and competitors to react to any price changes.

The plan of the paper is as follows. Section 1 reviews previous literature. Section 2 develops the models we will use to try to predict whether the price changes on any given day. The data used in this study are described in Section 3. Section 4 reports empirical results for the menu-cost model. Section 5 reports results for the alternative statistical models. Section 6 concludes.

1. PREVIOUS LITERATURE

The phrase "sticky prices" has been interpreted to mean different things by different researchers. One branch of the literature has used the expression to refer to a gradual distributed lag relating prices to changes in fundamentals, such as the lagged response of retail to wholesale prices or wholesale to bulk prices for individual commodities (Borenstein, Cameron, and Gilbert, 1997, Borenstein and Shepard, 2002, Levy, Dutta, and Bergen, 2002), or the gradual response of aggregate wages and prices to macroeconomic developments (Sims 1998). Theoretical explanations of such sluggishness include the suggestion that customers are less alienated by a string of small price changes than a single large change (Rotemberg 1982), physical barriers to rapid adjustment of production or inventories (Borenstein and Shepard 2002), and gradual processing of information (Sims 1998).

By contrast, the focus of the present paper is on the discreteness of the price adjustment process—fundamentals change continuously whereas prices change only occasionally. There are three main explanations for this form of price stickiness. One interpretation is based on the administrative expenses associated with changing a posted price, such as the cost of printing new catalogs. The quintessential example is the cost a restaurant must pay in order to print a new menu, and for this reason this class of models is often described as "menu-cost models." In these models, in response to a change in fundamentals, the firm either makes no change in the price or else adjusts completely to the new optimum. Theoretical treatments of such pricing behavior were provided by Barro (1972), Sheshinski and Weiss (1977, 1983), Benabou (1988), Dixit (1991), Tsiddon (1993), Chalkley (1997), Aguirregabiria (1999), Danzinger (1999), Hansen (1999), and Bennett and La Manna (2001), among others.[1]

Although such costs are presumably quite small, they could, nevertheless, exert a significant economic influence (Mankiw, 1985, Blanchard and Kiyotaki, 1987). Levy et al. (1997) sought to measure directly the costs of changing prices for five supermarket chains, and found these to be 0.70% of revenues. They found that the supermarket chain with higher menu costs changed prices much less frequently than the others. Dutta et al. (1999) similarly estimated the costs to be 0.59% for the drugstore chains. However, more detailed microeconomic evidence is difficult to reconcile with the menu-cost explanation. Direct surveys suggest that managers do not take these costs into account in pricing decisions (Blinder et al., 1998, Hall, Walsh, and Yates, 2000). Carlton (1986) studied industrial prices and Kashyap (1995) investigated catalog prices. Both noted that when firms change prices, they often do so in very small increments, a behavior inconsistent with the simple menu-cost interpretation. Other studies that reach a similar conclusion include Cecchetti's (1986) analysis of magazine prices, Benabou's (1992) investigation of retail mark-ups, Lach and Tsiddon's (1992) and Eden's (2001) study of Israeli supermarket prices, and Carlson's (1992) survey of price changes. Supermarket scanner data further reveal a tendency of the price to return to its earlier value after a sale (Levy, Dutta, and Bergen, 2002, Rotemberg, 2002), a form of stickiness that could not be explained in terms of the cost of posting a new price.

A second explanation for the discreteness of price adjustment posits the discrete arrival of market information. Calvo (1983) proposed that firms are subject to random shocks that "prevent them to observe and verify changes in the 'state of nature' that would otherwise lead to price changes" (p. 384). Eden (1990, 2001) suggested that price stickiness arises from the fact that firms must precommit to

1. Other models allowing both a fixed cost of changing prices (implying discreteness) and a convex penalty (implying gradual responses) include Konieczny (1993) and Slade (1998, 1999).

capacity constraints before knowing the realization of the money supply. Mankiw and Reis (2002) proposed that for each period, only a fraction of wage setters receive new information about the economy and are able to adjust their plans accordingly. If acquisition of information requires a fixed expenditure of resources, such information-based stories could be fit into the menu-cost framework in which the cost associated with changing the price is not a physical cost of posting a new price but rather a personnel or management cost in determining a new value for the price. Calvo-type models have recently become popular explanations for observed aggregate price dynamics; see, for example, Galí and Gertler (1999) and Sbordone (2002), or, for a dissenting viewpoint, Bils and Klenow (2002).

A third explanation for price stickiness is the feared response by customers or competitors if the firm changed its price. Stiglitz (1984) discussed asymmetric customer responses with costly search, limit pricing and entry deterrence, and coordinating collusive behavior as possible explanations. McCallum (1989) elaborated on Okun's (1981) suggestion that the firm does not want to turn its repeat customers into buyers who routinely comparison-shop. Rotemberg (2002) suggested that consumers punish sellers whose prices they deem to be "unfair."

The goal of this paper is to fit an explicit optimizing menu-cost model of price dynamics developed by Dixit (1991) and Hansen (1999) to observed data. This generalizes the Sheshinski and Weiss menu-cost model employed in Dahlby's (1992) analysis of Canadian automobile insurance premiums in a very critical direction, allowing the frictionless optimal price to be stochastic rather than deterministic. We investigate whether this model can account for the dynamic adjustment of individual wholesale gasoline prices to changes in bulk spot prices. By further comparing this structural model with atheoretical summaries of pricing dynamics, we hope to shed light on which of the three explanations (menu costs, information processing, or market responses) best fits the observed facts.

2. MODELS OF PRICING DYNAMICS

2.1 The Dixit Menu-Cost Model

Let $p(t)$ denote the log of the price charged by the firm and $p^*(t)$ the log of the target price, where time is regarded as continuous. The firm chooses dates $t_1, t_2, \ldots$ at which to change price so as to minimize

$$E_{t_0}\left\{\sum_{i=1}^{\infty}\left[\left(\int_{t_{i-1}}^{t_i} e^{-\rho t}\, k[p(t_{i-1}) - p^*(t)]^2\, dt\right) + g e^{-\rho t_i}\right]\right\},$$

with $p(t_0) = p^*(t_0)$ given and

$$dp^*(t) = \sigma dW(t)$$

for $W(t)$ standard Brownian motion. Here, g is a lump-sum cost of changing the price of the good, the scalar k controls the cost of deviating from the target price, and σ is the standard deviation of the change in the target price. Dixit (1991) and Hansen (1999) showed that the solution is to change the price to $p(t_i) = p^*(t_i)$ at any date t_i for which $|p(t_{i-1}) - p^*(t_i)| = b$, with the optimal maximal deviation b given by

$$b = \left(\frac{6g\sigma^2}{k}\right)^{1/4} . \tag{1}$$

Suppose that the firm is following this policy, and is charging a price $p(t)$ at date t. One can approximate the probability that the price changes between dates t and $t + 1$ by the probability that $|p(t) - p^*(t + 1)| > b$. Note that for the upper bound,

$$\begin{aligned} \Pr[p(t) - p^*(t + 1) > b] &= \Pr\{[p(t) - p^*(t) - b] > [p^*(t + 1) - p^*(t)]\} \\ &= \Pr\left\{\frac{p(t) - p^*(t) - b}{\sigma} > Z\right\} \\ &= \Phi\left(\frac{p(t) - p^*(t) - b}{\sigma}\right) \end{aligned} \tag{2}$$

for $Z \sim N(0,1)$ and $\Phi(\cdot)$ the cumulative distribution function for a standard Normal variable. Reasoning analogously for the lower bound, the probability of a change in the price between t and $t + 1$ can be approximated by

$$h[p(t), p^*(t)] = \Phi\left(\frac{p(t) - p^*(t) - b}{\sigma}\right) + 1 - \Phi\left(\frac{p(t) - p^*(t) + b}{\sigma}\right) . \tag{3}$$

For observed discrete-time data, let $x_t = 1$ if the price changes on day t, and zero otherwise. The log of the likelihood of observing the sample $\{x_1, x_2, \ldots, x_T\}$ is then given by[2]

$$\sum_{t=0}^{T-1} \{x_{t+1} \log h(p_t, p_t^*) + (1 - x_{t+1}) \log[1 - h(p_t, p_t^*)]\} . \tag{4}$$

2.2 *Atheoretical Logit Specification*

The second model we investigate is an atheoretical specification in which the probability of a price change at $t + 1$ depends on a vector of variables $\mathbf{z}_t$ observed

2. Equation (4) is more general than the model actually estimated, which depends on p_t and p_t^* only through the difference $(p_t - p_t^*)$. This is important because whereas p_t and p_t^* are each $I(1)$, the difference $(p_t - p_t^*)$ is $I(0)$. The reader will note that in all the estimations below, the arguments of $h(.)$ are always such $I(0)$ transformations, thus avoiding some of the econometric issues raised by Park and Phillips (2000).

at time t, which includes p_t, p_t^*, and their lagged values. We assume that $\mathbf{z}_t$ helps to forecast the probability of a price change based on a logistic functional form

$$h_{t+1} = \exp(\boldsymbol{\gamma}'\mathbf{z}_t)/[1 + \exp(\boldsymbol{\gamma}'\mathbf{z}_t)] \,, \tag{5}$$

where $\boldsymbol{\gamma}$ is a vector of parameters, to be estimated by maximizing the likelihood

$$\sum_{t=0}^{T-1} \{x_{t+1} \log h_{t+1} + (1 - x_{t+1})\log(1 - h_{t+1})\} \,. \tag{6}$$

2.3 The Autoregressive Conditional Hazard Model

Our third approach attempts to model the serial correlation properties of the observed sequence $\{x_t\}$ using an approach proposed by Hamilton and Jorda (2002). Their starting point was the Autoregressive Conditional Duration model developed by Engle and Russell (1998). Let u_n denote the number of days between the nth and the $(n + 1)$th time that a firm is observed to change its price, and let ψ_n denote the expectation of u_n given past observations $u_{n-1}, u_{n-2}, \ldots, u_1$. The ACD(1,1) model posits that this forecast duration is obtained by a weighted average of past durations,

$$\begin{aligned} \psi_n = {} & \alpha u_{n-1} + \beta\alpha u_{n-2} + \beta^2 \alpha u_{n-3} + \beta^3 \alpha u_{n-4} \\ & + \ldots + \beta^{n-2} \alpha u_1 + \beta^{n-1} \alpha \bar{u} \,, \end{aligned} \tag{7}$$

for $\bar{u}$ the average length of time observed between price changes. In the exponential ACD specification, if the expected length of time until the next price change is $\psi_n = 3$ days, the probability of a price change tomorrow is 1/3. More generally, if $n(t)$ denotes the number of times the firm has been observed to change its price as of day t, the probability of a change on day $t + 1$ would be

$$h_{t+1} = 1/\psi_{n(t)} \,. \tag{8}$$

The forecast probability of a change is thus the reciprocal of a weighted average of recent durations between changes. Hamilton and Jorda proposed a generalization of the exponential ACD specification in which expected duration depends linearly on other variables observed at t in addition to lagged durations, replacing Equation (8) with

$$h_{t+1} = 1/[\psi_{n(t)} + \gamma'\mathbf{z}_t] \,. \tag{9}$$

Again the log likelihood is obtained by using this expression for h_{t+1} in Equation (6), which is maximized with respect to α, β, and $\boldsymbol{\gamma}$.

A probability must fall between zero and unity. To ensure this condition, we replace the denominator of Equation (9) with the larger of $[\psi_{n(t)} + \gamma'\mathbf{z}_t]$ and 1.0001, and employ a differentiable smooth pasting function for the transition of values between 1.0001 and 1.1, as detailed in Hamilton and Jorda (2002).

3. DATA

Refined gasoline is transported by pipeline from New York to Philadelphia, where it is stored and resold in smaller wholesale lots either directly to individual retail gasoline stations or to independent "jobbers" who in turn may resell it to the retailers. We purchased daily prices for all of the wholesalers of Philadelphia gasoline for the period 1989–91 from Oil Pricing Information Services (http://www.opisnet.com/). Although we have Saturday observations for part of the sample, for consistency we use only Monday through Friday data throughout the analysis, treating the Friday to Monday change the same as that between any two consecutive days. Apart from weekends, for five of the firms we have no missing observations over the three-year period. Firms 4 and 6 have missing observations at the end of the sample, and Firm 9 has missing observations at both the beginning and the end of the sample. Firm 7 has three missing observations in the middle, which we treated by artificially setting $h_{t+1} = 1$ for the day following this gap, in effect dummying out its influence. Several other Philadelphia wholesalers had more extensive missing observations and were not used in the analysis.

We base our target price series p_t^* on the cash price of unleaded gasoline delivered to the New York Harbor, as quoted by the New York Mercantile Exchange. These data were obtained from Datastream (http://www.datastream.com/). We assume that each wholesaler's target price p_t^* is a constant markup over the NYMEX price, where we estimate this desired markup for each firm from the average value of $p_t - p_t^*$ over the sample. The wholesalers set their price to go into effect at midnight. Hence p_{t+1} should respond to p_t^* but not to p_{t+1}^*.

The data used for the nine firms are summarized in Table 1. The average markups range from 2 to 4 cents per gallon. The NYMEX price of gasoline changes almost every day, whereas these wholesalers typically change their price every two or three days. This is the essential friction that we seek to explain.

The Dixit model assumes that p_t^* follows a random walk, which appears to be an excellent description of these data. For example, OLS estimation of an AR(2) model for 100 times the first difference of the log of the New York price results in (standard errors in parentheses)

$$\Delta p_t^* = \underset{(0.103)}{0.016} + \underset{(0.036)}{0.057}\Delta p_{t-1}^* - \underset{(0.036)}{0.018}\Delta p_{t-2}^* + e_t\,.$$

TABLE 1

SUMMARY OF DATA

Firm	Number of observations	Average markup	Frequency of price change
1	782	4.25	0.35
2	782	2.12	0.46
3	782	1.81	0.57
4	641	2.82	0.37
5	782	2.78	0.48
6	743	3.74	0.41
7	779	3.40	0.45
8	782	3.71	0.45
9	681	3.25	0.40

All three coefficients are individually statistically insignificant, and a test of the joint null hypothesis that all three are zero is accepted with a p-value of 0.44. We also regressed Δp_t^* on 12 monthly dummies, accepting the null hypothesis of no seasonality with a p-value of 0.43. All of these results are fully consistent with the Dixit assumption that p_t^* follows a random walk.

4. RESULTS FOR THE MENU-COST MODEL

Our first step was to use the menu-cost model to predict the days on which each firm would change its price. Let $P_{\mathrm{NY},\,t}$ denote the bulk price (in cents/gallon) in New York, P_{it} the price charged by wholesaler i in Philadelphia, $\delta_{it} = \log\,(P_{it}/\mathrm{P}_{NY,\,t})$ the percentage gap, and $\overline{\delta}_i = T^{-1}\,\Sigma_{t=1}^{T}\,\delta_{it}$ the average percentage markup for firm i. We replaced $p_t - p_t^*$ in Equation (3) with $\delta_{it} - \overline{\delta}_i$ and then chose b and σ so as to maximize Equation (4) for each firm. These maximum likelihood estimates of b and σ and are reported in the first two columns of Table 2.

As a first check on the reasonableness of these estimates, we calculate the implied value of g, the cost imputed to the firm each time it changes the price, relative to k, the parameter governing the curvature of its profit function. Note from rearrangement of Equation (1) that

$$g/k = \frac{b^4}{6\sigma^2},$$

estimated values of which are reported in the third column of Table 2. To interpret

TABLE 2

MENU COST MODEL ESTIMATION

Firm	b (MLE)	σ (MLE)	g/k	σ (direct)	b (direct)	log L	Obs	Vars	SBC
1	0.153** (0.015)	0.141** (0.017)	0.0046	0.029	0.0090	−486.96	782	2	−493.62
2	0.138** (0.028)	0.176** (0.039)	0.0020	0.029	0.0076	−536.13	782	2	−542.79
3	0.055** (0.009)	0.088** (0.015)	0.00020	0.029	0.0116	−527.26	782	2	−533.93
4	0.154** (0.020)	0.152** (0.023)	0.0041	0.029	0.0104	−412.40	641	2	−418.86
5	0.128** (0.021)	0.168** (0.031)	0.0016	0.029	0.0090	−535.89	782	2	−542.55
6	0.105** (0.008)	0.103** (0.010)	0.0019	0.029	0.0076	−477.80	743	2	−484.41
7	0.130** (0.016)	0.153** (0.022)	0.0020	0.029	0.0081	−524.65	779	2	−531.31
8	0.119** (0.015)	0.140** (0.021)	0.0017	0.029	0.0075	−528.70	782	2	−535.37
9	0.120** (0.010)	0.117** (0.012)	0.0025	0.029	0.0078	−436.14	681	2	−442.66

NOTES: Asymptotic standard errors (based on second derivatives of log likelihood) are in parentheses. Asterisk (*) denotes statistically significant at the 5% level. Double-asterisk (**) denotes statistically significant at the 1% level.

these values, consider a monopolistic firm facing demand curve $Q_t = A_t P_t^{-\gamma}$, $\gamma > 1$ and total cost $C_t Q_t$, for Q_t the level of output, P_t the level of prices, and C_t the constant marginal cost. Profits are given by

$$\Pi_t = A_t P_t^{1-\gamma} - C_t A_t P_t^{-\gamma} .$$

In the absence of menu costs, profit maximization calls for setting

$$P_t^* = \frac{\gamma}{\gamma - 1} C_t .$$

Let $p_t = \log P_t$ and $p_t^* = \log P_t^*$. Write profits as

$$\Pi_t(p_t) = A_t \exp[(1 - \gamma)p_t] - C_t A_t \exp(-\gamma p_t) .$$

Note that

$$\left.\frac{\partial \Pi_t(p_t)}{\partial p_t}\right|_{p_t = p_t^*} = [(1 - \gamma)P_t Q_t + \gamma Q_t C_t] = 0$$

$$\left.\frac{\partial^2 \Pi_t(p_t)}{\partial p_t^2}\right|_{p_t = p_t^*} = [(1 - \gamma)^2 P_t Q_t - \gamma^2 Q_t C_t]_{p_t = p_t^*} = -\gamma Q_t C_t .$$

A second-order Taylor approximation then gives

$$\begin{aligned}\Pi_t(p_t) &\cong \Pi_t(p_t^*) + \left.\frac{\partial \Pi_t(p_t)}{\partial p_t}\right|_{p_t = p_t^*} (p_t - p_t^*) + \frac{1}{2} \left.\frac{\partial^2 \Pi_t(p_t)}{\partial p_t^2}\right|_{p_t = p_t^*} (p_t - p_t^*)^2 \\ &= \Pi_t(p_t^*) - k_t(p_t - p_t^*)^2\end{aligned}$$

for $k_t = (\gamma/2)Q_t C_t$. Maximizing profit is thus approximately equivalent to minimizing $k_t(p_t - p_t^*)^2$. Hence, the estimate of g/k can be interpreted as the ratio of the cost of changing prices (g) relative to one-half of total costs times the elasticity of demand ($(\gamma/2)Q_t C_t$). For example, with a demand elasticity of $\gamma = 2$, the estimate g/k can be interpreted as menu costs as a fraction of total costs. The fact that the values of g/k found in Table 2 are typically well below 1% is thus a very encouraging indicator of the plausibility of these estimates.

Two alternative checks of the menu-cost model are more troubling. The estimate of σ in the second column of Table 2 is based solely on the frequency with which firm i changes prices, that is, solely on the probability that $x_{t+1} = 1$, given $p_t - p_t^*$. (We will suppress the i subscript for clarity in this discussion.) In the structural model from which Equation (3) was derived, the parameter σ corresponds to the standard deviation of daily changes in p_t^*. Under our assumptions, this magnitude can also be inferred directly from the standard deviation of log $(P_{\mathrm{NY},\,t}/P_{\mathrm{NY},\,t-1})$, which is reported in the fourth column of Table 2. This direct estimate is typically smaller than the MLE estimate in column 2 by a factor of 5. In other words, firms are acting as if they have much more uncertainty about where the future fundamentals are headed than is warranted, given the observed behavior of the New York price.

If our proxy for the firm's target price $\hat{p}_t^*$ differs from the true target price p_t^* by measurement error ($\hat{p}_t^* = p_t^* + u_t$), this might account for an overly large estimated value for σ(MLE). However, one would expect measurement error to also result in an overly large value for σ(direct), which is based on the observed standard deviation of $\hat{p}_t^*$. The puzzle is not simply the large value for σ(MLE), but further the difference between σ(MLE) and σ(direct).

A separate issue on the plausibility of the parameter estimates is the estimated value of b. According to the model, in continuous time whenever the firm changed the price, it should do so by exactly b. For a typical firm, this corresponds to a 10%–15% change in prices. We report in column 5 of Table 2 a direct estimate of b based on the median absolute value of the logarithmic change in price for those days when the firm did change its price. This is an order of magnitude smaller than the MLE in the first column for almost all firms.

To summarize, the parameter estimates imply a ratio of b^2 to σ that is reasonable given a menu-cost interpretation of pricing, but the level of b is much larger than can be reconciled with the observed magnitude of price changes, and the level of σ is much larger than can be reconciled with the difficulty in forecasting the price of bulk gasoline in New York Harbor. The basic mechanism that accounts for sticky prices in the Dixit model is that the firm tolerates a spread between p_t and p_t^* in the anticipation that future changes in p_t^* may make a change in p_t unnecessary. That such a trade-off accounts for the firm's decision not to change its price is difficult to reconcile with the rational level of uncertainty about p_t^* and the magnitude of the price change that the firm will ultimately end up making.

Our results thus reinforce Borenstein and Shepard's (2002) conclusion that menu costs cannot account for the sluggish behavior of wholesale gasoline prices. They base their conclusion on distributed lag regressions involving spot and futures prices. We study here a different kind of sluggishness, the fact that particular spot prices remain frozen for several days, but reach the same overall conclusion.

5. COMPARISON WITH OTHER MODELS

In this section, we explore a variety of alternatives to the Dixit menu-cost model. Let capital letters denote levels rather than logs, so that $\Delta_{it} = P_{it} - P_{\mathrm{NY},t}$ is the difference in price between Philadelphia and New York in cents per gallon, $\overline{\Delta}_i = T^{-1} \Sigma_{t=1}^{T} \Delta_{it}$ is the average markup reported in column 2 of Table 1, and $\left| P_{it} - P_{it}^* \right| = \left| \Delta_{it} - \overline{\Delta}_i \right|$ is the absolute value of the deviation of the firm's current price from the target.

A logit framework affords a flexible class of models for characterizing the dynamics of price changes. We first consider a model in which the probability of a price change depends on the same variables as in the menu-cost model

$$\mathbf{z}_{it} = \left(1, \left| P_{it} - P^*_{it} \right| \right)', \tag{10}$$

but with a logistic functional form for the probability (Equations (5) and (6)) rather than the menu-cost functional form (Equations (3) and (4)). The value of the log likelihood achieved with the logistic functional form is compared with that for the menu-cost specification in columns 1 and 2 of Table 3. The menu-cost specification does better for three of the firms and the logit specification does better for the other six, though the values of the log likelihood are quite close in most cases. Since the logistic functional form does as good or better job of describing the data, it offers a convenient framework for investigating the role of additional explanatory variables besides $\left| P_{it} - P^*_{it} \right|$ as factors that may influence the decision to change prices.

We first investigate the Calvo possibility that information processing delays rather than a physical cost of posting new prices could account for the stickiness of prices by testing for delays in the response of firms to available information. According to the menu-cost model, only the current day's gap $\left| P_{it} - P^*_{it} \right|$ should predict a price change on day $t + 1$. If there are delays in a firm's ability to process information, the previous day's gap $\left| P_{i,t-1} - P^*_{i,t-1} \right|$ may contain additional predictive power. Column 1 of Table 4 reports the p-value for a likelihood test of the null hypothesis that the coefficient on $\left| P_{i,t-1} - P^*_{i,t-1} \right|$ is zero, when this is added as a third explanatory variable to Equation (10). This test finds evidence of information delays for only two of the nine firms.

Next, we look for evidence of Rotemberg's (1982) suggestion that the firm deliberately stretches out price changes so as to keep from upsetting customers, as in the quadratic adjustment cost model. Let $w1_i(t)$ denote the date of firm i's most recent price change as of date t. Thus, if the firm changed the price on day t, then $w1_i(t) = t$. If the firm changed the price on day $t - 2$ and left it at that level on days $t - 1$ and t, then $w1_i(t) = t - 2$. If the firm only partially adjusted the price on

TABLE 3

Log Likelihood for Alternative Models

Firm	Menu cost	Logit	ACH
1	−486.96*	−487.43	−505.37
2	−536.13	−533.82*	−539.74
3	−527.26	−524.05*	−533.35
4	−412.40	−411.72*	−421.57
5	−535.89	−537.15	−532.61*
6	−477.80	−476.32*	−501.38
7	−524.65	−524.17*	−534.88
8	−528.70	−527.44*	−537.73
9	−436.14*	−437.65	−455.39

Note: Asterisk (*) denotes best model by Schwarz condition.

date $w1_i(t)$, intending to make additional changes shortly, then the size of the gap remaining after the previous correction $\left|P_{i,w1_i(t)} - P^*_{i,w1_i(t)}\right|$ should help to predict a price change over and above the value of the current gap $\left|P_{i,t} - P^*_{i,t}\right|$. Column 2 of Table 4 displays no evidence of gradual price adjustment for any of the firms. Taking the results of columns 1 and 2 together, we conclude that for most firms, the hypothesis that the probability of a price change depends on the past only through the value of $\left|P_{i,t} - P^*_{i,t}\right|$ appears to be consistent with observed pricing behavior, so that this qualitative prediction of the menu-cost story is consistent with the data.

A more telling way to distinguish the menu-cost and information hypotheses from a response to market concerns is to look for evidence of possible asymmetry. It is commonly believed that firms are willing to increase their prices in response to a rise in costs, but either are slow to react or do not adjust fully to a drop in costs. Borenstein, Cameron, and Gilbert (1997), Peltzman (2000), and Ball and Mankiw (1994) suggested some reasons why we might find asymmetries in prices. For the gasoline market in particular, Borenstein, Cameron, and Gilbert (1997) used an error-correction model to estimate cumulative adjustment functions using monthly data. They found asymmetry in the price responses of spot gasoline to crude oil and retail gasoline to wholesale, though not in the link we investigate, wholesale gasoline to spot. Balke, Brown, and Yucel (1998) reported more mixed evidence of asymmetry with weekly data depending on how one estimates the cumulative adjustment functions. Karrenbrock (1991) concluded that retail gasoline firms raise prices within a month of cost increases but take up to two months to lower them. Godby et al. (2000) found little evidence of asymmetry in the response of weekly Canadian retail gasoline prices to crude oil prices.

We revisit this asymmetry question using our daily data, exploring the effect of the sign of the price gap on the probability of a price change on any given day. Let θ_{it} be a dummy variable taking on the value of unity if $P_{i,t} - P^*_{i,t} \geq 0$ and zero

TABLE 4

Tests for Significance of Additional Variables in Logit Specification

Firm	$\lvert P_{t-1} - P^*_{t-1}\rvert$	$\lvert P_{w1(t)} - P^*_{w1(t)}\rvert$	$\{\theta_t, P_t - P^*_t\}$
1	0.006**	0.283	0.035*
2	0.083	0.485	0.000**
3	0.000**	0.294	0.265
4	0.280	0.488	0.000**
5	0.354	0.753	0.511
6	0.237	0.642	0.000**
7	0.842	0.642	0.235
8	0.147	0.573	0.188
9	0.963	0.417	0.056

Notes: Table reports *p*-value of test of null hypothesis that the indicated variable does not belong as an additional explanatory variable to the logit model in Table 2. Asterisk (*) denotes statistically significant at the 5% level. Double-asterisk (**) denotes statistically significant at the 1% level.

otherwise. A logit model with asymmetric effects could be estimated by letting

$$\mathbf{z}_{it} = [\theta_{it}, \theta_{it}(P_{i,t-1} - P^*_{i,t-1}), (1 - \theta_{it}), -(1 - \theta_{it})(P_{i,t-1} - P^*_{i,t-1})]' \tag{11}$$

and comparing Equation (11) with Equation (10) (which it nests) by a likelihood ratio test. This test is reported in the final column of Table 4. Here, the evidence of a deviation from the menu-cost model is more widespread. For four of the nine firms, we would reject at the 5% level the null hypothesis of symmetry with respect to price increases and decreases, and nearly reject for one other.

Table 5 reports parameter estimates for the asymmetric logit model based on Equation (11). For all but two of the firms, the coefficient on $(1 - \theta_{it})$ is larger than the coefficient on θ_{it} which means that the firm is more likely to raise the price when $P_{it} - P^*_{it} = -\varepsilon$ than it is to lower the price when $P_{it} - P^*_{it} = \varepsilon$ for ε a small positive number. A second source of asymmetry is that, for every firm, the coefficient on $\theta_{it}(P_{it} - P^*_{it})$ is bigger than the coefficient on $-(1 - \theta_{it})(P_{it} - P^*_{it})$. This means that the firm is less likely to raise the price when $P_{it} - P^*_{it} = -\varepsilon$ than it is to lower the price when $P_{it} - P^*_{it} = \varepsilon$ for ε a large positive number. Figure 1 gives a visual representation of this asymmetry, plotting the value of Equation (5) for $\mathbf{z}_{\text{it}}$ given by Equation (11) as a function of $P_{it} - P^*_{it}$ for each of the nine firms. The graphs indicate the probability that the firm would change its price on day $t + 1$ as the gap between P_t and P^*_t varies from -20 to $+20$ cents per gallon.

Such a pattern of asymmetry seems much more likely to be due to concerns about the responses of customers or competitors to price changes than to administrative costs of changing prices. For example, being the first firm to make a big price increase

TABLE 5

Asymmetric Logit Estimates

Firm	Pos const	Pos gap	Neg const	Neg gap	log L	Obs	Vars	SBC
1	−1.2338**	0.1507**	−0.9253**	0.0604**	−484.08	782	4	−497.40
	(0.1526)	(0.0295)	(0.1568)	(0.0211)				
2	−0.6251**	0.1633**	−0.1906	0.00058	−526.09	782	4	−539.41
	(0.1431)	(0.0358)	(0.1502)	(0.0282)				
3	−0.0242	0.1967*	−0.0356	0.1119*	−522.72	782	4	−536.05
	(0.1074)	(0.0511)	(0.1491)	(0.0489)				
4	−1.3315**	0.1961**	−0.5600**	0.0228	−402.74	641	4	−415.66
	(0.1731)	(0.0363)	(0.1692)	(0.0227)				
5	−0.3701**	0.0824**	−0.1807	0.0379	−536.48	782	4	−549.80
	(0.1394)	(0.0312)	(0.1455)	(0.0236)				
6	−1.4714**	0.2658**	−0.5068**	0.0704**	−466.48	743	4	−479.70
	(0.1793)	(0.0414)	(0.1590)	(0.0258)				
7	−0.5209**	0.1030**	−0.5854**	0.0666**	−522.72	779	4	−536.04
	(0.1386)	(0.0286)	(0.1508)	(0.0229)				
8	−0.6786**	0.1343**	−0.4027**	0.0574*	−525.78	782	4	−539.10
	(0.1431)	(0.0343)	(0.1556)	(0.0256)				
9	−1.1268**	0.1712**	−0.7210**	0.0757**	−434.77	681	4	−447.82
	(0.1645)	(0.0323)	(0.1684)	(0.0244)				

Notes: Standard errors in parentheses. Asterisk (*) denotes statistically significant at the 5% level. Double-asterisk (**) denotes statistically significant at the 1% level.

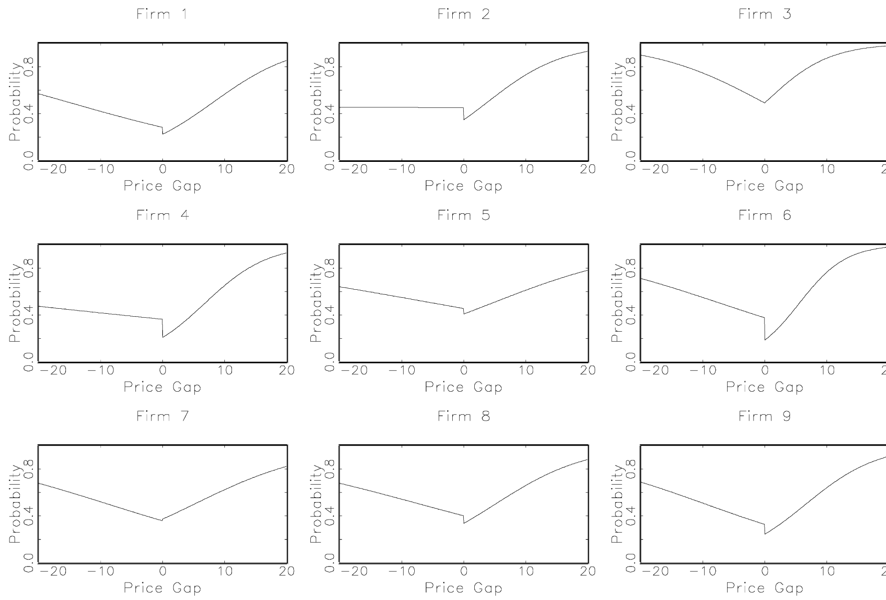

FIG. 1. Probability of a price change (logit estimates)

may be costly in terms of customer trust and loyalty, leading firms to postpone such a move even if it means selling at a loss for a short while. By contrast, being the first with a small price increase may be much less important for customer loyalty.

The conclusion that concerns about the response of customers or competitors to price changes is the central explanation for price stickiness is also consistent with Borenstein and Shepard's (2002) observation that wholesale gasoline prices adjust most gradually to changes in costs in the less competitive markets, and is also consistent with the explanations for price stickiness that emerge from the direct surveys of Blinder et al. (1998) and Hall, Walsh, and Yates (2000).[3]

Finally, we look for evidence of general serial dependence in the timing of price changes using the ACH model.[4] We first fit an ACH model that ignores all information other than the recent frequency of price changes, choosing α and β so as to maximize the likelihood given by Equations (6)–(8). This was successful for firms 1, 5, and 6. For the remaining firms, we had difficulty obtaining convergence of the ACH specification without a constant term ($\mathbf{z}_t = 0$). To keep within a two-parameter family, for these firms we estimated an ACH(1,0) model ($\beta = 0$) and included a constant term ($\mathbf{z}_t = 1$). For firm 3, the estimated α parameter was

3. Other papers investigating strategic considerations in the timing of gasoline price changes include Henly, Potter, and Town (1996) and Noel (2002a, 2002b).

4. Engle and Russell (1997) have an application of the related Autoregressive Conditional Duration model to predict the timing of changes in foreign exchange rates.

negative, indicating negative serial correlation; if this firm changed its price quickly on the previous interval, it is more likely to be a little slower next time. Column 3 of Table 3 reports the value for the log likelihood achieved by a two-parameter ACH model for each of the firms. The pure time-series model offers an improvement over the menu-cost specification for only one firm, and does substantially worse for most. We interpret this as further support for the claim that the history of prices matters for the probability of a price change only through the current value of the price gap.

We next explored a nested model in which both the price gap and time-series terms enter, by estimating an ACH model of the form of Equation (9) with $\mathbf{z}_t$ given by Equation (10), and investigated whether the price gap captures all the dynamics by testing the hypothesis $\alpha = \beta = 0$. The p-value for this hypothesis test is reported in the first column of Table 6. We find a statistically significant contribution at the 5% level of lagged durations in two of the firms, and a nearly statistically significant contribution in two others.

To see whether our conclusions from Table 4 were proxying for some general features of omitted serial correlation, we repeat those hypothesis tests in a base model that includes nonzero α and β as well as the vector of variables $\mathbf{z}_t$ as in Equation (10). The conclusions in Table 6 are very similar to those in Table 4. We continue to find some evidence of information delays for firms 1 and 3, but no evidence of partial adjustment for any of the firms. The evidence of asymmetry (column 4 of Table 6) is also very similar across the firms as was found in Table 4, and the pattern of asymmetry (Table 7) is very similar to what we found for the logit specification in Table 5. Note that while $\gamma' \mathbf{z}_t$ appears in the numerator of Equation (5), it is in the denominator of Equation (9), causing coefficients to switch signs. Figure 2 plots the probabilities of a price change as a function of the price gap implied by the ACH estimates in Table 7. In the ACH model, the probability of a price change is also influenced by the past history of price changes. To construct Figure 2, we set ψ_{it} equal to its average value for firm i. The overall patterns in

TABLE 6

Tests for Significance of Additional Variables in ACH Specification

Firm	Lagged duration	$\lvert P_{t-1} - P^*_{t-1}\rvert$	$\lvert P_{w1(t)} - P^*_{w1(t)}\rvert$	$\{\theta_t, P_t - P^*_t\}$
1	0.000**	0.036*	0.907	0.005**
2	0.059	0.428	0.261	0.037*
3	0.393	0.001**	0.656	0.018*
4	0.458	0.802	0.426	0.000**
5	0.000**	0.611	0.872	0.425
6	0.171	0.237	0.949	0.000**
7	0.632	0.576	0.522	0.067
8	0.573	0.139	0.443	0.061
9	0.057	0.474	0.833	0.001**

Notes: Table reports p-value of test of null hypothesis that the indicated variable does not belong as an additional explanatory variable to an ACH model that already includes a constant and $\lvert P_t - P^*_t\rvert$. In columns (2)–(4), the ACH model includes nonzero α and β. Asterisk (*) denotes statistically significant at the 5% level. Double-asterisk (**) denotes statistically significant at the 1% level.

TABLE 7

ASYMMETRIC ACH ESTIMATES

Firm	Pos const	Pos gap	Neg const	Neg gap	α	β	log L	Obs	Vars	SBC
1	2.9455**	−0.1180**	2.5903**	−0.0446**	0.1204	0.2669	−483.81	782	6	−503.79
	(0.4169)	(0.0202)	(0.3964)	(0.0142)	(0.0642)	(0.3614)				
2	2.0009**	−0.0580**	1.8077**	−0.0002**	0.0180	0.8915**	−530.14	782	6	−550.12
	(0.4097)	(0.0125)	(0.4279)	(0.0236)	(0.0199)	(0.0833)				
3	1.9611**	−0.0651**	2.0082**	−0.0274*	−0.0678*	0.00	−524.47	782	5	−541.12
	(0.1099)	(0.0113)	(0.1234)	(0.0131)	(0.0332)	—				
4	3.7869**	−0.1609**	2.9703**	−0.0283	−0.0533**	0.3470	−404.71	641	6	−424.10
	(0.3465)	(0.0205)	(0.3212)	(0.0238)	(0.0195)	(0.3908)				
5	1.5191**	−0.0610**	1.3144**	−0.0311**	0.1006*	0.7503**	−527.12	782	6	−547.11
	(0.3295)	(0.0158)	(0.2980)	(0.0084)	(0.0503)	(0.1486)				
6	3.3324**	−0.1870**	2.1597**	−0.0344**	0.0194	0.7812**	−473.08	743	6	−492.92
	(0.4326)	(0.0262)	(0.3709)	(0.0139)	(0.0316)	(0.2606)				
7	2.3710**	−0.0721**	2.4904**	−0.0496**	0.0122	0.7328	−522.94	779	6	−542.91
	(0.3086)	(0.0133)	(0.3042)	(0.0126)	(0.0301)	(0.3833)				
8	3.0532**	−0.0770**	2.7954**	−0.0328*	−0.0457	0.7863**	−528.06	782	6	−548.05
	(0.5259)	(0.0113)	(0.5082)	(0.0142)	(0.0360)	(0.1839)				
9	2.9341**	−0.1294**	2.4118**	−0.0474**	0.1138	0.0037	−435.69	681	6	−455.27
	(0.3368)	(0.0243)	(0.2727)	(0.0102)	(0.0828)	(0.1043)				

NOTES: Standard errors in parentheses. Asterisk (*) denotes statistically significant at the 5% level. Double-asterisk (**) denotes statistically significant at the 1% level.

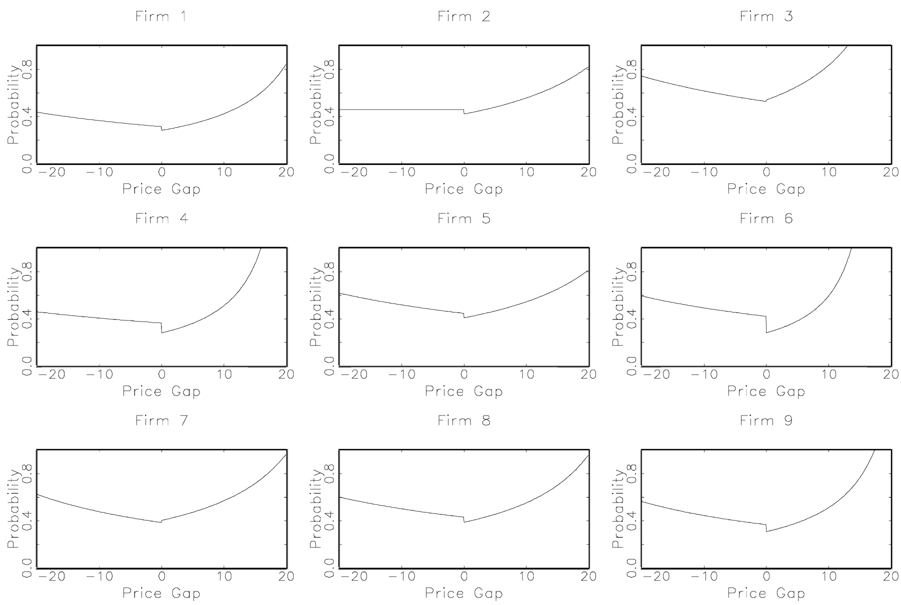

FIG. 2. Probability of a price change (ACH estimates)

Figure 2 are quite similar to those we found from the asymmetric logit specification in Figure 1.

As a final way to compare the various models explored, we look at the Bayesian criterion suggested by Schwarz (1978). This measure penalizes the log likelihood by subtracting (r/2) times the log of the number of observations, where r is the number of parameters used by the model. The SBC is reported in the final columns of Tables 2, 5, and 7. This criterion penalizes additional parameters more heavily than the hypothesis tests relied on earlier, so that, despite the statistical significance of the various departures from the menu-cost framework documented above, the SBC would end up selecting one of the two-parameter models of Table 3 over any of the specifications in Table 5 or 7. The menu-cost model was always close to having the best performance of any of the two-parameter models. Particularly impressive is the fact that for two of the firms (firms 1 and 9), the menu-cost model performed the best by Schwarz's criterion of any of the models considered.

6. CONCLUSIONS

The menu-cost interpretation of price stickiness implies that the past history of the firm's prices and fundamentals should help predict a price change only through the current gap between price and fundamentals. This appears to be a reasonable parsimonious summary of the pricing behavior observed for most of the nine gasoline wholesalers we studied. Although we can find other variables that also help predict price changes, the price gap appears to be the most important magnitude. In this respect, we might liken the hypothesis to Samuelson's (1965) and Fama's (1970) suggestion that stock prices follow a random walk; although not literally true, it seems to be a good approximation.

We found surprising heterogeneity across the firms in the way that their pricing behavior seems to deviate from the menu-cost model. Some firms seem to experience a delay in processing information. For most firms, we found some evidence of asymmetry. For big changes, firms are more reluctant to increase prices than to lower them. For small changes, by contrast, firms are more reluctant to lower prices than to raise them.

Even ignoring these possible departures from menu-cost behavior, it is difficult to accept the menu-cost model as a literal description of firms' pricing behavior. Although the size of the estimated menu costs are of a reasonable magnitude, the model imputes to firms much more uncertainty about fundamentals than is warranted by the data, and would call for much larger price changes than firms actually make.

Our overall conclusion is that firms' decision to change prices is based on the trade-off between the benefits of having an optimal price and some sort of cost associated with changing the price itself. However, the evidence suggests that this cost is not an administrative cost that is associated with a price change per se, nor a failure to obtain adequate information. Instead, it seems to reflect strategic considerations of how customers and competitors will react to a particular change.

LITERATURE CITED

Aguirregabiria, Victor (1999). "The Dynamics of Markups and Inventories in Retailing Firms." *Review of Economic Studies* 66, 275–308.

Balke, Nathan S., Stephen P.A. Brown, and Mine K. Yucel (1998). "Crude Oil and Gasoline Prices: An Asymmetric Relationship?" *Federal Reserve Bank of Dallas Economic Review* First Quarter, 2–11.

Ball, Laurence, and Gregory N. Mankiw (1994). "Asymmetric Price Adjustment and Economic Fluctuations." *Economic Journal* 104, 247–261.

Barro, Robert J. (1972). "A Theory of Monopolistic Price Adjustment." *Review of Economic Studies* 39, 17–26.

Benabou, Roland (1988). "Search, Price Setting and Inflation." *Review of Economic Studies* 55, 353–376.

Benabou, Roland (1992). "Inflation and Markups: Theories and Evidence from the Retail Trade Sector." *European Economic Review* 36, 566–574.

Bennett, John, and Manfredi M.A. La Manna (2001). "Reversing the Keynesian Asymmetry." *American Economic Review* 91, 1556–1563.

Bils, Mark, and Peter J. Klenow (2002). "Some Evidence on the Importance of Sticky Prices." University of Rochester Working Paper.

Blanchard, Olivier, and Nobu Kiyotaki (1987). "Monopolistic Competition and the Effects of Aggregate Demand." *American Economic Review* 77, 647–666.

Blinder, Alan S., Elie R. Canetti, David E. Lebow, and Jeremy B. Rudd (1998). *Asking About Prices*. New York: Russell Sage Foundation.

Borenstein, Severin, and Andrea Shepard (2002). "Sticky Prices, Inventories, and Market Power in Wholesale Gasoline Markets." *RAND Journal of Economics* 33, 116–139.

Borenstein, Severin, A. Colin Cameron, and Richard Gilbert (1997). "Do Gasoline Prices Respond Asymmetrically to Crude Oil Price Changes?" *Quarterly Journal of Economics* 112, 305–339.

Calvo, Guillermo A. (1983). "Staggered Prices in a Utility-Maximizing Framework." *Journal of Monetary Economics* 12, 383–398.

Carlson, John A. (1992). "Some Evidence on Lump Sum Versus Convex Costs of Changing Prices." *Economic Inquiry* 30, 322–331.

Carlton, Dennis W. (1986). "The Rigidity of Prices." *American Economic Review* 76, 637–658.

Cecchetti, Stephen G. (1986). "The Frequency of Price Adjustment: A Study of the Newsstand Prices of Magazines." *Journal of Econometrics* 31, 255–274.

Chalkley, Martin (1997). "An Explicit Solution for Dynamic Menu Costs with Zero Discounting." *Economic Letters* 57, 189–195.

Dahlby, Bev (1992). "Price Adjustment in an Automobile Insurance Market: A Test of the Sheshinski–Weiss Model." *Canadian Journal of Economics* 25, 564–583.

Danzinger, Leif (1999). "A Dynamic Economy with Costly Price Adjustments." *American Economic Review* 89, 878–901.

Dixit, Avinash (1991). "Analytical Approximations in Models of Hysteresis." *Review of Economic Studies* 58, 141–151.

Dutta, Shantanu, Mark Bergen, Daniel Levy, and Robert Venable (1999). "Menu Costs, Posted Prices, and Multiproduct Retailers." *Journal of Money, Credit, and Banking* 31, 683–703.

Eden, Benjamin (1990). "Marginal Cost Pricing When Spot Markets are Complete." *Journal of Political Economy* 98, 1293–1306.

Eden, Benjamin (2001). "Inflation and Price Adjustment: An Analysis of Microdata." *Review of Economic Dynamics* 4, 607–636.

Engle, Robert F., and Jeffrey Russell (1997). "Forecasting the Frequency of Changes in Quoted Foreign Exchange Prices with the Autoregressive Conditional Duration Model." *Journal of Empirical Finance* 4, 187–212.

Engle, Robert F., and Jeffrey Russell (1998). "Autoregressive Conditional Duration: A New Model for Irregularly Spaced Transaction Data." *Econometrica* 66, 1127–1162.

Fama, Eugene (1970). "Efficient Capital Markets: A Review of Theory and Empirical Work." *Journal of Finance* 25, 383–417.

Galí, Jordi, and Mark Gertler (1999). "Inflation Dynamics: A Structural Econometric Analysis." *Journal of Monetary Economics* 44, 195–222.

Godby, Rob, Anastasia Lintner, Thanasis Stengos, and Bo Wandschneider (2000). "Testing for Asymmetric Pricing in the Canadian Retail Gasoline Market." *Energy Economics* 22, 349–368.

Hall, Simon, Mark Walsh, and Anthony Yates (2000). "Are UK Companies' Prices Sticky?" *Oxford Economic Papers* 52, 425–446.

Hamilton, James D., and Oscar Jorda (2002). "A Model for the Federal Funds Rate Target." *Journal of Political Economy* 110, 1135–1167.

Hansen, Per Svejstrup (1999). "Frequent Price Changes Under Menu Costs." *Journal of Economic Dynamics and Control* 23, 1065–1076.

Henly, John, Simon Potter, and Robert Town (1996). "Price Rigidity, the Firm, and the Market: Evidence from the Wholesale Gasoline Industry During the Iraqi Invasion of Kuwait." Federal Reserve Bank of New York Working Paper.

Karrenbrock, Jeffrey D. (1991). "The Behavior of Retail Gasoline Prices: Symmetric or Not?" *Federal Reserve Bank of St. Louis Review* (July/August 1991), 19–29.

Kashyap, Anil K. (1995). "Sticky Prices: New Evidence from Retail Catalogs." *Quarterly Journal of Economics* 110, 245–274.

Konieczny, Jerzy D. (1993). "Variable Price Adjustment Costs." *Economic Inquiry* 31, 488–498.

Lach, Saul, and Daniel Tsiddon (1992). "The Behavior of Prices and Inflation: An Empirical Analysis of Disaggregate Price Data." *Journal of Political Economy* 100, 349–389.

Levy, Daniel, Shantanu Dutta, and Mark Bergen (2002). "Heterogeneity in Price Rigidity: Evidence from a Case Study Using Microlevel Data." *Journal of Money, Credit, and Banking* 34, 197–220.

Levy, Daniel, Mark Bergen, Shantanu Dutta, and Robert Venable (1997). "The Magnitude of Menu Costs: Direct Evidence From Large U.S. Supermarket Chains." *Quarterly Journal of Economics* 112, 791–825.

Mankiw, N. Gregory (1985). "Small Menu Costs and Large Business Cycles: A Macroeconomic Model of Monopoly." *Quarterly Journal of Economics* 100, 529–537.

Mankiw, N. Gregory, and Ricardo Reis (2002). "Sticky Information Versus Sticky Prices: A Proposal to Replace the New Keynesian Phillips Curve." *Quarterly Journal of Economics* 117, 1295–1328.

McCallum, Bennett T. (1989). *Monetary Economics*. New York: MacMillan Publishing Co.

Noel, Michael (2002a). "Edgeworth Price Cycles, Cost-Based Pricing and Sticky Pricing in Retail Gasoline Markets." UCSD Working Paper.

Noel, Michael (2002b). "Edgeworth Price Cycles: Firm Interaction in the Toronto Retail Gasoline Market." UCSD Working Paper.

Okun, Arthur M. (1981). *Prices and Quantities: A Macroeconomic Analysis*. Washington, DC: Brookings Institution.

Park, Joon, and Peter C.B. Phillips (2000). "Nonstationary Binary Choice Models." *Econometrica* 68, 1249–1280.

Peltzman, Sam (2000). "Prices Rise Faster than They Fall." *Journal of Political Economy* 108, 466–502.

Rotemberg, Julio J. (1982). "Monopolistic Price Adjustment and Aggregate Output." *Review of Economic Studies* 49, 517–531.

Rotemberg, Julio J. (2002). "Customer Anger at Price Increases, Time Variation in the Frequency of Price Changes and Monetary Policy." NBER Working Paper No. 9320.

Samuelson, Paul (1965). "Proof that Properly Anticipated Prices Fluctuate Randomly." *Industrial Management Review* 6, 41–49.

Sbordone, Argia M. (2002). "Prices and Unit Labor Costs: A New Test of Price Stickiness." *Journal of Monetary Economics* 49, 265–292.

Schwarz, Gideon (1978). "Estimating the Dimension of a Model." *Annals of Statistics* 6, 461–464.

Sheshinski, Eytan, and Yoram Weiss (1977). " Inflation and the Costs of Price Adjustment." *Review of Economic Studies* 44, 287–303.

Sheshinski, Eytan, and Yoram Weiss (1983). "Optimum Pricing Policy Under Stochastic Inflation." *Review of Economic Studies* 50, 287–303.

Sims, Christopher A. (1998). "Stickiness." *Carnegie-Rochester Conference Series on Public Policy* 49, 317–356.

Slade, Margaret E. (1998). "Optimal Pricing with Costly Adjustment: Evidence from Retail–Grocery Prices." *Review of Economic Studies* 65, 87–107.

Slade, Margaret E. (1999). "Sticky Prices in a Dynamic Oligopoly: An Investigation of (*s*, *S*) Thresholds." *International Journal of Industrial Organization* 17, 477–511.

Stiglitz, Joseph E. (1984). "Price Rigidities and Market Structure." *American Economic Review* 74, 350–355.

Tsiddon, Daniel (1993). "The (Mis)Behavior of the Aggregate Price Level." *Review of Economic Studies* 60, 889–902.