The Dynamics of Daily Retail Gasoline Prices

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Abstract

Previous research has analyzed the behavior of retail gasoline stations in how they adjust their prices. In this paper we analyze the daily movements in prices of four retail gasoline stations located in Newburgh, New York. We find some evidence to support the notion that the behavior is explained by menu costs. There is substantial evidence that the firms adjust their prices asymmetrically, being more inclined to increase than to decrease prices. We conclude that the pricing behavior is being determined by a combination of search costs for the consumers and menu costs for the producers.

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Applied analysis of pricing patterns using microeconomic data is an excellent way to understand how best to incorporate incomplete pricing changes into macroeconomic models. This paper continues a literature that has looked at firm level price changes. In this study we analyze the movements of four retail gasoline stations' prices. By examining daily retail price movements our research will contribute more fully to the understanding of gasoline price movements, extending the previous research analyzing daily wholesale price movements and weekly retail price movements.

Our starting point is a menu-cost model of pricing. We estimate a dynamic structural menu cost that is based on a firm's changing its price at any time costs have changed enough to make a price change beneficial. Because there is a cost that the firm must pay every time it makes a price change, it is not always correct to change prices. We find that a menu-cost model describes the data fairly well, but not completely. Therefore we conclude that the menu-cost model is not an exact description of the behavior of the firms but is likely affecting the firms' behavior.

Alternative aspects of price dynamics are analyzed as well. Most research looking at gasoline prices has found substantial evidence of an asymmetric response of prices to changes in input prices, finding that firms are more likely to raise their prices than to lower them. With retail data we also find that the firms are much more likely to adjust their prices upward than downward. These findings of asymmetry may be the cause of our menu-cost model's not performing as well as possible.

In addition to an asymmetric response we check for a lagged response or a partial adjustment to changes in the input prices, finding little evidence supporting either hypothesis. All three alternative aspects, asymmetric response, lagged response and partial adjustment, are analyzed using two econometric models, the Autoregressive Conditional Hazard (ACH) rate model and the logit model. Both can be used to model the probability of a change in any period as being dependent on various factors, but only the ACH includes variables that allow for serial correlation in the probability of a change.

This study follows in the vein of Borenstein and Shepard (2002), Davis and Hamilton (2004) and Henly, Potter and Towne (1996), three studies which also looked at gasoline prices movements. The methodology used is very similar to that of Davis and Hamilton. Both Henly et al. and Davis and Hamilton analyzed firm specific wholesale gasoline prices as opposed to retail prices. The biggest difficulty in analyzing firm specific retail prices is that the data are not as complete as the wholesale data. The missing observations can vary across firms and be missing for many consecutive days. Therefore, we must adjust our models to account for the missing observations.

This paper also elaborates the literature on general price stickiness, which is of importance to macroeconomic models of the economy. In addition to the studies analyzing gasoline prices mentioned above, previous empirical work has looked at magazine prices (Cecchetti, 1986), catalog prices (Kashyap, 1995), industrial prices (Carlton, 1986), Coke (Levy and Young, 2004) and supermarket scanner data (Lach

and Tsiddon, 1992; Eden, 2001; Levy, Dutta and Bergen, 2002; Dutta, Bergen and Levy, 2002; Rotemberg, 2002).

A more complete description of the retail data follows in Section 1 below. In Section 2, the theories that are tested are described, while the econometric models used to test those theories are explained in Section 3. The results and conclusions are given in Sections 4 and 5.

1. DATA

For this study we obtained two years of data for a number of retail gasoline stations from Oil Pricing Information Services. This data set provided daily retail gasoline prices for individual firms, a nice feature that was not readily available in the past. Having daily data allows us to monitor when each firm changes its price, use our time-series methods, and test for menu-costs on each firm.

The gasoline stations in our data set were all located in Newburgh, New York (population 26,000), about halfway between Albany and New York City and near the intersection of two major highways, the north-south Interstate 87 (New York Thruway) and the east-west Interstate 84, leading to Hartford, Connecticut from Scranton, Pennsylvania. This location had several factors that in combination made it a good choice. First, since Newburgh was also a wholesale location, it was highly likely that the stations all bought their gasoline from the local wholesaler and that their transportation costs would be minimal. Secondly, Newburgh had a large number of gasoline stations so we expected to find sufficient firms to examine.

Also, since Newburgh was located on an Interstate highway and had a local population, we would be examining gasoline stations that supply to both local and traveling consumers. By choosing a general location, our results should be representative of a typical gasoline station.

The most serious problem with the data is that there are many missing observations. Of the 29 retail stations, only four stations are included in our analysis. Unfortunately, for many of the other stations there are too many missing observations to use our estimation procedures. There are also a few stations whose prices are intermingled with those of other stations and because we cannot back out the individual series, those stations have to be dropped. One additional firm is not used because it sells a brand of gasoline (British Petroleum) for which we do not have the wholesale prices. Of the four stations that are included, two sell Mobil (Firms 1 and 2) and two sell Citgo gasoline (Firms 3 and 4). For these four firms, since there are very few observations on Saturdays and Sundays, we drop from the sample the few weekend observations that do exist. The exception is late in the sample where the data set includes many Saturday observations, but is missing Mondays instead. In these cases the Saturday observations are adjusted to Monday. The Monday observations should be thought of as representing the entire weekend, since a change on any day during the weekend would be recorded in the Monday data. The other missing observations pose general estimation issues, the solutions to which are given in Section 2, where we explain the ACH, logit and the menu-cost models. There is one particularly long period of missing observations that should be

noted. From early March to late June of 2000 all of the firms are missing all observations with the exception of May 19. After we remove these May 19 observations, for three of the firms, Firm 1, Firm 2 and Firm 3, there is a period of missing data encompassing all of March, April, May and all but the last day of June. The remaining firm (Firm 4) has a missing period over the same days but also including the last two days of February.

Column 3 of Table 1 presents the frequencies of price changes for the four firms. These values show that the firms change prices on between 8% and 13% of days, leaving a large number of days on which the firms do not change prices. Crude oil prices change almost every day, and the wholesale prices which are the input prices for retail prices change much more often than the retail prices. These observations suggest that there is price stickiness in the data. Section 2 looks at possible explanations for this stickiness.

We follow the methodology of Davis and Hamilton (2004) and determine a proxy for the optimal price that the firm would like to charge. In this study we have the actual input costs that the retailer must pay, in the form of the wholesale gasoline price. For each firm we take the specific brand of gasoline that the firm sells (either Mobil or Citgo) and develop a series for its optimal price by calculating the average markup of retail over wholesale. These results are presented in column 2 of Table 1. The wholesale prices represent the majority of the costs associated with the retail prices, and constitute almost all of the short-term variation in the retail price. Most of the markup of retail prices over wholesale prices is due to taxes. Federal taxes in this

period were 18.4 cents/gal and state taxes varied around 28 cents/gal. Taxes account

for all but about 10 cents/gal in the constant term, which is close to the typical values

found for gasoline stations.

From the markups we can create a series for the frictionless price for each

firm as simply the wholesale price plus the average markup. We assume that this

frictionless price is the optimal price that the firm would charge if there were no

imperfections in the market.

2. THEORETICAL MODELS

We test for four different patterns of price changes. Our starting model is the

menu-cost model of Dixit (1991). Like many menu-cost models this model

incorporates menu-costs as a fixed cost the firm must pay every time it changes its

price. The firm decides to change its price at any time that the current price is

substantially different from a hypothetical frictionless price without menu-costs.

One key feature that differentiates this model from many other menu-cost models is

that it allows the underlying frictionless price to vary stochastically. The assumption

is that the underlying frictionless price follows a Brownian motion process. If we let

$p^*(t)$ designate the frictionless price at time t, then

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

where $W(t)$ is a standard Brownian motion process. The firm's decision then is to

choose dates to change its price, in order to minimize

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

The first part of the summation represents the cost to the firm of being away from its frictionless price and $ge^{-\rho t}$ represents the cost of changing its price.

Dixit showed that the optimal decision for the firm is to choose to change its price back to the optimal at any time that $|p(t_{i-1})- p^*(t_i)|=b$. Therefore the optimal value for b will be:

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

Davis and Hamilton showed that the probability of a price change in any period t is equal to:

$$(2.1) \quad h[p(t), p^*(t)] = \Phi\left(\frac{p(t) - p^*(t) - b}{\sigma}\right) + 1 - \Phi\left(\frac{p(t) - p^*(t) + b}{\sigma}\right)$$

where $\Phi(.)$ is the cumulative distribution for a standard normal variable.

Gasoline price movements in response to changes in input prices have been studied extensively. Borenstein, Cameron and Gilbert (1997), Karrenbrock (1991) and Eckert (2002) all found evidence of an asymmetric response of retail gasoline to input prices, while Godby et al. (2000) did not find an asymmetric response of retail prices to crude oil prices with Canadian data. Investigations of how wholesale prices respond to spot prices have yielded inconsistent results. Although Davis and Hamilton (2004) found an asymmetric response, Borenstein et al. found very little asymmetry. Bachmeier and Griffin (2003) showed that the asymmetric response of spot prices to crude oil prices found by Borenstein et al. disappear either when using a different specification or when using daily prices instead of weekly prices. Balke,

Brown and Yucel (1998) suggested that how the asymmetry is specified determines whether an asymmetric response will be found with gasoline prices.

Using our retail prices, we wish to determine whether the firm is more likely to increase or decrease prices. We assume that if the price is above optimal, the firm will raise prices, and if the price is below optimal it will lower them. Therefore, we define θ to be a dummy variable which is 1 if P-P^*>0 and 0 otherwise. We then set up a vector of variables to test for two types of asymmetric responses used in the ACH and logit models described below. The vector is:

$$(2.2) \quad \mathbf{z}_{it} = [\theta_{it}, \theta_{it}(P_{i,t-1} - P^*_{i,t-1}), (1-\theta_{it}), -(1-\theta_{it})(P_{i,t-1} - P^*_{i,t-1})]'.$$

We can compare the first and third terms to examine whether a firm is more likely to raise or lower prices, and compare the second and fourth terms to determine whether the firm is more likely to make large upward or large downward changes.[1]

Davis and Hamilton also suggested two more tests of theories that can be incorporated in ACH and logit specifications. The first is based on the "sticky information" work formulated by Calvo (1983) and Mankiw and Reis (2002), who suggested that firms need to take a small amount of time before realizing new information is available. To test this theory, we can add into the model the gap between the actual and the optimal price from the day before ($|P_{i,t-1} - P^*_{i,t-1}|$) as well as the current gap ($|P_{i,t} - P^*_{i,t}|$). The addition of this second variable will improve the model's performance if the firm takes a while to process information.

The other test is to determine whether firms are only partially adjusting to changes in wholesale prices, which is similar to the model in Rotemberg (1982). Let

wl$_i$(t) represent the date of the last change. Then $| P_{i,wl_i(t)} - P^*_{i,wl_i(t)} |$ is the gap after

the last change in the retail price. If this variable adds to the predictive power when

included with the current gap, it would suggest the firm did not adjust fully to the last

change. In their analysis of wholesale prices, Davis and Hamilton found little

support for either of these theories.

3. ECONOMETRIC METHODS

One of the econometric methods used is the Autoregressive Conditional

Hazard Rate (ACH) model of Hamilton and Jorda (2002), which is similar to the

Autoregressive Conditional Duration model of Engle and Russell (1998). The

ACH(*r,m*) specification is:

(3.1) $$h_t = \frac{1}{1 + m(\psi_t + \delta' z_{t-1})}$$

where z_{t-1} is the vector of explanatory variables. ψ_t is the expected duration and

defined as,

(3.2) $$\psi_t = \sum_{j=1}^{m} \alpha_j (w_{j,t-1} - w_{j+1,t-1}) + \sum_{j=1}^{r} \beta_j \psi_{w_{j,t-1}}$$

where $w_{j,t-1}$ is the date of the jth most recent change. Therefore the expected

duration is dependent upon past durations ($w_{j,t-1} - w_{j+1,t-1}$) and the expectations of

those durations. Here, *m* represents the number of past durations included and *r* is

the number of autoregressive terms that are included. In the analysis that follows,

either an ACH(1,1) or an ACH(1,0) model is always estimated. The function $m\{v_t\}$

is defined as:

$$(3.3) \qquad m(v_t) = \begin{cases} .0001 \ldots\ldots\ldots\ldots\ldots\ldots v_t \leq 0 \\ .0001 + 2\Delta v_t^2 / (\Delta^2 + v_t^2) \ldots 0 < v_t < \Delta \\ .0001 + v_t \ldots\ldots\ldots\ldots\ldots v_t \geq \Delta \end{cases}$$

and included so that the probability h_t is always positive but also differentiable close

to zero.

In the data section we mention that there are many missing observations,

most of which appear to come from the data processor's neglecting to enter data

when the retail price remains unchanged for long periods. Therefore, for most of the

missing points we assume that the retail price stays the same as the last recorded

price. The exception to this rule is in the spring of 2000. Most of the data from this

period is missing probably because it is not being collected. The dates for which we

have observations for the four firms are also highly correlated suggesting that data

were only collected on certain dates during the spring.

This long period of missing observations is problematic for ACH estimation

since we do not know whether price changes occurred on those dates. To correct this

deficiency, we remove the few observations that exist in the period and treat the

three missing months as one gap in the data. For Firms 1, 2 and 3, we have data on

2/29/00, 3/6/00, 5/19/00 and 6/29/00. We treat 2/29/00 as the last observation before

the gap, remove 3/6/00, 5/19/00 and 6/29/00 from the estimation, and then start the

second part of the sample with 6/30/00. Firm 4 has similar data, except that the last

known value is on 2/25/00, so the gap is longer by two weekdays. Dropping close to

four months from the sample may seem troubling, but there are only three known values being removed and since we do not know their preceding values, it is difficult to determine whether the price changed on those days.

To analyze the menu cost model, we set up a structural model based on Equation 2.1 above. This model allows us to estimate the values of b (the maximum deviation from the optimal price before a change) and σ (the standard deviation of the Brownian motion process for the optimal price series).

Also, there are two ways to analyze how the missing observations affect the menu-cost model discussed in Section 2. The first is to make the same adjustments regarding the data that we did for the ACH model, by assuming that if the observation is missing then it is the same as the observation in the period before. Since the only variables that go into the model are p and p^* and they are only lagged one period, there is no difficulty in correcting for the long gap in the spring of 2000.

A second way to estimate the menu-cost model is to make less stringent assumptions about the missing data. Here we need to determine the probability of the price's changing between t and $t+n$, where n-1 is the number of missing observations. As described above, b is still the optimal allowable deviation before the firm will change its price and is still defined as:

$$(3.4) \qquad b = \left(\frac{6g\sigma^2}{k} \right)^{1/4}.$$

Since the probability of a change is the probability that $|p(t)-p^*(t+n)|>b,$ the upper bound is:

$$\Pr[p(t) - p*(t+n) > b] = \Pr\{[p(t) - p*(t) - b] > [p*(t+n) - p*(t)]\}.$$

If there are no missing observations, $p*(t+n)-p*(t)$ is the first difference of Brownian motion which is distributed as $N(0,\sigma^2)$. But $p*(t+n)-p*(t)$ is distributed as a $N(0,n\sigma^2)$ variable because the difference of Brownian motion between dates s and t is $N(0,(s-t)\sigma^2)$. Thus, the above probability becomes:

$$\Pr\left\{\frac{p(t) - p*(t) - b}{n\sigma} > Z\right\}$$
$$= \Phi\left(\frac{p(t) - p*(t) - b}{n\sigma}\right)$$

If we calculate the lower bound similarly, the probability of a change is:

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

For both models for h the log-likelihood is the same:

$$\sum_{t=1}^{T}\left\{x_t \log h(p_{t-n}, \hat{p}^*_{t-n}) + (1 - x_t)\log[1 - h(p_{t-n}, \hat{p}^*_{t-n})]\right\},$$

where x_t is the a dummy variable for whether a change occurred in period t.

The strength of the ACH model is that it contains the time series terms. However, if there is no serial correlation in the durations, this model will not perform well, and we may not be able to analyze the asymmetric, lag response and partial response theories. Therefore we estimate the data with a logit model as well:

$$\Pr(y_i = 1 \mid x_i, \beta) = \frac{e^{z_i'\beta}}{\left(1 + e^{z_i'\beta}\right)}$$

where again z_{t-1} is the vector of explanatory variables. The data adjustments are the same as those made in the ACH and menu-cost models, and the explanatory variables are the same as those used in the ACH model.

4. RESULTS

The results of the menu-cost model using the original specification are given in Table 2. Both coefficients, b and σ, are significant for all four firms, and the ratios of g/k are small. As explained by Davis and Hamilton (2004), we can analyze these g/k ratios to estimate the portion of total costs represented by the menu costs. If we assume $\gamma=1$ (the lowest value allowed), the firm with the largest menu costs would have menu costs which are 1.9% of production costs and the other firms would have even smaller menu costs. These ratios of menu to production costs seem reasonable. We are also able to compare the estimated values for σ with the estimates measured directly. For all of the firms the σ estimated by the model is substantially larger, suggesting that the estimates for σ are not perfect. Also the values for b are too large compared to the size of changes that we observe. On first inspection they may seem small, ranging between .1 and .2, but these are the minimum differences between the log values. These coefficients suggest a minimum change of approximately 10-20 cents, which is greater than most of the price changes the firms make. The values estimated by the model are therefore unrealistic.

As Table 3 shows, estimations of b and σ from the new specification of the menu-cost model are much lower than the results from the original specification.

For all four firms, the values for b and σ are very similar to the values measured directly. However, the coefficients are not significant. If we were willing to assume that this is the accurate way to view the data, this would be very strong evidence in support of the menu-cost model.

Table 4 presents the log-likelihoods for the menu-cost model, as well as for simple specifications of the logit and ACH models, each with two variables included for easy comparison with the menu-cost model. In the case of the logit model, the only variables that are included are a constant and the current gap between the price and the frictionless price ($|P_t-P*_t|$). As can be seen in the table, the logit model fails to outperform the menu-cost model for all four firms.

For the ACH model, an attempt was made to estimate a model in which the two variables were the past duration and the expectation of the duration. The log-likelihood of this estimation is shown for Firm 4 in the third column of Table 4. For the other three firms, the model was not able to converge to a solution without a constant term. Therefore, in the fourth column the results are presented when β is constrained to be 0 and the model estimated with a constant term and the past duration. The ACH model is unable to outperform the menu-cost model and the logit for all four firms. These results are encouraging for a menu-cost explanation, but the menu-cost model is only slightly better than the simple logit model. Therefore, it is reasonable to examine other hypotheses of pricing behavior.

Table 5 shows the tests of the alternative explanations for the price stickiness. These columns show a test of whether the model with the given variable, a constant

and the current gap is significantly different from a model with just the constant and

the current gap. The results for the delayed information model in column 1 clearly

show that the extra variable does not belong in the model. In column 2, the partial

adjustment model does a little better than the delayed information model, and we can

reject the null hypothesis for Firm 1. Column 3 shows the results of testing the

asymmetric hypothesis, as θ represents a dummy variable for whether the actual

price is above its target price and $P_i - P_i*$ is the interaction of $|P_i - P_i*|$ and θ. This

explanation performs the best of these three models. While only Firm 1 allows us to

reject the null hypothesis that only the current gap and a constant are needed, Firms 2

and 4 also have fairly low p-values (.067 and .129 respectively).

      The encouraging results for the asymmetric model suggest further analysis of

that model using Equation 2.2, the results of which are presented in Table 6. The

first and third columns show the positive and negative constants. Across the firms

the negative constant is considerably greater in absolute value than the positive

constant, a counter-intuitive result which suggests that the firm is more likely to

decrease than increase its price. That implication is only true for very small

differences between the expected price and the actual price. Looking at columns 2

and 4, we see that only the negative gap is significant for all of the firms, and that the

negative gap is greater than the positive gap for all four firms. Also, the coefficient

is positive on all of the negative gap coefficients, which suggests that the firm is

unlikely to make large downward changes, but it is not nearly as averse to making

large upward changes. The asymmetry graphs in Figure 1 clearly show that firms are more likely to increase their prices than to decrease them for almost any size gap.

The logical direction for an asymmetry and the direction found by most studies is that the firm would be more likely to increase than decrease its price, which is the type of asymmetry found here. However, the asymmetric results found here are different from those found by Davis and Hamilton (2004). They found that wholesalers are more likely to increase than decrease price, but also more likely to make large decreases than large increases. With the retail stations studied here, firms are more likely to raise than lower their prices for most size changes.

The most likely explanation for the results are search costs for the consumers. Johnson (2002) discussed how search costs for consumers could lead retail gasoline stations to be less likely to change prices in general and adjust them asymmetrically. If a change in price triggers retailers that it is time to search, the firms will have an incentive to change their prices less often. The firms will not be able to take advantage of a decrease in price, because the consumers of other firms will not have engaged in searching for the lowest price. Borenstein, Cameron and Gilbert (1997) and Benabou and Gertner (1993) also explained that search costs can cause firms to be less competitive and therefore allow them to pass on cost increases but not decreases. Figure 1 shows that the firms are very reluctant to change their prices in general and particularly reluctant to lower them.[2] The existence of search costs does not preclude the existence of menu costs as well. The menu-cost model tested here

assumes a symmetric adjustment, but here we see there is substantial evidence of an asymmetric adjustment by the firms.

Tests of alternative hypotheses using the ACH model are presented in Table 7. First we test that there is no serial correlation in the durations of price changes. Column 1 of Table 7 shows the p-values for the test of the hypothesis that $\alpha=\beta=0$ in equation 3.1. These p-values fail to reach significance for any of the four firms.

The next three columns of Table 7 show that the results of the tests are similar to the ones performed using the logit model. As with the logit model, adding $|P_{i,t-1}- P^*_{i,t-1}|$ seems to have very little effect on the model. The partial adjustment test does quite well in the ACH model, though reaches significance for only one firm (Firm 2); it is close for Firms 1 and 4.

However, as for the logit model the best variables to include in the ACH model are those that test for an asymmetric response of prices. The variables are significant for Firms 1 and 4 and approach significance for Firm 2. Table 8 shows that neither the constants nor the gaps suggest a consistent asymmetry across firms. Also the coefficients on Firm 3 seem unrealistically large.[3] The best explanation for these findings is that the ACH model is not a particularly good fit for this data set. This result is particularly true for Firms 1 and 3, which showed no advantage of including autoregressive terms in Table 7 and have the most unusual coefficients in Table 8.

4. CONCLUSIONS

All four firms show at least some evidence of following a menu-cost model of pricing, the majority of the evidence does not support a menu-cost conclusion. Even though the unrealistic estimates for b and σ run counter to the menu-cost model, the values are not extremely far off from what the actual numbers show and are quite close when using the gaps in the data. The most important piece of evidence in support is that the menu-cost model seems to be the best model for all four firms, when compared to the ACH and logit models.

In analyzing the departures from the menu cost model, the asymmetric response is best supported by the data. There is substantial evidence that the retail gasoline stations in this study are more willing to raise their prices than to lower them. Neither a partial adjustment nor a lagged information model is supported extensively by the data. The great degree of rigidity and the nature of the asymmetry suggest that the behavior of the firms is being determined by search behavior on the part of consumers.

Future work should continue to analyze the presence of search and menu costs in gasoline markets. In particular further work should examine whether a structural model which includes a menu-cost but also allows for an asymmetric adjustment can explain the pricing pattern of these and other gasoline stations.

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[1] A discussion of the implications of the particular signs on the coefficients will follow in the results section since the signs have opposite meanings for the ACH and logit models.

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[2] See also Noel (2003, 2004), Eckart (2002) and Borenstein, Cameron and Gilbert (1997) for more on causes for gasoline price setting and causes of asymmetry.

[3] Note that the signs for all of the coefficients are opposite those found in the logit model. However, this is what we should expect to find. In the logit model a positive coefficient shows a variable that increases the probability of a change, whereas in the ACH a negative coefficient shows a variable that increases the probability of a change.

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Table 1
Summary of Data

Firm	Number of observations	Average markup (¢/gal)	Percentage of days with a price change
1	437	59.65	9.4%
2	437	57.61	12.8%
3	437	59.98	8.5%
4	431	57.12	13.0%

Table 2
Menu Cost Model Estimation

Firm	b (MLE)	σ (MLE)	g/k	σ (direct)	β (direct)	log L	Obs	Vars	SBC
1	0.111**	0.0566**	0.0081	0.0135	0.0194	-126.15	437	2	-132.24
	(0.016)	(0.0105)							
2	0.148**	0.0895**	0.0099	0.0135	0.0194	-162.89	437	2	-168.97
	(0.037)	(0.0257)							
3	0.170**	0.0848 **	0.0192	0.0113	0.0277	-120.03	437	2	-126.11
	(0.032)	(0.0205)							
4	0.140**	0.0785**	0.0103	0.0110	0.0171	-158.71	431	2	-164.77
	(0.022)	(0.0158)							

This table presents the results of the menu cost estimation using the assumption that missing observations are the same as the observation on the previous day. Asymptotic standard errors (based on second derivatives of log likelihood) are in parentheses. An asterisk (*) denotes a statistically significant finding at the 5% level, and a double-asterisk (**) denotes a statistically significant finding at the 1% level.

Table 3
Menu Cost Model Estimation (Alternative Specification)

Firm	b (MLE)	σ (MLE)	g/k	σ (direct)	β (direct)	log L	Obs	Vars	SBC
1	0.012	0.0035	0.0003	0.0138	0.0194	-126.51	369	2	-132.42
	(0.041)	(0.0152)							
2	0.080	0.0291	0.0082	0.0138	0.0194	-154.56	365	2	-160.46
	(0.303)	(0.1102)							
3	0.058	0.0157	0.0077	0.0115	0.0277	-110.33	303	2	-116.05
	(0.2180)	(0.0598)							
4	0.041	0.0104	0.0042	0.0132	0.0171	-122.88	222	2	-128.29
	(0.247)	(0.0640)							

This table presents the results of the estimation of the menu cost model making no assumptions about the missing data points. Asymptotic standard errors (based on second derivatives of log likelihood) are in parentheses. An asterisk (*) denotes a statistically significant finding at the 5% level, and a double-asterisk (**) denotes a statistically significant finding at the 1% level.

Table 4
Log Likelihood for Alternative Models

Firm	Menu cost	Logit	ACH (no constant)	ACH (with constant)
1	-126.15#	-127.52	-	-133.50
2	-162.89#	-163.20	-	-165.05
3	-120.03#	-120.55	-	-124.26
4	-158.71#	-158.91	-165.90	-163.74

This table displays basic models of menu cost, logit and ACH. Each model includes two explanatory variables. The best model based on the Schwarz condition is denoted by a #.

Table 5
Tests of Significance of Additional Variables in Logit Specification

Firm	$|P_{t-1} - P^*_{t-1}|$	$|P_{w1(t)} - P^*_{w1(t)}|$	$\{\theta_t, P_t - P^*_t\}$
1	0.274	0.031*	0.008**
2	0.663	0.153	0.067
3	0.718	0.276	0.626
4	0.675	0.393	0.129

This table reports *p*-value of test of null hypothesis that the indicated variable does not belong as an additional explanatory variable to a logit model already including a constant and $|P_t - P_t^*|$. An asterisk (*) denotes a statistically significant finding at the 5% level, and a double-asterisk (**) denotes a statistically significant finding at the 1% level.

Table 6

Asymmetric Logit Estimates

Firm	Pos const	Pos gap	Neg const	Neg gap	log L	Obs	Vars	SBC
1	-2.9825**	0.0972	-3.4775**	0.3313**	-122.74	437	4	-134.90
	(0.4567)	(0.0606)	(0.4290)	(0.0792)				
2	-2.0613**	0.0171	-2.7912**	0.2156**	-160.50	437	4	-172.66
	(0.2984)	(0.0496)	(0.3903)	(0.0708)				
3	-3.0009**	0.0909	-3.4378**	0.1728**	-120.08	437	4	-132.24
	(0.4964)	(0.0581)	(0.5259)	(0.0703)				
4	-2.6295**	0.0951*	-3.0443**	0.2274**	-156.86	431	4	-169.00
	(0.3838)	(0.0423)	(0.4723)	(0.0740)				

Standard errors in parentheses. This table presents the results of logit model with positive and negative constants and positive and negative gaps between the actual and target prices. An asterisk (*) denotes a statistically significant finding at the 5% level, and a double-asterisk (**) denotes a statistically significant finding at the 1% level.

Table 7
Tests of Significance of Additional Variables in ACH Specification

Firm	Lagged duration	$|P_{t-1} - P^*_{t-1}|$	$|P_{w1(t)} - P^*_{w1(1)}|$	$\{\theta_t, P_t - P^*_t\}$
1	1.000	0.581	0.062	0.036*
2	0.266	0.858	0.031*	0.120
3	1.000	0.723	0.231	0.916
4	0.388	0.794	0.063	0.008**

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 $|P_t - P_t^*|$. In columns (2)-(4), the ACH model includes nonzero α and β An asterisk (*) denotes a statistically significant finding at the 5% level, and a double-asterisk (**) denotes a statistically significant finding at the 1% level.
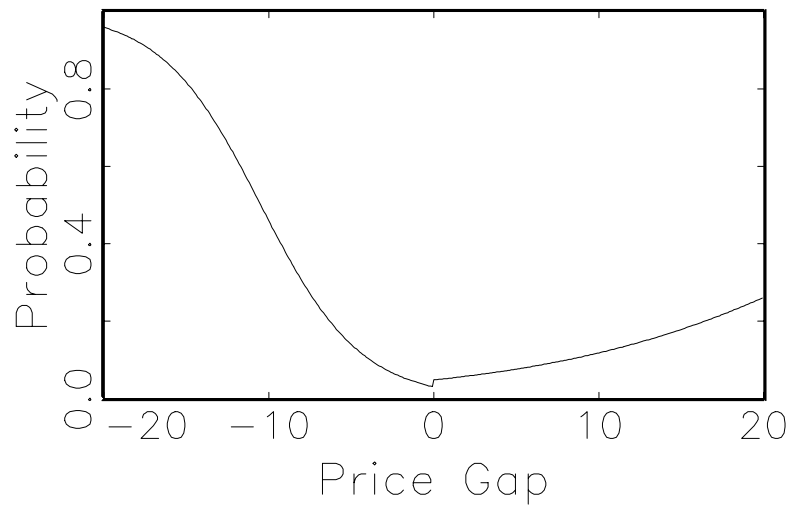
Table 8
Asymmetric ACH Estimates

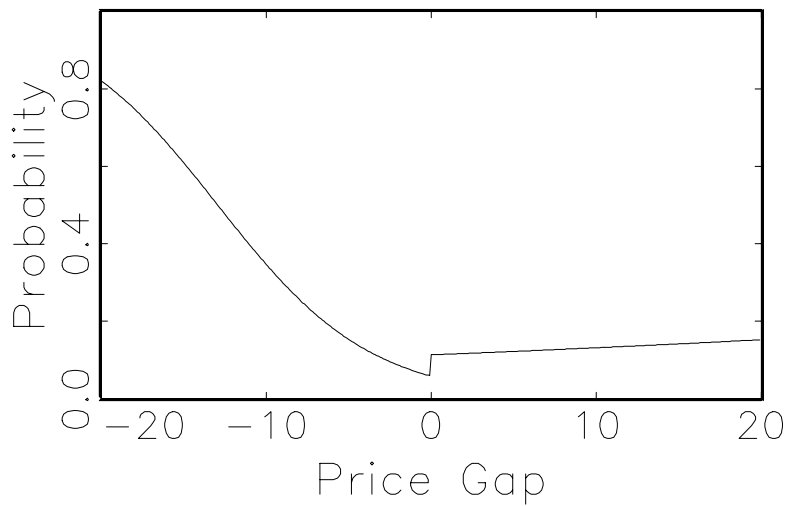| Firm	Pos const	Pos gap	Neg const	Neg gap	α	log L	Obs	Vars	SBC
1	17.9076	-0.9478	13.1698	-1.0011	-0.0100	-126.04	437	5	-141.24
	(6.5858)	(0.5426)	(3.0966)	(0.2168)	(0.0992)				
2	5.4990*	-0.2115	8.9872	-0.9340	0.3743	-160.24	437	5	-175.44
	(5.3708)	(0.4240)	(4.5866)	(0.2273)	(0.9427)				
3	22.4411**	-1.0922*	18.1314*	-0.6503	-0.1820*	-120.70	437	5	-135.90
	(5.6623)	(.3350)	(4.4188)	(0.3603)	(0.0512)				
4	9.2613**	-0.3820	11.7003**	-1.1489	0.1517	-156.29	431	5	-171.45
	(2.9067)	(0.2048)	(2.8905)	(0.3132)	(0.0793)				

Standard errors in parentheses. This table presents the results of ACH model with positive and negative constants and positive and negative gaps between the actual and target prices. For all four firms the most recent past duration is also included, and Firm 1 also has an autoregressive term included as well. An asterisk (*) denotes a statistically significant finding at the 5% level, and a double-asterisk (**) denotes a statistically significant finding at the 1% level.

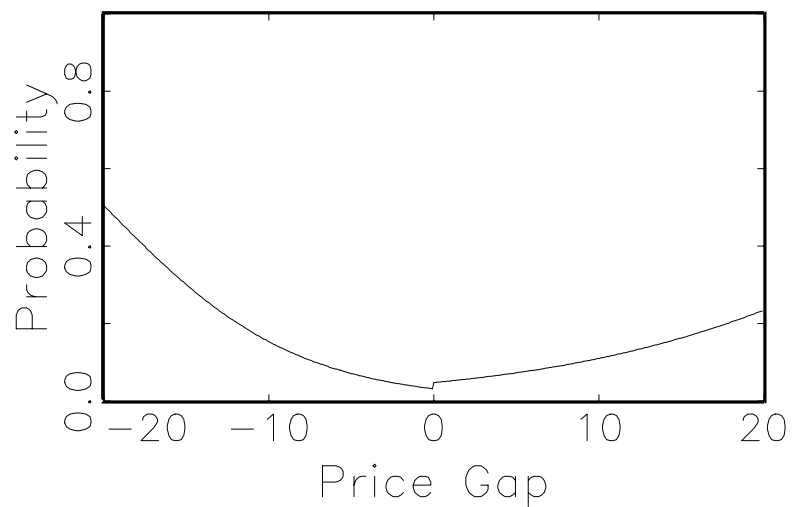# Figure 1: Probability of a Price Change (for Logit Estimates)