Why are Gasoline Prices Sticky?

A Test of Alternative Models of Price Adjustment

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Abstract

Several macroeconomic models of business cycles rely on the assumption that firms adjust prices infrequently to generate the short-run non-neutrality of money documented by the literature on monetary transmission. These models posit different mechanisms to generate price stickiness, with correspondingly different implications for inflation dynamics. While empirical implications regarding the response to macro shocks are indistinguishable on a time series of daily price changes, the models have distinct predictions on the dynamic patterns of price adjustment. In this paper, we use daily data on wholesale gasoline prices to test three explanations for price stickiness: menu-costs, information processing, and strategic interactions. Using an autoregressive conditional binomial (ACB) model, we show that both the past distribution of price changes and the lagged gap have significant explanatory power for the probability of a price change over and above the current price-cost gap. Our results have important implications regarding which of the three explanations (menu-costs, information processing, or strategic interactions) best fits the observed wholesale gasoline data. First, the significant effect of the historic distribution of price changes leads us to reject menu-costs as an explanation for price stickiness. Instead, it suggests that strategic considerations play an important role in accounting for price stickiness. Additionally, we find some evidence that costly information processing on the part of consumers may play a role in explaining price stickiness.

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1 Introduction

In the last three decades, macroeconomic models of business cycles have often made the assumption that firms adjust prices infrequently.[1] The theoretical arguments for this assumption include (1) the existence of a *menu-cost* firms must incur to change their price (Barro, 1972; Sheshinski and Weiss, 1977, 1983; Mankiw, 1985), (2) bounded rationality related to the costs of *processing information* (Mankiw and Reis, 2002; Sims, 2003, Reis, 2006), and (3) *strategic interactions* between a firm and its customers or competitors (Okun, 1981; Rotemberg, 1982, 2002, 2006).

Despite this rich theoretical background, the number of empirical studies on price rigidities was rather limited until the early 1990's (Levy, 2006). Yet, in recent years, the increasing popularity of the New Keynesian research program has bolstered a line of inquiry into various empirical features of price stickiness. This literature has provided interesting insights into the prevalence of price stickiness, the relevance of menu costs, and the incidence of strategic interactions.[2]

It is fair to say, however, that the empirical literature has been mostly silent on the implications of alternative theoretical models for the structure of time dependence. Specifically, does the probability of a price change reflect the history of price adjustments through channels other than the current price-cost gap? Is a firm more or less likely to change its price if it did so in the recent past? Given the widespread use of time-dependent pricing models in macroeconomics, we believe studying the prevalence and form of time dependence in micro level data on price changes can aid in choosing among alternative models of price stickiness.

Our aim is to explore whether the empirical implications of menu-cost, information processing, and strategic interaction models are borne out by micro level data on price changes. In particular,

[1] Some examples are Rotemberg and Woodford (1997), Clarida, Gali and Gertler (1999), Chari, Kehoe and McGrattan (2000), Erceg, Henderson and Levin (2000) and Dotsey and King (2001).

[2] For instance, Levy, Bergen, Dutta and Venable, (1997), Slade (1998) and Aguirregabiria (1999) find evidence in favor of the menu costs hypothesis; whereas Slade (1999), Borenstein, Cameron, and Gilbert (1997) and Davis and Hamilton (2004) find some indication that strategic interactions play an important role in explaining price stickiness.

while menu cost models suggest the probability of a price change should only depend on the current gap, models with information processing delays (or "sticky information") and models with strategic interactions imply otherwise. For instance, information processing delays suggest a negative correlation between current and lagged probabilities of price adjustment as firms do not continuously update their production plans due to the cost of acquiring and processing information. Hence, a firm that recently incurred in these costs and changed its price is not likely to do so in the near future. In contrast, strategic interactions motivated by the idea of a "fair price" suggest a positive correlation (Rotemberg, 2002, 2006). That is, if customers feel they are entitled to their "reference price" and firms are entitled to a "reference profit", the probability of a price change should depend positively on the history of price changes. That is, firms and customers feel entitled to what they received in the past.

In this paper, we test these alternative models of price stickiness based on the daily pattern of price adjustment of nine Philadelphia gasoline wholesalers. This data set provides a good testing ground for various reasons. First, wholesale gasoline is a physically homogenous good, which has the advantage of controlling for the influence of product heterogeneity in pricing decisions. Second, by focusing on the city of Philadelphia, we minimize the impact of changes in transportation costs and taxes on the pattern of price adjustment. Because refined gasoline is transported via pipeline from New York to Philadelphia's wholesale terminal, the cash price of bulk unleaded gasoline delivered to the New York Harbor represents the main input cost (i.e., around 96% of the wholesale price on average). Further, changes in this upstream price are easily observable, as the delivery price to the New York Harbor is quoted in the New York Mercantile Exchange (NYMEX). Third, changes in wholesale gasoline (downstream) prices take place only at particular points in time, and often remain unchanged in the face of observable cost shocks (i.e., over 40% of the days in our sample). Price stickiness is thus evident since changes in wholesale prices are discrete, despite fundamentals (e.g., the upstream price) changing continuously. Fourth, since wholesale gasoline is sold in standardized lots of one gallon, suppliers cannot simply reduce quantity in lieu of increasing price. Finally, while empirical implications regarding the response of price setters to macro shocks are indistinguishable on a daily basis, the models have distinct predictions on the dynamics of price adjustment. Indeed, at first sight, changes in wholesale gasoline prices appear to have distinct dynamics with price movements being more likely followed by movements in the same direction (see Table 1). This positive correlation suggests past firm behavior may play an important role in explaining price stickiness.

Our work takes as a starting point Davis and Hamilton's (2004) investigation of price stickiness, which uses the same data set of the Philadelphia's wholesale gasoline market. Their paper investigates whether menu costs capture the dynamic adjustment of individual wholesalers to changes in the upstream price of gasoline. In addition, using an Autoregressive Conditional Hazard (ACH) model they find that "the history of prices matters for the probability of a price change only through the current value of the price gap."[3] As a result, they find that the menu cost model makes predictions that are "broadly consistent" with the data. As noted above, we generalize this by directly examining the testable implications of three theories of price rigidities regarding the dynamics of price adjustment. Moreover, to implement such a test we make our second contribution by considering more general patterns of time dependence that can be found using the ACB model, which we detail next.

To capture the discreteness in price changes and allow for general patterns of time-dependence, we estimate an Autoregressive Conditional Binomial (ACB) model.[4] Specifically, we model the

[3] The gap is defined as the difference between the daily wholesaler's price and optimal price, where the latter is measured as the sum of the cash price of unleaded gasoline delivered to the New York Harbor quoted by the New York Mercantile Exchange (NYMEX) plus the average markup over the sample period.

[4] Because the model is a binomial calendar time version of the Autoregressive Conditional Multinomial model of Engle and Russell (2005), the model is called Autoregressive Conditional Binomial (ACB).

probability that a firm will change its price on day t as a function of the historic distribution of price changes, past price change realizations, and the current and lagged gap between the wholesale price and the optimal price. In addition, by estimating the ACB jointly with the Autoregressive Conditional Duration (ACD) model, we allow the probability to depend on the duration between price changes as purported by the ACH model. Thus, whereas in the ACH model (Davis and Hamilton, 2004), dynamics enter the probability of a price change only through the effect of past durations, in the $ACB-ACD$ model, dynamics also enter via the historic distribution of the data and past realizations. Furthermore, the ACB model nests the logit model, thus allowing us to directly test whether the probability of a price change reflects the history of price adjustments through channels other than the current price-cost gap. In fact, contrary to Hamilton and Davis, we find significant evidence that the history of price changes plays a key role in accounting for price stickiness, beyond what the current price gap would explain. Specifically, the autoregressive component of the ACB model is significant at a 5% level for all firms, and the lag of the price gap is significant at a 5% level for all but one firm. In contrast, the duration between price changes is rarely a significant factor.

Our results have important implications regarding which of the three explanations (menu-costs, information processing, or strategic interactions) best fits the observed wholesale gasoline data. First, the significant effect of the historic distribution of price changes leads us to reject menu-costs as an explanation for price stickiness. However, it suggests that strategic considerations (possibly linked to the idea of "fair pricing" in Kahneman, Knetsch, Thaler, 1986; Rotemberg 2002, 2006), play an important role in accounting for price stickiness. Additionally, we find evidence that is consistent with the idea that costly information processing on the part of consumers may play a role in explaining price stickiness.

Our paper also contributes to work in industrial organization that examines asymmetric adjustment in gasoline prices. The main focus of this research has been what has come to be known as the "rockets and feathers" paradigm. That is, whether prices rise as rockets and fall as feathers with the response of the downstream price to an increase in the upstream price being systematically faster than the response to a decrease in the upstream price.[5] Research in the area has been fostered both by anecdotal evidence and by economic theory linking imperfect competition to asymmetric movements in prices. Indeed, the former has lead to allegations of collusion, spurring numerous investigations by the U.S. and Canadian governments into anti-competitive pricing behavior by gasoline retailers (Eckert and West, 2004). As to the latter, extensive gasoline data allows for careful testing of alternative models of asymmetric pricing.

In the "rockets and feathers" literature, a gradual lagged response of downstream gasoline prices to upstream prices has been commonly interpreted as evidence of price stickiness. In this paper we address the question of asymmetric adjustment from a different angle. We inquire whether, on a particular day, wholesalers are more likely to increase their price in the face of a cost increase, than to decrease it in face of a cost decrease. We find that firms are more prone to raise the price when the gap between the actual and the optimal price is small and negative, than to lower it when the current or lagged gap is small and positive. In contrast, firms are less likely to raise their price when the gap is large and negative, than to lower it when the gap is large and positive. This asymmetry is consistent with the idea of strategic interactions as firms readily make larger, frequent price cuts, yet are hesitant to do the same with regard to increases.

The paper is organized as follows. Section 2 briefly presents the theoretical models of price stickiness and discusses their implications for the pattern of price adjustments. Section 3 describes the data and the structure of the wholesale gasoline market. Section 4 introduces the empirical

[5] For instance, Borenstein, Cameron, and Gilbert (1997) and Balke, Brown, and Yucel (1998) investigate the reaction of retail gasoline prices to changes in the price of crude oil, whereas Borenstein and Shepard (2002) examine the lagged response of wholesale gasoline prices to changes in the price of crude oil. Recent contributions are Lewis (2003), Deltas (2004), Verlinda (2005) and Tappata (2006).

methodology and discusses the predictions that can be tested using the ACB model. Section 5 presents the empirical results. Section 6 compares our results to previous work, and Section 7 concludes.

2 Theoretical Background

During the last three decades, the increasing popularity of the New Keynesian research program has bolstered a line of inquiry into the theoretical underpinnings of price rigidities. Price stickiness has often been abstracted to take the form of time dependence by assuming that firms only adjust their prices after a certain amount of time has passed (Fisher 1979; Taylor 1979, 1980) or that each period only a fixed fraction of firms are able to adjust prices to new information (Calvo, 1983). Macroeconomic models of price adjustment generally motivate this assumption by the existence of menu costs, the role of information processing or the effect of strategic interactions. In this section, we briefly describe these alternative hypothesis and discuss possible testable implications for the path of price adjustments.

2.1 Menu Costs

Menu cost models such as Barro (1972), Sheshinski and Weiss (1977, 1983), and Dixit (1991) posit that there exists a *fixed cost* a firm must pay in order to adjust its price. The classic example is a restaurant having to print new menus if it wants to change the price of the food it serves (hence the name). The implication is that unless the additional profit received from a price change is greater than the cost of changing the price, the firm will elect to leave its price unchanged (Mankiw, 1985). Although, menu costs are usually estimated to be quite small (e.g., Levy et al (1997) measure them to be 0.70% of total revenues for supermarket chains), they can exert a large impact on the business cycle (Mankiw, 1985), especially in the face of large cost shocks (Fishman and Simhon, 2005).

An important formalization of the menu cost model, which has some precise testable implications, is in Dixit (1991). Specifically, define $p(t)$ as the natural log of the price charged by the firm at time t and $p^*(t)$ the natural log of the firm's optimal price. In Dixit's model under continuous time, the firm chooses the dates $t_1, t_2, ...$ to change its price in order to minimize the objective function

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

where $p(t_0) = p^*(t_0)$ is given, $dp^*(t) = \sigma dW(t)$, and $W(t)$ is a standard Brownian motion. In equation (1), the term in parenthesis represents the cost a firm faces for charging a price that differs from the optimal price; the following term, $ge^{-\rho t}$, represents the fixed cost of the firm changing its price.

The Dixit model is quite useful because it allows the optimal price to follow a random walk, rather than remaining fixed. Davis and Hamilton (2004, henceforth "DH") show that this assumption fits the wholesale gasoline data remarkably well, when $p^*(t)$ is computed as the daily cash price of unleaded gasoline delivered to the New York Harbor plus a constant mark-up that is defined by the average of $p(t) - p^*(t)$ over the sample.[6] DH show that the probability of a price change under the Dixit menu cost model is

$$h_{t+1} = h\left[p(t), p^*(t)\right] = 1 + \Phi\left(\frac{p(t)-p^*(t)-b}{\sigma}\right) - \Phi\left(\frac{p(t)-p^*(t)+b}{\sigma}\right) \tag{2}$$

where $\Phi(\cdot)$ is the standard normal c.d.f.[7] The optimal decision rule is for the firm to change its

[6] All coefficients for an $AR(2)$ model for 100 times the first difference of the NYMEX price are jointly insignificant with a p-value of 0.44. And, regressing the first difference of the NYMEX price on 12 monthly dummies fails to reject the null hypothesis of no seasonality with a p-value of 0.43. Thus, the random walk assumption is likely satisfied.

[7] Data on the mark-up of wholesale price over cost is unavailable. Thus, following DH, we must approximate it. However, transportation costs, averaging 1¢-2¢ per gallon, (Hastings and Gilbert, 2005) are constant. The average mark-up ranges from 2¢-4¢ per gallon. Thus, approximating the optimal mark-up as constant seems reasonable.

price whenever $|p(t_{i-1}) - p^*(t_i)| > b$ where b is defined as

$$b = \left(\frac{6g\sigma^2}{k}\right)^{\frac{1}{4}}. \tag{3}$$

Dixit's model has the advantage of illustrating two testable features of price adjustments which are common to theoretical frameworks where price stickiness derives from menu costs, such as Barro (1972), Sheshinski and Weiss (1977), and Mankiw (1985). These features can be summarized as follows:

- *The probability of a price change should depend only on the current value of the price gap.* That is, neither the past history of price adjustments nor the past distribution of price changes should affect the frequency of price adjustments (see equation (1)).

- *The probability of a price change should respond symmetrically to positive and negative price-cost gaps.* Note that because in Dixit's model the firm minimizes expected value of the square deviation of the price from the optimal price, equation (1) implies a symmetric response to equal sized positive and negative gaps between the price and the input cost.

2.2 Information Processing

There are several theories regarding information processing that have distinct testable implications. Specifically, theories proposed recently by Sims (1998, 2003) and Mankiw and Reis (2002) contend that the costly gathering, absorbing and processing of information may explain why prices adjust infrequently or do not react to every change in market conditions. In Sims' (1998) setup, limited information processing capacity stems from the fact that individuals have limited amount of time they can devote to gather and analyze data. Hence, individuals are inattentive to changes in market conditions (especially to macro shocks), which results in delayed responses to market signals. This implies that firms with frequent price changes should respond strongly to older information and weakly to newer information. Alternatively, Mankiw and Reis (2002) assume that only a fraction of firms receive information on the state of the economy and, adjust prices accordingly. Here, the slow diffusion of information among the population stems from costs of acquiring information as well as costs of reoptimization. Thus "sticky information" suggests a firm's probability of changing the price in consecutive days is low.

Recent theoretical work on the micro foundations of "rational inattention" distinguish between "inattentive" producers (Reis, 2006b) and consumers (Reis, 2006a). Rational inattention by producers suggests that firms do not continuously update their production plans. Instead, producers choose a price for their output and then derive an optimal time at which to be inattentive. Once the inattentive period is over, the producer then reoptimizes. While producers are inattentive, they receive no news about the economy, until it is time to plan again. Thus, as above, the firm's probability of changing its price on consecutive days is low. Additionally, an implication of this model is that it predicts no asymmetry in the response to cost shocks. Since price setters are not aware of new information as it arrives, they cannot respond asymmetrically to it.

Rational inattention by consumers suggests that time-constrained consumers would rationally choose to update their information sporadically. Levy, Chen, Ray and Bergen (2006) contend consumers will ignore small changes in prices when the benefit of updating does not exceed the cost of processing and gathering information. For example, they quote customers who claim not to notice a 2% increase in the price of cereal at the grocery store. Consequently, firms will have an incentive to make small price increases, as these will not result in a loss of business. In contrast, firms will have no incentive to make small decreases, as such a decrease will not generate an increase in business. Related to this idea, Ray, Chen, Bergen and Levy (2006) show that in model where menu costs increase as you move to successively lower positions in the supply chain, wholesalers have incentive to price asymmetrically "in the small" because the menu cost precludes the retailers from matching the increase.

Summarizing, information processing models allow us to derive the following testable implications:

- *Information processing delays would result in the probability of a price change responding relatively strongly to past information.* Delays in the processing of information due to limited information processing capacity suggest a delayed response of agents to market signals (Sims, 1998). Hence, the magnitude of the firm's response to past cost changes should exceed the response to current cost changes.

- *The probability of a price change should exhibit autocorrelation.* In general, models with information processing delays suggests that agents update their consumption and production plans infrequently due to costs of acquiring, absorbing, and processing information. Hence, periods with high probability of a price change should be followed by periods where this probability is low. On the other hand, autocorrelation with rationally inattentive producers stems from information following a Markov process (see Reis 2002b), and the solution to the producers planning problem depending on the time since the last planning.

- *The probability of a price change should be a decreasing function of recent price changes.* If the producer has recently incurred in the cost of processing information and re-optimizing at time t, it is likely to remain inattentive for the following periods and to leave the price unchanged at time $t+1$. Related to this, the duration, or time between successive price changes, should contain predictive power for future price changes. That is, the greater the duration, the longer the producer has been inattentive, and the closer he becomes to updating his information set and changing his price.

- *In the presence of inattentive consumers the probability of a price change should respond asymmetrically to "small" positive and negative cost shocks.* That is, a firm would be more likely to raise its price in response to a small cost increase than lower it in response to a small cost decrease.

- *In the presence of inattentive producers, there should be no asymmetry in the producer's price change decision.* That is, they do not price asymmetrically "in the small" or "in the large".

2.3 Strategic Considerations

Finally, an alternative explanation for price rigidity stems from the importance of strategic interactions between a firm and its customers. In particular, if customers retaliate after a firm increases its price, the firm will be less likely to increase its price when it falls below what is optimal, even in the absence of a menu cost. In this vein, Rotemberg (1982) proposes that firms may deliberately stretch out a large price change over a successive string of smaller price changes in order to avoid upsetting customers. Thus, strategic interactions would result in prices adjusting slowly to cost shocks, with the adjustment taking place over an extended period of time.

On the other hand, "fair pricing" theories suggests markets may fail to clear immediately as firms hesitate to raise prices "unfairly" (Okun, 1981). In particular, Rotemberg's (2002, 2006) models of inflation where price stickiness is linked to the idea of "fair pricing" can be traced to Kahneman, Knetsch, and Thaler's (1986) study on the importance of fairness in price setting. They contend that, in long term relationships, customers feel they are entitled to their reference (past) price, but they also believe suppliers are entitled to their reference profit. When this reference profit is threatened, customers deem it fair for a firm to raise its price at the customers' expense, and even pass the complete loss onto them. However, customers consider it is unfair for a firm to take advantage of an increase in demand by raising its price. In addition, customers believe it is unfair for a firm to ration shortages by raising its price, as both of these actions result in a "unfair" windfall for the firm. That is, profit over-and-above the firm's reference profit. In short, absent a cost shock, customers believe that maintaining the status quo is fair. "Fair pricing" should thus induce autocorrelation in the probability of a price change as the history of price changes contains information regarding the "reference price".

Summing up, the described models with strategic interactions suggest the following testable predictions:

- *The probability of a price change should exhibit positive autocorrelation.* In the case of partial adjustment, this correlation is a result of the firm preferring a series of small price changes over a large one-time change. In the case of "fair pricing", this correlation reflects the dependence of today's probability on the past distribution of price changes as consumers feel entitled to their reference price.

- *The past history of price changes should have explanatory power for the probability of a price change.* In the case of partial adjustment, as firms would be deliberately stretching price increases over time, the probability of a price change today would increase in the event a price change took place in the previous days. In the case of "fair pricing", the explanatory power of the history of price changes stems from the idea of the consumers being entitled to their reference price.

- *Under strategic interactions in the form of partial adjustment (Rotemberg, 1982), the size of the gap remaining after the most recent price change should have explanatory power for the probability of a price change.* That is, if the firm is deliberately stretching large price changes over a period of time, the amount of this gap the firm chooses to keep in place after a price change should contain predictive power for subsequent price changes.

- *Under strategic interactions in the form of "fair pricing" the probability of a price change should respond asymmetrically to "large" positive and negative cost shocks.* Given that customers believe large price increases to be unfair, a firm would be less likely to make a large price increase over a large price decrease. In other words, we would expect firms to use non-price methods of rationing in lieu of a big price increase to ration a shortage.

3 Data and Market Structure

Having discussed the testable implications of alternative theories of price stickiness, we now turn our attention to the wholesale gasoline data and the structure of the gasoline market. The Department of Energy has divided the United States into five Petroleum Administration for Defense Districts (PADDs). Pennsylvania resides in subdistrict 1B in PADD 1 along with Delaware, the District of Columbia, Maryland, New Jersey and New York. After it is refined, gasoline is transported to a region where the refiner has a city terminal. Since Philadelphia has a city terminal and lies in the same PADD subdistrict as New York, refined gasoline is transported via pipeline from New York to Philadelphia where it is stored and resold as wholesale gasoline to either middlemen (called “jobbers”) or directly to individual retailers. Thus, the cash price of bulk unleaded gasoline delivered to the New York Harbor as quoted by the New York Mercantile Exchange (NYMEX) can be interpreted as the main input cost to Philadelphia gasoline wholesalers.[8]

If a retail station purchases "branded" wholesale gasoline (or gasoline containing additives and marketed as a specific brand) from a wholesaler, the contract between the retailer and wholesaler can take one of three forms. If the retail station is a “company-op”, the refiner owns the station and an employee of the refiner manages the station. If it is a “lessee-dealer”, the refiner owns the station but leases it to another party, who operates the station. Finally, if a branded station

[8] The nine wholesalers in our data set are Amoco, ARCO, BP, Chevron, Exxon, Gulf, Mobil, Sunoco and Texaco.

is "dealer-owned", the individual retailer owns the station but is under contract to sell a specific brand of gasoline. Given that there are approximately 243 retail stations in Philadelphia[9], it is likely that the wholesalers in the data set hold all three types of contracts. Unfortunately, this contract information is proprietary and thus is not available in the data set.

Company-op stations are supplied directly by the refiner once the wholesale gasoline reaches the terminal station. Lessee-dealers and independently owned stations usually purchase wholesale gasoline from jobbers. Jobbers also can sell to unbranded retail stations (firms selling gas not marketed as a specific brand). Roughly 55% of gasoline in the United States is distributed by jobbers (Borenstein, Cameron, and Gilbert, 1997).

In this paper we use daily data for nine wholesale gasoline firms in Philadelphia and, as a measure of upstream prices, the NYMEX price quoted for bulk unleaded gasoline. The data are measured in cents per gallon and span the period between January 1, 1989 and December 31, 1991. The wholesale data were originally collected by the Oil Pricing Information Service (http://opisnet.com) and made available to us by DH.[10]

Table 2 presents summary statistics for the nine wholesale firms in the data set. All the wholesalers in the data set are large vertically integrated firms, comprised of familiar gasoline brand names. The phenomenon of price stickiness studied in this paper is illustrated by the frequencies of changes in the wholesale price relative to the NYMEX price. Whereas the NYMEX price changed nearly everyday (frequency = 0.95), the firms changed the wholesale price less than 60% of the days in the sample. Price stickiness is thus evident in the reduced frequency of wholesale price changes compared to the NYMEX price.

To get a sense of how wholesale gasoline prices behave relative to other prices, it is usefult to

[9] According to a search of gas stations on Verizon's superyellowpages.com

[10] We are thankful to Michael Davis and Jim Hamilton for making the data publicly available through the *Journal of Money, Credit, and Banking* data archive (http://webmail.econ.ohio-state.edu/john/IndexDataArchive.php).

compare our data to those analized by Bils and Klenow (2004). Using monthly data from the Bureau of Labor Statistics from 1995-1997, Bils and Klenow (2004) find that retail gasoline prices are adjusted more frequently than the other 350 final goods examined. They compute an average duration of 0.6 for price changes in retail gasoline (See Appendix Table in Bils and Klenow), which corresponds to an average duration of 18 days for a 30 day month. This is comparable to the average duration between price changes in Philadelphia's retail stations between January 1, 2002 and December 31, 2004 (Douglas and Herrera, 2007) and in Newburgh's retail stations between January 1, 1999 and December 31, 2000 (Davis, 2006), which are 12 and 10 days respectively. As one would expect, wholesale price change far more often with the average duration between price changes being only 2.4 days in our data set.

Of interest are also the frequencies and average magnitudes of price increases and decreases. Note that whereas the frequency of increases and decreases in the NYMEX price are almost identical (0.48 and 0.46, respectively), increases in the wholesale price are less likely than decreases (see last columns of Table 2).[11] These summary statistics suggest that wholesalers are more likely to decrease their price than increase it, despite the fact that the input cost is about equally likely to increase or decrease. Furthermore, note that the average magnitude of price decreases is smaller than the magnitude of price increases for all firms. All in all, these statistics suggest that wholesale prices may respond asymmetrically to increases and decreases in the upstream price of gasoline.

4 Empirical Methodology

In this section, we explore whether the observed pattern of price adjustment is consistent with the testable implications discussed in section 2. To explore alternative theories of price adjustment,

[11] Lewis (2003) reports a similar pattern for retail prices using weekly data for approximately 420 gas stations in San Diego for the period between January 2000 and December 2001.

we utilize the Autoregressive Conditional Binomial (ACB) model.[12] The ACB model is a flexible specification that allows the current probability of a price change to depend on the history of price changes through lags of the link function $G^{-1}(h_{t+1})$, lags of the binary dependent variable x_t, and other predetermined variables $\mathbf{z}_t$, such as the price gap. The function $G(h_{t+1})$ is a strictly increasing continuous c.d.f. such as the standard normal or the logistic, where h_{t+1} is the probability that the firm changes its price on day $t+1$. Because changes in wholesale gasoline prices go into effect at midnight, we follow DH's notation and specify the probability of a price change in day $t+1$ as a function of the price gap observed on day t. Furthermore, since $G(\cdot)$ is strictly increasing, $G^{-1}(h_{t+1})$ is a link function well-defined by $G^{-1}(h_{t+1}) = y_t \Longleftrightarrow G(y_t) = h_{t+1}$. That is, $G^{-1}(\cdot)$ is a 1-1 mapping from h_{t+1} to $\Re$.

Define the probability that the firm changes its price on day $t+1$ as,

$$h_{t+1} \equiv \Pr(x_{t+1} = 1 \mid x_t, x_{t-1}, ..., x_1, \mathbf{z}_t) \tag{4}$$

where h_{t+1}, x_{t+1} and $\mathbf{z}_t$ are defined as before. Then the $ACB(q,r,s)$ model is defined as

$$G^{-1}(h_{t+1}) = \omega + \sum_{j=1}^{q} \alpha_j (x_{t-j+1} - h_{t-j+1}) + \sum_{j=1}^{r} \beta_j G^{-1}(h_{t-j+1}) + \sum_{j=1}^{s} \delta_j x_{t-j+1} + \boldsymbol{\gamma}\mathbf{z}_t, \tag{5}$$

where the probability of a price change is given by

$$h_{t+1} = G\left[\omega + \sum_{j=1}^{q} \alpha_j (x_{t-j+1} - h_{t-j+1}) + \sum_{j=1}^{r} \beta_j G^{-1}(h_{t-j+1}) + \sum_{j=1}^{s} \delta_j x_{t-j+1} + \boldsymbol{\gamma}\mathbf{z}_t\right]. \tag{6}$$

Note that given initial conditions for x_t and h_t, the path of price change probabilities can be constructed recursively and estimates for the parameters $\theta = \{w, \alpha_1, ..., \alpha_q, \beta_1, ..., \beta_r, \delta_1, ..., \delta_s\}$

[12] This model is a calendar time version of the Autoregressive Conditional Multinomial (ACM) model of Engle and Russell (2005).

obtained by maximizing the likelihood function

$$\sum_{t=\max\{q,r,s\}+1}^{T-1} \left[x_{t+1} \log h_{t+1} + (1 - x_{t+1}) \log (1 - h_{t+1})\right] \tag{7}$$

If we assume that $G(\cdot)$ is the logistic c.d.f. –as we will do hereafter–, then by setting $q = r = s = 0$ and $\mathbf{z}_t = |P_t - P_t^*|$ (where the uppercase denotes prices in levels, rather than logs), the $ACB(0,0,0)$ is equivalent to the baseline logit specification considered in DH.

As in Engle and Russell (2005), we can incorporate the information regarding the duration between price changes in the ACB model. This is done by (a) including the logarithm of the contemporaneous duration, $u_{N(t)}$, (and possibly lags of it) as a covariate in equation (5); (b) modelling the expected duration process following Nelson's (1991) form ACD

$$\ln\left(\psi_{N(t)}\right) = \phi + \rho \frac{u_{N(t)-1}}{\psi_{N(t)-1}} + \xi \ln\left(\psi_{N(t)-1}\right), \tag{8}$$

(or other ACD specification), and (c) estimating the ACB and the ACD models simultaneously.

In addition, to test for the predictive power of the previous day's information, we follow DH by defining $\left|P_{t-1} - P_{t-1}^*\right|$ as the absolute value of the previous day's price gap and defining $\left|P_{w1(t)} - P_{w1(t)}^*\right|$ as the amount of the gap remaining after the most recent price change. Because competing theoretical explanations imply various predictions of asymmetry, we also allow for an asymmetric response by defining θ_{it} as a dummy variable taking on the value of unity if $P_{i,t} - P_{i,t}^* \geq 0$ and zero otherwise, and replacing the constant (ω) and the vector of explanatory variables $\mathbf{z}_{it} = (|P_{it} - P_{it}^*|)'$ with

$$\mathbf{z}_{it} = \left[\theta_{it}, (1 - \theta_{it}), \theta_{it}(P_{it} - P_{it}^*), -(1 - \theta_{it})(P_{it} - P_{it}^*)\right]'. \tag{9}$$

Separating the constant into a positive (θ_{it}) and a negative ($1-\theta_{it}$) component addresses the question: is the firm more (or less) likely to raise its price in response to a small negative gap than lower it in response to a small positive gap? Whereas, separating the gap into the positive ($\theta_{it}\left(P_{it}-P_{it}^{*}\right)$) and negative ($\left(1-\theta_{it}\right)\left(P_{it}-P_{it}^{*}\right)$) elements addresses the question: is the firm more (or less) likely to raise its price in response to a large negative gap than lower it in response to a large positive gap?

The motivation for this ACB specification is threefold. First, the ACB model provides a flexible framework to analyze the role of menu costs, information processing delays, and strategic interactions in the discreteness of price adjustments. For instance, if price stickiness is motivated by a physical menu costs or if there are no delays in processing information, neither lags of the price gap nor the previous history of price adjustments should enter significantly in the current probability of a price change. Second, because the ACB model nests the logit model, likelihood ratio tests regarding the relevance of the history of price changes are straightforward to compute. For instance, if we assume that $G(\cdot)$ is the logistic c.d.f. and we use an $ACB(0,1,1)$ specification, testing that "the history of prices matters for the probability of a price change only through the current value of the price gap" (DH, p31) amounts to testing whether $\beta=\delta=0$. Finally, by estimating the $ACB-ACD$ model in the fashion just described we can directly test the effect of the duration process on the probability of a price change. Furthermore, whereas a zero effect of lagged durations in the ACH model precludes any effect of the history of price changes –other than through the current value of the gap (see section 6)–, it does not in the $ACB-ACD$. Thus the latter allows for more general forms of time dependence.

Given the discussion in section 2, we can make the following empirical predictions with regards to the ACB:

- *Menu Cost (or "broadly consistent" with a menu cost)*: $\beta=\delta=0$. Neither the past history of price adjustments nor the past distribution of price changes should affect the probability of observing a price adjustments. That is, the probability of a price change should depend only on the current value of the price gap. For this reason, the estimated coefficients on $\left|P_{t-1} - P^*_{t-1}\right|$ and $\left|P_{w1(t)} - P^*_{w1(t)}\right|$ should not be statistically different from zero. And, we should expect no asymmetry "in the small" or "in the large". In other words, $\theta_t = (1 - \theta_t)$ and $\theta_t \left(P_t - P^*_t\right) = -\left(1 - \theta_t\right)\left(P_t - P^*_t\right)$.

- *Information processing delays:* $\beta < 0$, $\delta < 0$. If the probability of a price change was high yesterday and the firm changed its price, it is unlikely to do so again today. The coefficient on $\left|P_{t-1} - P^*_{t-1}\right|$ should be positive, indicating that a large gap yesterday will increase the probability of a price change today, if firms process yesterday's information today.

- *Rational Inattention by Producers*: $\delta < 0$, indicating that if a firm changed its price yesterday, it is likely to be inattentive today and let the price unchanged. The coefficient on $u_{N(t)}$ should be positive, indicating as the time between price changes becomes larger, the planning period draws to a close, increasing the probability of a price change. And, given the discussion in section 2, we expect no asymmetry "in the small" or "in the large". That is, $\theta_t = (1 - \theta_t)$ and $\theta_t \left(P_t - P^*_t\right) = -\left(1 - \theta_t\right)\left(P_t - P^*_t\right)$.

- *Rational Inattention by Consumers*: Asymmetry "in the small" with $(1 - \theta_t) > \theta_t$, meaning a firm is more likely to increase its price in response to a small negative gap than lower it in response to a small positive one. No asymmetry "in the large".

- *Partial Adjustment*: $\beta > 0$ and $\delta > 0$, meaning that if the probability of a price change yesterday was high and the firm changed its price, it will be likely to change it again today, since it is deliberately stretching out price changes. For that reason, the coefficient on the amount of the gap remaining after the most recent price change, $\left|P_{w1(t)} - P^*_{w1(t)}\right|$, should be positive.

- *Fairness*: $\beta > 0$. Since retail gasoline stations are entitled to their "reference price", yesterday's probability of a price change should be positively correlated with today's. Price changes should be immediately passed through from wholesalers to retailers. Thus, $\left|P_{w1(t)} - P^*_{w1(t)}\right|$ should contain no additional predictive power for a price change. And, given that retailers believe that large price increases may be unfair, we should expect to see asymmetry "in the large" in the form of $-(1-\theta_t)(P_t - P_t^*) < \theta_t (P_t - P_t^*)$, meaning a firm is more likely to make a large price decrease over a large price increase.

This latter idea of asymmetry is along the lines of Henly, Potter, and Town (1996) who argue that because wholesalers are bound to retailers by long-term contracts, they have an incentive to use non-price methods of rationing in lieu of large price increases.

5 Time Dependence and the History of Price Changes

5.1 The Dynamics of Price Adjustment

Estimation results for the $ACB(0,1,1)$ model reported in Table 3 suggests the presence of time dependence in 7 out of the 9 gasoline wholesalers in Philadelphia.[13] A likelihood ratio test rejects the null hypothesis that β and δ are jointly insignificant for 7 of the 9 firms. Note that the lagged price gap, $\left|P_{t-1} - P^*_{t-1}\right|$, is statistically significant for eight of the nine firms. As for the distribution of past price changes, β, the coefficient on the lagged link function $G^{-1}(h_t)$, is significant at a 5% level for all firms, and δ, the coefficient on the lagged indicator x_t, is statistically significant for firms 3, 4, 5 and 9. Moreover, we can reject the null hypothesis that $\beta = \delta = \gamma_2 = 0$, where γ_2 is

[13] A likelihood ratio test strongly rejects the $ACB(1,1,1)$ in favor of the $ACB(0,1,1)$ model for all firms. Additionally, for all firms but 2, the Schwarz Bayesian Criterion (SBC) is lowest for the $ACB(0,1,1)$ over a specification with additional lags of β and δ. The SBC for firm 2 is only slightly lower for $ACB(0,2,2)$ specification (-546.08 vs -545.49). For ease of comparison, we use an $ACB(0,1,1)$ for all firms.

the coefficient on $\left|P_{t-1} - P^*_{t-1}\right|$ at the 5% level for all but two firms.[14] For the remaining two firms, firms 7 and 8, the p-value for the likelihood ratio test are 0.099 and 0.114, respectively. Thus, the test results suggest that the $ACB(0,1,1)$ –hereafter ACB– with current and lagged price gap fits the data better than the restricted logit for 7 of the 9 firms (see second-to-last column of Table 3).

To better understand the dynamics, let us take a closer look at the effects of the history of price changes and the price gap. First, for all firms except for firms 1 and 8, the sign on β is positive. Given that the link function $G^{-1}(h_t)$ is strictly increasing in h_t, this implies that an increase in the probability of a price change at time t would lead to an increase in the probability at $t+1$, h_{t+1}. For these firms, an increase in the absolute value of the current price gap implies a larger probability of a price change ($\gamma_1 > 0$), and a higher lagged gap implies a decrease in the probability of a price change ($\gamma_2 < 0$). Second, for firms 1 and 8, where β is negative, information regarding the price gap is processed with a longer delay. Note that for these two firms γ_1 is not statistically different from zero, but γ_2 is positive and significant. Lastly, regarding the realizations of price changes, less than half of the firms are more likely to adjust the prices in $t+1$ if they changed the price in t ($\delta > 0$).

These findings of time dependence run contrary to the prediction of Dixit's menu cost model that suggests the probability of a price change matters only through the current gap (see equation (1)). Instead, for 7 of the 9 firms price changes appear to be clustered. That is, because the probability of price changes are positively correlated, periods of high probability are followed by other periods of high probability and periods of low probability by periods of low probability. Note that given the theoretical predictions of the previous section, this clustering is consistent with fair pricing and partial adjustment.

Thus, to differentiate between the strategic motivations of fairness and partial adjustment,

[14] Given that the regressors are stationary and the number of lags are enough to capture serial correlation, likelihood ratio tests are valid.

we included the absolute value of the size of the gap remaining after the previous correction, $\left|P_{i,w1_{i(t)}} - P^*_{i,w1_{i(t)}}\right|$, in the z-vector of the ACB and reestimated the model. The null hypothesis that this variable belongs is rejected for all the firms at the 5% level (see Table 6).

We now proceed to illustrate the difference in dynamics between the ACB and the logit by simulating the change in the response probability to a one-time 10¢ increase in the price gap. This also allows us to distinguish between partial adjustment and fair pricing. These simulations can be interpreted as the dynamic response to an unexpected 10¢ increase in the NYMEX price of gasoline while holding the desired markup for each firm constant. A 10¢ shock corresponds to the maximum NYMEX increase observed in the data set, which occurred on October 25th, 1990 possibly in response of increased fear of war and long-term supply disruptions as Hussein threatens Israel on October 9th.

The simulations are calculated in the following manner. Suppose that the probability of a price change at time $t = 0$ is equal to the steady state probability in the $ACB(0,1,1)$ model $(G^{-1}(h_{t+1}) = G^{-1}(h_t) = G^{-1}(\overline{h}))$. Solving equation (5) for $G^{-1}(\overline{h})$ gives:

$$G^{-1}\left(\overline{h}\right) = \frac{\omega + \gamma\overline{\mathbf{z}}}{1-\beta} \tag{10}$$

where $\overline{\mathbf{z}}$ contains the averages of $|P_t - P_t^*|$ and $\left|P_{t-1} - P_{t-1}^*\right|$ respectively and $x_t = 0$.[15] Replacing this value for $G^{-1}\left(\overline{h}\right)$ into our $ACB(0,1,1)$ specification, we obtain the steady-state probability of a price change:

$$\begin{aligned} \overline{h} &= G\left[\omega + \beta G^{-1}\left(\overline{h}\right) + \gamma_1 \left|\overline{P_t - P_t^*}\right| + \gamma_2 \left|\overline{P_{t-1} - P_{t-1}^*}\right|\right] \qquad (11) \\ &= G\left[\omega + \beta G^{-1}\left(\overline{h}\right) + (\gamma_1 + \gamma_2)\left|\overline{P - P^*}\right|\right]. \end{aligned}$$

[15] For ease of comparison of the dynamics in the ACB and the logit model, we assume that at time $t = 1$ the price gap is positive. However, the dynamic responses are unchanged if we start from a zero gap. That is to say, if the wholesaler is pricing at the optimal price.

Now, assume that at time $t = 1$, the price gap experiences a 10¢ one-time increase over the sample average so that $|P_1 - P_1^*| = \left|\overline{P - P^*}\right| + 10$. We then assume that the firm adjusts its price so as to set $|P_t - P_t^*| = \left|\overline{P - P^*}\right|$ for $t > 2$, the price change enters in effect at midnight of day 1, and there are no further shocks or price adjustments in the forecast horizon ($x_2 = 1$, $x_t = 0$ for $t \neq 2$). Thus, the probability of a price change for the $ACB(0,1,1)$ specification is

$$h_t = \left\{ \begin{array}{cc} G\left[\omega + \beta G^{-1}\left(\overline{h}\right) + \gamma_1\left(\left|\overline{P - P^*}\right| + 10\right) + \gamma_2\left|\overline{P - P^*}\right|\right] & \text{for} \quad t = 1 \\ G\left[\omega + \beta G^{-1}\left(h_{t-1}\right) + \delta + \gamma_1\left|\overline{P - P^*}\right| + \gamma_2\left(\left|\overline{P - P^*}\right| + 10\right)\right] & \text{for} \quad t = 2 \\ G\left[\omega + \beta G^{-1}\left(h_{t-1}\right) + \left(\gamma_1 + \gamma_2\right)\left|\overline{P - P^*}\right|\right] & \text{for} \quad t > 2. \end{array} \right\} \tag{12}$$

The response probability for the logit model can be computed by setting $\beta = \delta = 0$. Therefore the simulated probability is given by[16]

$$h_t = \left\{ \begin{array}{cc} G\left[\widetilde{\omega} + \widetilde{\gamma_1}\left(\left|\overline{P_t - P_t^*}\right| + 10\right)\right] & \text{for} \quad t = 1 \\ G\left[\widetilde{\omega} + \widetilde{\gamma_1}\left|\overline{P - P^*}\right|\right] & \text{for} \quad t \geq 2 \end{array} \right\} \tag{13}$$

Where a tilde (˜) denotes the estimated parameters in the logit specification.

To compare the response probabilities implied by the ACB and the logit, we plot these simulations in Figure 1. For firms with $\beta > 0$, the pattern of adjustment implied by the ACB and the logit are generally similar.[17] The probability of a price change rises immediately after the shock and then quickly returns to the initial level. This is evidence against partial adjustment, as the estimates indicate that the likelihood of further adjustment is low. Notice in Table 3 that, for some of the firms, the coefficients on the current and lagged price gap are roughly equal and of

[16] Recall that in the logit the lagged price gap is not significantly different from zero for 7 out of 9 firms. Yet, the results are similar if we include the lagged gap.

[17] A difference between the ACB and the logit responses, is that for the majority of the firms the steady-state probability of a price change is lower for the ACB. These differences result from the formulas used to compute the steady-state in the logit (equation (13)) and the ACB (equation (12)) models.

opposite sign. This allows for the price-change probability to immediately return to steady state following a price change. This immediate rise and fall of probability is consistent with the idea of customers believing that it is fair for firms to raise prices in the face of cost chocks in order to protect profits. In addition, for firm 3, the probability of a price change drops considerably after the price has been adjusted. Interestingly, this firm (BP) is the only wholesaler identified as selling unbranded gasoline in the sample.[18] This is suggestive evidence that unbranded dealers compete more intensely than branded dealers (Hastings 2004, Borenstein, Cameron, and Gilbert 1997). Finally, for firms 1 and 8, where $\beta < 0$, information processing delays are apparent. The increase in the probability of a price change takes place only after one day rather than immediately after the shock.

Notice that the magnitude of the shock used in the simulation is an order of magnitude higher than the average price increase in the NYMEX price (1.36¢). Using such a large shock has the advantage of facilitating the comparison between the dynamics implied by the ACB and the logit model. However, to get a better grasp on the dynamics of price adjustment implied by the ACB it is worth to contrast the response to an average 1.36¢ shock with the response to the 10¢ shock. Figure 2 illustrates how the probability that a firm will change its price reacts to these two shocks. Notice how for all firms but firm 3 (the unbranded wholesaler) the probability remains below 50% for an average shock, reflecting price stickiness.

Another scenario worth exploring is what happens if the firm does not immediately increase its price in response to the shock? As before, for ease of illustration, we use a 10¢ shock.[19] In this

[18]Most wholesalers participate in both the branded and unbranded market, quoting a daily price for each type of wholesale gasoline. The OPIS data set clearly indicates if the daily price observation is for the wholesaler's branded or unbranded gasoline. For all wholesalers but BP, the branded observations yielded a more complete data set to be used in the analysis.

[19]It is worth noting that following the 10¢ NYMEX shock on October 25th, 1990, only 6 of the 9 wholesalers instantly increased their prices, thus making Figure 3 within the realm of possibility.

case, the response probabilities for the ACB and the logit, respectively, would be given by:

$$h_t = \left\{ \begin{array}{cc} G\left[\omega + \beta G^{-1}\left(\overline{h}\right) + \gamma_1\left(\left|\overline{P-P^*}\right| + 10\right) + \gamma_2\left|\overline{P-P^*}\right|\right] & \text{for} \quad t=1 \\ G\left[\omega + \beta G^{-1}\left(h_{t-1}\right) + \gamma_1\left(\left|\overline{P-P^*}\right| + 10\right) + \gamma_2\left(\left|\overline{P-P^*}\right| + 10\right)\right] & \text{for} \quad t>2 \end{array} \right\} \tag{14}$$

and

$$h_t = G\left[\widetilde{\omega} + \widetilde{\gamma_1}\left(\left|\overline{P_t - P_t^*}\right| + 10\right)\right] \quad \text{for} \quad t \geq 1. \tag{15}$$

Figure 3 plots the simulated probabilities for this scenario. Here the logit predicts that the probability of a price change rises immediately following the shock and remains at the same level throughout the days when the price remains unchanged. Contrast this with the ACB. Here too, the probability of a price change rises immediately following a shock. However for the firms with $\beta > 0$, each day that passes without a price change lowers the probability of a price change the next day, until a new steady state is reached. Thus, price stickiness is related to the past history of non-adjustment by the firm. Again, this offers evidence in favor of the fairness argument. If firms do not instantly increase their price in the face of a cost shock, it becomes less and less likely they will do so in the future.

Additional evidence that strategic interactions play an important role in explaining price stickiness can be found by testing whether the past behavior of other wholesalers affects a specific wholesaler's price change probability. To test this hypothesis, we construct an average indicator of the lagged price change, y_{t-1}^{other}, for all the wholesalers other than the wholesaler in question. This variable ranges from 0, when none of the other firms in the sample changed their price, to 1, when all other firms in the sample changed their price. For example, when looking at Firm 1, $y_{t-1}^{other} = 0.5$ would indicate half of the other firms (a total of 4) changed their price on the previous day. This variable appears in a positive and statistically significant manner in the ACB for all firms except for 3, 5, and 9 (see Table 6). Because we only have information on 9 wholesalers, and not the universe of wholesalers in Philadelphia, we take this result only as suggestive of strategic interactions among competitiors.

5.2 Asymmetry in the "Small" or in the "Large"?

As competing explanations of price stickiness offer different predictions of asymmetry, we test the hypothesis of asymmetric price adjustment following the methodology described in section 4. Because we find the previous day's gap, $\left|P_{t-1} - P^*_{t-1}\right|$, to be statistically significant in the ACB specification, we explore the asymmetry of price adjustments by including one lag of the positive $(\theta_{it-1}\left(P_{it-1} - P^*_{it-1}\right))$ and negative $(-\left(1-\theta_{it-1}\right)\left(P_{it-1} - P^*_{it-1}\right))$ gaps in the set of explanatory variables in equation (9). Table 4 presents these estimation results. Three sources of asymmetry are evident here. First, for 5 of the 9 firms, the positive and/or negative constant is statistically significant, and the negative constant is larger than the positive constant. This suggests that firms are more likely to increase their price in response to a small negative gap than to lower it in response to a small positive one. Second, we find the coefficient on the positive current gap to be significant for 6 of the 9 firms with the positive gap being larger than the negative gap. Hence, firms are more likely to cut their price in response to a large positive gap than raise it in response to a large negative one. Finally, for four firms, a log-likelihood test rejects the symmetric ACB model in favor of the asymmetric model (last column, Table 4). Lastly, another source of asymmetry here is that for all firms, the coefficient on $\theta_{it-1}\left(P_{it-1} - P^*_{it-1}\right)$ is larger than the coefficient on $-\left(1-\theta_{it-1}\right)\left(P_{it-1} - P^*_{it-1}\right)$, indicating a firm is more likely to cut its price today if yesterday's gap is large and positive than raise it today if yesterday's gap is large and negative.

To better illustrate the asymmetry, Figure 3 plots the probability of a price change as the difference between P_{it} and P^*_{it} varies between -20 and +20 cents per gallon for both the asymmetric logit and the ACB with current and lagged asymmetry. The dashed line reproduces the asymmetric logit results illustrated in Figure 1 of DH.[20] The solid line is the asymmetric ACB found by setting $G^{-1}(h_t)$ equal to its average, x_t equal to the frequency of a price change for that firm, and the lagged gap equal to the previous day gap. Remarkably, the lagged asymmetric ACB specification results in asymmetric plots that look similar to the logit. Firms 5, 7, and 9 have somewhat flatter response probabilities compared to the logit, suggesting a somewhat smaller degree of asymmetry, but the general shape of the curve is the same.[21] For firm 3, the ACB implies a higher degree of asymmetry than the logit specification.

5.3 Discussion

Authors of theoretical models of price stickiness based on information processing delays and strategic interactions readily concede that on the surface, their explanations can essentially seem like a menu cost one. For example, Rotemberg (2002) states that "fear of customer revaluation of the firm's fairness can act as a 'fixed' cost of price changes that keeps firm prices constant" (p17), while Reis (2006) points out that "the inattentiveness model instead stresses an interpretation of menu cost as fixed costs of acquiring information, and especially of absorbing and processing it" (p24). However, as Reis (2006) also points out, "this change in interpretation [menu cost versus information processing delays] may seem slight, but it turns out to imply a very different model and implications for inflation dynamics" (p24).

Thus, rejecting the pure menu cost model, but finding a menu cost being "broadly consistent" with the data makes it difficult to make this important distinction between competing explanations. Fortunately, the ACB results allow us to do so. First, $\beta > 0$ suggests that current day's probability

[20] Because he asymmetric logit and asymmetric ACH plots in DH are nearly identical, we only report the former.

[21] Note that we reject the null hypothesis of symmetry for firm 7 despite the asymmetric plot being somewhat flatter than in DH. Figure 3 indicates that the likely reason for this is asymmetry in the "small" for values of the gap close to zero.

of a price change is strongly correlated with the previous day's, for 7 of the 9 firms. Second, Figure 1 suggests that in the face of a cost shock, the probability of a price change instantly rises and then immediately returns to steady state, suggesting that firms instantly pass this cost increase to their consumers. Yet, as Figure 2 illustrates, the response probability in face on an average size shock is almost always lower than 0.5. Additionally, Figure 3 indicates that if firms do not immediately increase their price in response to a cost shock, they are less likely to do so on subsequent days. Third, the asymmetric results in Table 4 and Figure 4 imply asymmetry "in the large" in the form of firms being more likely to decrease their price in response to a large positive gap than increase it in response to a large negative gap. Recall from sections 2 and 4 that these three findings are what we would expect if "fairness" was responsible for price stickiness in this market.

Also note from Table 4 and Figure 4 that we observe "asymmetry in the small" with firms being more likely to raise their price when the gap is small and negative than when it is small and positive. This is the predicted result if we observe "rational inattention" by consumers in this market, either in the form of them not paying attention to small price increases (Levy, Bergen, Dutta, and Venable, 2005), or because of a menu cost further down the supply chain. (Ray, Chen, Bergen, and Levy). Consider the latter motivation with regards to the wholesale gasoline market. Table 2 suggests that price increases are, on average, less than 1¢. Yet, when retail gasoline stations change their price, they must do so in increments of 1¢ or greater. This "menu cost" may prevent them from matching small wholesale price increases.

Contrast these two explanations with the competing ones in sections 2 and 4. The finding of β, δ, and the coefficient on $\left|P_{t-1} - P^*_{t-1}\right|$ to be statistically significant, as well as the finding of asymmetry, runs contrary to the predictions of a menu cost model. Thus, we can reject both the pure Dixit (1991) menu cost model, and the idea that the results are "broadly consistent" with the predictions made by a typical menu cost model. The finding of β and δ both estimated to be positive and significant for 7 of the 9 firms runs contrary to the ideas of information processing delays and rational inattention by producers. Recall that information processing delays on the part of producers suggests that the probability of a price change on successive days is very low. Thus, the estimated sign on β and δ is opposite of what these two explanations would imply.

Another way to test for rationally inattentive producers would be to include the absolute value of the price gap at the last adjustment, $|P_{last} - P^*_{last}|$. The reason for this is that adjustment in the inattentiveness model is recursively time-contigent and a function of the state at the last adjustment. The inattentiveness period is shorter, the faster losses accumulate from being inattentive. Thus, a large difference between the actual and optimal price at the last adjustment date should signal to a firm that losses will rapidly occur if the firm remains inattentive for long. That is, $|P_{last} - P^*_{last}|$ should contain positive predictive power for a subsequent price change. The results for this additional variable are very similar to those for $\left|P_{t-1} - P^*_{t-1}\right|$.[22] That is, for 7 out of the 9 firms $|P_{last} - P^*_{last}|$ enters with a negative sign, contrary to what would be implied by "sticky information" due to inattentive producers.

Additionally, rational inattention by producers predicts no asymmetry. Yet, we find asymmetry both in the small and in the large. The asymmetry suggests deliberate behavior, rather than information processing delays, on the part of the firm. If retailers are concerned about fairness, wholesalers have an incentive to make large price decreases over large price increases. And, if retailers cannot match small price changes, wholesalers have an incentive to make small price increases over small price decreases. Thus, rather than being inattentive themselves, wholesalers can take advantage of the inattentiveness of retailers.

To summarize, our results suggest that the motivation for price stickiness in the wholesale gasoline market stems mainly from fairness concerns in everyday pricing, especially with regards to

[22] As a result, we do not include them here, but are available upon request.

large price increase. Whereas rational inattention in conjunction with a menu cost farther down the supply chain, may play some role in explaining stickiness for very small price gaps.

6 Comparison With Previous Studies

6.1 Stickiness in Wholesale Gasoline Prices

As previously stated, the majority of the literature on gasoline prices investigates the issue of "rockets and feathers" and price stickiness using data aggregated on the weekly level or higher. Hence the emphasis on the gradual distributed lag in the response of downstream gasoline prices to the upstream price.[23] To the best of our knowledge, Davis and Hamilton (2004, henceforth DH) is the only other exploration of the source of price stickiness in daily gasoline prices that focuses on the discreteness of price changes.

Recall from Section 2 that DH began their investigation by fitting the Dixit menu cost model to the Philadelphia wholesale data. Although the model fit the data well, the estimated parameters implied a range of stickiness and average price change that were larger than what could be reconciled with the observed data. For instance, their estimates would imply a range of stickiness of about 10¢, whereas in the data, the average price change was less than 1¢ (see Table 2).[24] Furthermore, evidence against the model was that it was outperformed (in terms of goodness of fit) by an atheoretical logit model containing only the price gap (Table 5).

The authors then explored two alternative specifications: (a) an atheoretical logit specification where the probability of a price change for firm i is modeled as a function of the absolute deviation of the firm's current price from the target, $|P_{it} - P_{it}^{*}|$; and (b) the Autoregressive Conditional Hazard

[23] We refer the reader to Peltzman (2000) for comprehensive documentation of the rockets and feathers phenomenon in over 200 industries, Geweke (2004) for a summary of the empirical rockets and feathers literature on gasoline prices, and Tappata (2006) for an overview of theoretical explanations of the phenomenon.

[24] We refer the reader to Davis and Hamilton (2004) for a careful discussion and estimation of Dixit's model using wholesale gasoline prices, as well as a detailed table and discussion of the parameter estimates.

(ACH) model of Hamilton and Jordà (2002), which is intended to capture time dynamics in a firm's decision whether or not to change its price.

The ACH model generalizes the autoregressive conditional duration (ACD) model of Engle and Russell (1998) by converting the ACD into a $\{0,1\}$ Bernoulli process and allowing for the expected duration to depend on exogenous covariates in a linear manner. Let u_n denote the amount of time, or duration, between the n^{th} and the $(n+1)^{th}$ time a firm changes its price; ψ_n denote the conditional expectation of u_n given past durations $u_{n-1}, u_{n-2}, ...u_1$, and $N(t)$ denote the number of times that the firm has been observed to change the price as of day t. Following Hamilton and Jordà (2002), DH assume an exponential specification for the durations. Hence, the probability of a price change on day $t+1$ is given by

$$h_{t+1} = \frac{1}{\psi_{N(t)} + \gamma' \mathbf{z}_t} \tag{16}$$

where

$$\psi_n = \alpha \sum_{i=1}^{n-1} \beta^{i-1} u_{n-i} + \beta^{n-1} \overline{u} \tag{17}$$

and $\overline{u}$ is the average duration over the sample. The log likelihood for the ACH is given by equation (7) and thus can be numerically maximized to obtain estimates of α and β.[25] The value of the log likelihood achieved for these three models is reported in Table 5, which reproduces DH's Table 3. Using both models, the authors find $\left|P_{it-1} - P^*_{it-1}\right|$ to be significant for only two firms (in contrast with the ACB, which finds it significant for seven firms) and $\left|P_{i,w1_{i(t)}} - P^*_{i,w1_{i(t)}}\right|$ significant for none (see Table 6). Additionally, since the ACH outperforms the atheoretical logit in terms of goodness of fit for only one firm (see Table 5), the authors find little evidence of time dependence in the price change decision. They conclude that "the history of prices matters for the probability

[25] In order to ensure the estimated probability falls between 0 and 1, the denominator of 16 is replaced with a differentiable smoothing function as detailed in Hamilton and Jorda (2002).

of a price change only through the current value of the price gap." Thus, they find that the menu cost model makes predictions that are "broadly consistent" with the data.

Clearly, we find considerably more evidence of serial dependence in the probability of price changes with the ACB model than found by DH using the ACH specification. The ACB finds time dependence in the firm's pricing decision through the past response probabilities (β significant for all firms) and to a lesser extent, through the lagged indicator of a price change (δ significant for 4 out of 9 firms). Why do DH find only limited evidence of time dependence?

We begin to investigate the role of durations by estimating an $ACB(0,1,1)-ACD(1,1)$ model where the logarithm of the current duration, as well as the current and previous day's gaps, are included in the ACB. The ACD is assumed to take the Nelson form, given by equation (8). We then test the null hypothesis that the coefficient on the logarithm of the contemporaneous duration in the ACB is equal to zero. The p-value for this hypothesis test is reported on the first column of Table 7. We find evidence that contemporaneous durations have additional explanatory power only for two firms (1 and 3). The estimates for the remaining explanatory variables are virtually identical to those of the $ACB(0,1,1)$ reported in Table 3.[26]

One may argue that these results are driven by the fact that we include the logarithm of the contemporaneous duration and not the lagged duration as explanatory variable in the ACB specification. Recall from equation (17) that the ACH uses the lagged level of the duration, not the log-duration to predict price changes. To explore this possibility, we first replicate the $ACB(0,1,1)-ACD(1,1)$ estimation adding the logarithm of the lag duration, $\ln\left(u_{N(t-1)-1}\right)$, in the ACB. The second column of Table 7 reports the p-value for the test of the null hypothesis that the coefficient on $\ln\left(u_{N(t-1)-1}\right)$ is equal to zero. We cannot reject the null for any of the firms. We then estimate the logit – $ACB(0,0,0)$ – model with $|P_t - P_t^*|$ and the lagged level of

[26] Results available upon request. Estimation results are also robust to Engle and Russell (2005) event-time specification where we lag $(x_{t-1} - h_{t-1})$ rather than x_{t-1}.

the duration as explanatory variables, and test the null hypothesis that the lagged level of the duration is equal to zero. The third column of Table 7 reports the p-values for this test. For all firms except firm 5, the lagged duration is not significant in the logit model. Thus, it is not surprising that the ACH outperforms the logit only for this one firm in DH (see Table 5).

As a final comparison between the ACH and ACB we use Rivers and Vuong (2002) model selection test for non-nested models, which extends Vuong (1989) likelihood ratio statistic to dynamic models. The null hypothesis is

$$H_0 : E_0 \left[\widehat{l}_t^{ACH} - \widehat{l}_t^{ACB} \right] = 0,$$

which states that the two models are equally close to the true specification. The test follows a standard normal distribution. Hence, the ACB specification is preferred at a 5% significance level if the test statistic is greater than 1.65. The last column of Table 3 reports the test results. For 6 (8) of the 9 firms we reject the null hypothesis in favor of the ACB at the 5% (10%) level.

Summarizing, our $ACB(0,1,1) - ACD(1,1)$ estimation results suggest that dynamics play an important role in the probability of price changes. However, this time dependence does not stem from the role of durations (as posed by the ACH), but directly from the past distribution of the price changes and, less often, from the indicator of a price change.

6.2 Implications for Theories of Asymmetric Price Adjustment

Our evidence of asymmetric adjustment to cost shocks appears to be broadly consistent with the pattern documented in the 'rockets and feather' gasoline literature. Furthermore, some characteristics of the price adjustment process fit the implications of recent theoretical work on asymmetric price adjustment. For instance, Cabral and Fishman (2006) search model implies that whereas small increases and large decreases in the cost are fully reflected in the price, large increases and small decreases are not. Similarly, our estimation results indicate a larger probability for the price to change in the face of a small negative or a large positive gap, than in the face of a large negative or a small positive gap.[27]

A theoretical framework that appears to be relevant for the wholesale gasoline market is the 'reference price' search model developed by Lewis (2003). Lewis assumes that customers establish a "reference price" based on price observations from previous periods and search for a new gasoline station if the current price is dramatically higher or lower than this reference price. His model is able to match quite well the pattern of price adjustment in San Diego's retail gasoline market.

As we mentioned before, over 55% of the U.S. retail gasoline stations purchase their gasoline from jobbers (Borenstein, Cameron, and Gilbert, 1997).[28] Given that the NYMEX price changes very frequently (95% of the days in the sample), the distribution of wholesale prices is likely to change rapidly, thus making information costly to process for retailers. Thus, that retailers form their expectations about the price of wholesale gasoline based on past price observations seems to be reasonable assumption. If this is the case, we would expect to find the probability of a price change to be correlated over time as found by the ACB model. Additionally, it is likely that wholesalers want to prevent the retailers from searching, just as retailers want to prevent customers from searching. As Hastings and Gilbert (2005) point out, the retailer can switch refiners and/or suppliers in the long run if it is profitable to do so. The U.S. Senate Permanent Subcommittee on Investigations found that this is a real concern of wholesalers. It found that "refiners are averse to gaining market share through rack pricing as they are to losing market share." The former concern results from wholesalers fearing that a low price will lead to a run on supplies, leaving its other

[27] It is worth noting here that the structure of the wholesale gasoline market does not fit some of the assumptions in Cabral and Fishman; especially, the low probability of cost changes.

[28] According to the Senate Permanent Subcommittee on Investigations, as of 1999, two-thirds of retail gasoline stations in the U.S. were branded. Among those branded stations, half were dealer owned while the remaining half were split evenly between company-op and lessee-dealer.

customers with insufficient supplies. The latter concern results from wholesalers fearing that a high price will cause its customers to switch brands when their contract expires. And, contracts can expire rather quickly. The subcommittee found that contracts can cover a period "of one day to one year". Thus, it is likely that wholesalers use past prices in setting their current price in order to prevent undesirable search, both when the price is set too high and when it is set too low.

Our summary statistics are consistent with those of Lewis in that wholesalers prefer to make smaller, more frequent price reductions as large reductions send a signal to consumers to search. However, contrary to his empirical results for retail stations, we still find significant evidence of asymmetry when we control for the price gap.[29] Differences in market structure at the retail and wholesale level are likely to account for these differences. In particular, because wholesalers are bound to retailers through long-term contracts, they have an incentive to use non-price methods of rationing in lieu of large price increases (Henly, Potter, and Town, 1996). On the contrary, retail gasoline stations have no such incentive.

Additional strategic considerations consistent with our results are found in Borenstein, Cameron, and Gilbert (1997). In their model, collusion between firms is difficult to sustain, yet wholesalers may be able to use past prices as "focal points" at which to collude. If such collusion was present in the wholesale market on the daily level, we certainly would expect the current price change probability to be highly correlated with past price change probabilities (as found by the ACB model) and the response to cost increases and decreases to show some asymmetry. However, the direction of the asymmetry found in our data is opposite of what is implied by their hypothesis.

Finally, the theory of capacity adjustment costs (Peltzman, 2000), which posits that costs of increasing inventory capacity may lead to asymmetric adjustment to cost increases and decreases, would imply asymmetry in the "large". However, our results point towards asymmetry both for

[29] Note that Lewis defines the margin very closely to how we define the gap. Lewis defines the margin as $price-cost$ whereas we define the gap as $price-cost-average\ markup$.

large and small changes in the price gap.

7 Conclusions

Why are wholesale gasoline prices sticky? In this paper we reconsider three explanations for price stickiness: menu costs, information processing and strategic interactions. To evaluate these hypothesis we estimate an autoregressive conditional binomial (ACB) model where the probability that a firm will change its price on day t is modeled as a function of the historic distribution of price changes, past price change realizations, and the current and lagged gap between the wholesale price and the optimal price. While we do find some heterogeneity amongst firms, two important similarities stand out: the strong time dependence and the asymmetric response.

In contrast with previous studies (DH, 2004), we find significant evidence of time dependence in the probability of price changes. Specifically, our results indicate that the history of prices matters for the probability through the historic distribution, the value of the previous day's price gap, and the lagged indicator of a price change. Furthermore, by estimating the probability of a price change and the duration process jointly in the $ACB-ACD$ model, we show that the duration between price changes is only significant for two of the nine firms. Because the lag of the duration is the foundation of the ACH model (see equations (16) and (17)), these results suggest that time dynamics in wholesale gasoline prices are better captured through the past distribution of price changes (ACB) than through past durations (ACH).

Summing up, our results have important implications regarding which of the three explanations (menu-costs, information processing, or market responses) best fits the observed wholesale gasoline data. First, the empirical evidence for all of the firms is not consistent with the menu-cost explanation. As we mentioned before, menu cost models such as Dixit's posit that the history of price changes should only be significant through the current price gap and predicts a symmetrical response to a cost change. Neither is the case here. The finding of positive autocorrelation in the firm's price change decision ($\beta > 0$, and $\delta > 0$), as well as the finding of asymmetry, offers evidence against information processing delays on behalf of the firm. However, the strong autocorrelation of price change probabilities, the immediate pass-through of cost shocks (Figure 1), and finding that firms are more likely to make large price decreases over large price increases (Table 4 and Figure 3) are consistent with the idea of "fair pricing" (Kahneman, Knetsch, and Thaler, 1986). That is, it is likely that prices in this market go unchanged if the wholesaler's customers (retail gasoline stations) believe such a change would be unfair. Given that the relationship between wholesaler and retailer is long-term, fairness is likely to be a practical concern.

References

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

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

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

[4] Bils, Mark, and Peter J. Klenow (2002). "Some Evidence on the Importance of Sticky Prices." *Journal of Political Economy* 112, 947-985.

[5] 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.

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

[7] Cabral, Luís M.B. and Arthur Fishman (2006). "A Theory of Asymmetric Price Adjustment." Unpublished working paper.

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

[9] Chari, Varadarajan V., Patrick J. Kehoe, and Ellen R. McGrattan (2000). "Sticky Price Models of the Business Cycle: Can the Contract Multiplier Solve the Persistence Problem?" *Econometrica* 68, 1151-1180.

[10] Clarida, Richard, Jordi Gali, and Mark Gertler (1999). "The Science of Monetary Policy: A New Keynesian Perspective." *Journal of Economic Literature*, 37, 1661-1707.

[11] Davis, Michael C. (2006)). "The Dynamics of Daily Retail Gasoline Prices." *Managerial and Decision Economics,* forthcoming.

[12] Davis, Michael C., and James D. Hamilton (2004). "Why Are Prices Sticky? The Dynamics of Wholesale Gasoline Prices." *Journal of Money, Credit, and Banking* 36, 17-37.

[13] Deltas, George (2004). "Retail Gasoline Price Dynamics and Local Market Power." University of Illinois Working Paper.

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

[15] Dotsey, Michael, and Robert G. King (2001). "Pricing, Production, and Persistence." NBER working paper 8407.

[16] Douglas, Christopher, and Ana María Herrera (2007). "Dynamic Pricing and Asymmetries in Retail Gasoline Markets: What They Tell Us About Price Stickiness?, mimeo, Michigan State University.

[17] Eckert, Andrew, and Douglas S. West (2004). "Retail Gasoline Price Cycles Across Spatially Dispersed Gasoline Stations." *Journal of Law and Economics* 47, 245-273.

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

[19] Engle, Robert, and Jeffrey Russell (2005). "A Discrete-State Continuous-Time Model of Financial Transactions Prices and Times: The Autoregressive Conditional Multinomial-Autoregressive Conditional Duration Model." *Journal of Business and Economic Statistics* 23 166-180.

[20] Erceg, Christopher J., Dale W. Henderson, and Andrew T. Levin (2003). "Optimal Monetary Policy with Staggered Wage and Price Contracts." *Journal of Monetary Economics* 46 281-313.

[21] Fishman, Arthur, and Avi Simhon (2005). "Can Small Menu Costs Explain Sticky Prices?" *Economic Letters* 87, 227-230.

[22] "Gas Prices, How Are They Really Set?" (2002). Report Prepared by the Majority Staff on the Permanent Senate Subcommittee on Investigations.

[23] Geweke, John (2004). "Issues in the 'Rockets and Feathers' Gasoline Price Literature." Report to the Federal Trade Commission, March 2004.

[24] Hamilton, James D., and Oscar Jordà (2002). "A Model for the Federal Funds Rate Target." *Journal of Political Economy* 110, 1135-1167.

[25] Hastings, Justine S. (2004). "Vertical Relationships and Competition in Retail Gasoline Markets: Empirical Evidence from Contract Changes in Southern California." *American Economic Review* 94, 317-328.

[26] Hastings, Justine S., and Richard J. Gilbert (2005). "Market Power, Vertical Integration, and the Wholesale Price of Gasoline." *Journal of Industrial Economics* 53, 469-492.

[27] 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", unpublished working paper.

[28] Kahneman, Daniel, Jack L. Knetsch, and Richard Thaler (1986). "Fairness as a Constraint on Profit Seeking: Entitlements in the Market." American Economic Review 76, 728-741.

[29] 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, 791-220.

[30] Levy, Daniel, Allan Chen, Sourav Ray, and Mark Bergen (2006). "Asymmetric Price Adjustment 'in the Small:' An Implication of Rational Inattention." Unpublished working paper.

[31] Lewis, Matthew S. (2003). "Asymmetric Price Adjustment and Consumer Search: An Examination of the Retail Gasoline Market." Discussion Paper 0407010, Center for the Study of Energy Markets Working Paper.

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

[33] 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.

[34] Levy, Daniel (2006) "Price Rigidity and Flexibility: New Empirical Evidence, Introduction to the Special Issue of *Managerial and Decision Economics.*

[35] Nelson, Daniel B. (1991). "Conditional Heteroskedasticity in Asset Returns: A New Approach." *Econometrica* 59, 347-370.

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

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

[38] Ray, Sourav, Allan Chen, Mark Bergen, and Daniel Levy (2006). "Asymmetric Wholesale Pricing: Theory and Evidence." *Marketing Science* 25, 131-154.

[39] Reis, Ricardo (2006a). "Inattentive Consumers." *Journal of Monetary Economics*, 53 (8), 1761-1800.

[40] Reis, Ricardo (2006b). "Inattentive Producers." *Review of Economic Studies*, 73 (3), 793-821.

[41] Rivers, Douglas and Quang H. Vuong (2002). "Model Selection Tests for Nonlinear Dynamic Models." *Econometrics Journal* 5, 1-39.

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

[43] 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.

[44] Rotemberg, Julio J. (2006). "Fair Pricing." Harvard Business School working paper.

[45] Rotemberg, Julio J. and Michael Woodford (1997). "An Optimization-Based Econometric Framework for the Evaluation of Monetary Policy" *NBER Macroeconomics Annual*, 297-346.

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

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

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

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

[50] Sims, Christopher A. (2003). "Implications for Rational Inattention." *Journal of Monetary Economics* 50, 665-690

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

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

[53] Tappata, Mariano (2006). "Rockets and Feathers: Understanding Asymmetric Pricing." University of California-Los Angeles Working Paper.

[54] Taylor, John B. (1979). "Staggered Wage Setting in a Macro Model." *American Economic Review* 69, 108-113.

[55] Taylor, John B. (1980). "Aggregate Dynamics and Staggered Contracts." *Journal of Political Economy* 88 1-23.

[56] Verlinda, Jeremy (2005). "Price-Response Asymmetry and Spatial Differentiation in Local Retail Gasoline Markets." University of California-Irvine Working Paper.

[57] Vuong, Quang H. (1989). "Likelihood Ratio Tests for Model Selection and Non-Nested Hypotheses." *Econometrica* 57, 307-333.

Table 1: Description of Price Changes

Firm	Number of Price Changes	Increase Following Previous Increase	Increase Following Previous Decrease	Decrease Following Previous Increase	Decrease Following Previous Decrease
1	270	102	22	23	122
2	361	124	42	43	151
3	446	122	68	67	188
4	236	98	20	21	96
5	378	134	47	48	148
6	304	117	28	28	130
7	349	126	34	35	153
8	350	139	26	27	157
9	273	104	22	22	124

NOTE: Columns 3 through 6 sum to one less than column 2 because there is no way to know if the first price change observed in the data set followed an price increase or decrease.

Table 2: Summary Statistics

Firm	Brand	Number of Observations	Average Price	Average Mark-Up	Frequency of Price Change	Frequency of Price Increase	Frequency of Price Decrease	Average Increase	Average Decrease
1	Amoco	782	69.8	4.25	0.35	0.16	0.19	0.87	0.70
2	ARCO	782	67.6	2.12	0.46	0.21	0.25	0.85	0.70
3	BP	782	67.3	1.81	0.57	0.24	0.33	1.42	1.03
4	Chevron	641	68.8	2.82	0.37	0.19	0.18	0.95	0.81
5	Exxon	782	68.3	2.78	0.48	0.23	0.25	0.83	0.74
6	Gulf	743	69.6	3.74	0.41	0.2	0.21	0.87	0.70
7	Mobil	779	68.9	3.40	0.45	0.21	0.24	0.82	0.65
8	Sunoco	782	69.2	3.71	0.45	0.21	0.24	0.76	0.66
9	Texaco	681	69.7	3.25	0.40	0.19	0.21	0.90	0.66
	NYMEX	782	——	65.1	0.95	0.48	0.46	1.36	1.39

NOTES: Table reports summary statistics for the nine wholesale firms in the sample. The frequencies of price changes are the observed daily frequencies for the 1989-1991 period. The average price is in cents per gallon. The average markup is computed as the average difference between the wholesale price and the NYMEX price for bulk unleaded gasoline and is measured in cents per gallon. The average increase and decrease are measured in cents per gallon of unleaded gasoline.

Table 3: ACB(0,1,1) Estimates with Lagged Gap Included as Additional Explanatory Variables

Firm	ω	β	δ	$\|P_t - P_t^*\|$	$\|P_{t-1} - P_{t-1}^*\|$	log L	LR	RV
1	-1.601	-0.505**	-0.184	-0.0364	0.196**	-478.97	0.00070**	1.82
	(0.234)	(0.145)	(0.151)	(0.0386)	(0.0402)			.0344
2	-0.110	0.828**	0.149	0.107**	-0.102**	-529.43	0.0324*	0.968
	(0.0595)	(0.117)	(0.0802)	(0.0350)	(0.0331)			.1665
3	-0.0898	0.368*	0.320*	0.296**	-0.247**	-512.83	0.0000**	2.33
	(0.0987)	(0.174)	(0.140)	(0.0551)	(0.0525)			.0099
4	-0.638	0.467*	0.508**	0.106*	-0.0680	-405.37	0.00530**	2.26
	(0.272)	(0.239)	(0.174)	(0.0433)	(0.0581)			.0119
5	-0.0992	0.901**	0.202**	0.113**	-0.114**	-520.52	0.0000**	1.38
	(0.0513)	(0.0464)	(0.0900)	(0.0296)	(0.0292)			.0838
6	-0.209	0.827**	0.206	0.185**	-0.169**	-471.30	0.0183*	3.45
	(0.129)	(0.105)	(0.121)	(0.0333)	(0.0352)			.0003
7	-0.0672	0.899**	0.0686	0.121**	-0.117**	-521.19	0.1136	1.59
	(0.0507)	(0.0608)	(0.0696)	(0.0276)	(0.0267)			.0559
8	-0.868	-0.570*	-0.00605	0.0223	0.126**	-524.31	0.0990	2.11
	(0.253)	(0.256)	(0.210)	(0.0467)	(0.0419)			.0174
9	-0.267	0.780**	0.259*	0.157**	-0.141**	-432.65	0.0186*	2.09
	(0.101)	(0.0798)	(0.115)	(0.0321)	(0.0330)			.0183

NOTES: LR reports the p-value from the likelihood ratio test of the null hypothesis that this ACB specification reduces to the logit with only the current gap. RV reports the Rivers and Vuong (2002) test statistic for the test of the ACH versus the ACB (p-value reported underneath the statistic). Asterisk (*) indicates statistical significance at 5%. Double-asterisk (**) indicates statistical significance at 1%. Standard errors in parenthesis.

Table 4: Asymmetric ACB(0,1,1) Estimates

Firm	β	δ	Pos const	Neg const	Pos gap	Neg gap	Lag pos gap	Lag neg gap	log L	LR
1	-0.4745	-0.2068	-1.7162**	-1.5107**	0.0120	-0.0649	0.2139**	0.1831**	-476.30	0.1485
	(0.1547)	(0.1566)	(0.2787)	(0.3082)	(0.0910)	(0.0473)	(0.0777)	(0.0485)		
2	0.5955	0.0271	-0.2568	-0.0156	0.1528**	0.1273**	-0.0877	-0.1502**	-520.48	0.0005**
	(0.1965)	(0.1374)	(0.1570)	(0.1026)	(0.0548)	(0.0464)	(0.0573)	(0.0485)		
3	0.3775	0.3093	-0.1039	-0.0628	0.3601**	0.2574**	-0.2704**	-0.2490**	-510.75	0.2447
	(0.1965)	(0.1396)	(0.1278)	(0.1362)	(0.0855)	(0.0695)	(0.0884)	(0.0609)		
4	0.1989	0.4609	-1.2550**	-0.6091**	0.1222*	0.0623	0.0421	-0.0492	-396.87	0.0007**
	(0.2480)	(0.1747)	(0.3817)	(0.2257)	(0.0587)	(0.0570)	(0.0799)	(0.0623)		
5	0.8715	0.2622	-0.1180	-0.1460**	0.1347**	0.1420**	-0.1357**	-0.1419**	-520.52	1.0000
	(0.0517)	(0.0984)	(0.0626)	(0.0566)	(0.0441)	(0.0386)	(0.0448)	(0.0382)		
6	-0.2413	0.3126	-1.9085**	-0.8220**	0.1689**	0.0700	0.1567*	0.0212	-462.34	0.0005**
	(0.2275)	(0.1644)	(0.3541)	(0.2607)	(0.0677)	(0.0476)	(0.0789)	(0.0535)		
7	0.8485	0.0309	-0.0509	-0.1281	0.0826	0.1587**	-0.0710	-0.1507**	-515.71	0.0119*
	(0.0751)	(0.0821)	(0.0654)	(0.0666)	(0.0474)	(0.0406)	(0.0521)	(0.0392)		
8	-0.3144	-0.0048	-0.8584**	-0.6660	0.0283	0.0200	0.1526*	0.0756	-523.26	0.5519
	(0.4717)	(0.0701)	(0.2434)	(0.4345)	(0.0570)	(0.0502)	(0.0688)	(0.0900)		
9	0.7581	0.2245	-0.3476**	-0.1961*	0.1640**	0.1506**	-0.1286*	-0.1445**	-429.83	0.1305
	(0.0821)	(0.1152)	(0.1280)	(0.0948)	(0.0495)	(0.0400)	(0.0504)	(0.0411)		

Table 5: Log Likelihood of 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: * denotes best model by Schwarz (1978) criterion.

Table 6: Test for Significance of Additional Variables

Firm	$\lvert P_{t-1}-P^*_{t-1}\rvert$	$P_{w1(t)}-P^*_{w1(t)}$	$\{\theta_t, P_t-P^*_t\}$	$u_{N(t-1)-1}$	y^{other}_{t-1}
Logit					
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		
ACH					
1	0.036*	0.907	0.005**	0.000**	
2	0.428	0.261	0.037*	0.059	
3	0.001**	0.656	0.018*	0.393	
4	0.082	0.426	0.000**	0.458	
5	0.611	0.872	0.425	0.000**	
6	0.237	0.949	0.000**	0.171	
7	0.576	0.522	0.067	0.632	
8	0.139	0.443	0.061	0.573	
9	0.474	0.833	0.001**	0.057	
ACB					
1	0.0002**	0.3482	0.0257*		0.0000**
2	0.0348*	0.6390	0.0022**		0.0173*
3	0.0004**	0.6390	0.5273		0.2687
4	0.2741	0.0769	0.0003**		0.0000**
5	0.0000**	0.0931	0.7445		0.1517
6	0.1565	0.1345	0.0002**		0.0000**
7	0.0181*	0.7290	0.2725		0.0000**
8	0.0355*	1.0000	0.1281		0.0001**
9	0.0024**	0.2453	0.0537		0.4371

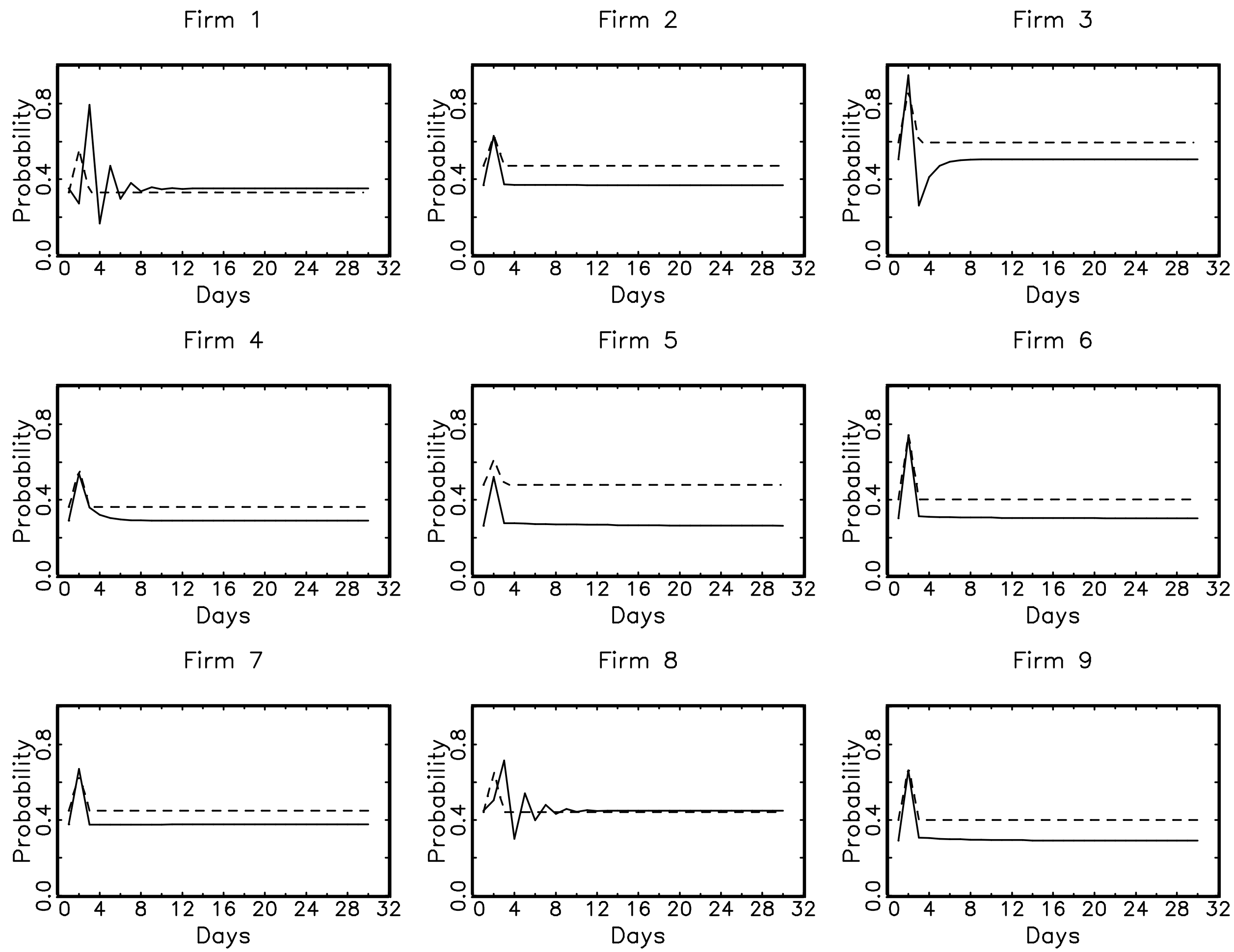
NOTES: Table reports p-value of test of null hypothesis that the indicated variable does not belong as an additional explanatory variable to the logit or ACH model. Asterisk (*) denotes statistically significant at the 5% level. Double-asterisk (**) denotes statistically significant at the 1% level.

Table 7: Tests for Significance of the Duration

Firm	$\ln\left(u_{N(t)}\right)$	$\ln\left(u_{N(t)-1}\right)$	$u_{N(t-1)-1}$
1	0.0080**	0.644	0.0513
2	0.7323	0.0557	1.000
3	0.0161*	0.1797	0.1573
4	0.2404	0.1923	0.9542
5	0.1948	0.1897	0.00130***
6	0.2744	0.1512	0.2184
7	0.4074	0.5271	0.8559
8	0.2806	0.8415	1.000
9	0.7675	0.4976	0.1505

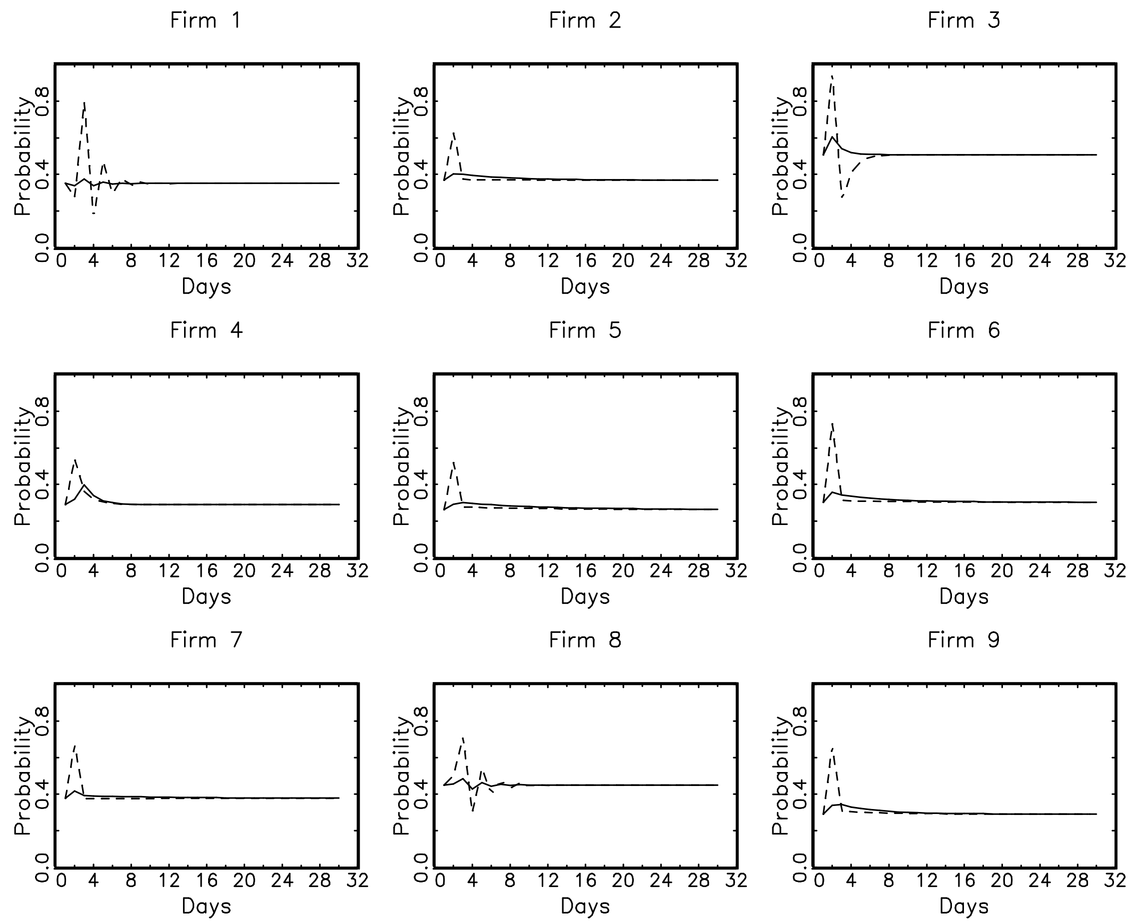
NOTES: Column 2 reports the p-value for the test of the null hypothesis that the natural log of the contemporaneous duration in the ACB-ACD model is zero. Column 3 reports the p-value for the test of the null hypothesis that the lagged duration is equal to zero in the logit model with the current price gap. Asterisk (*) denotes significance at the 5% level. Double-asterisk (**) denotes significance at the 1% level.

Figure 1: ACB and Logit Impulse Responses Assuming the Firm Changes Its Price



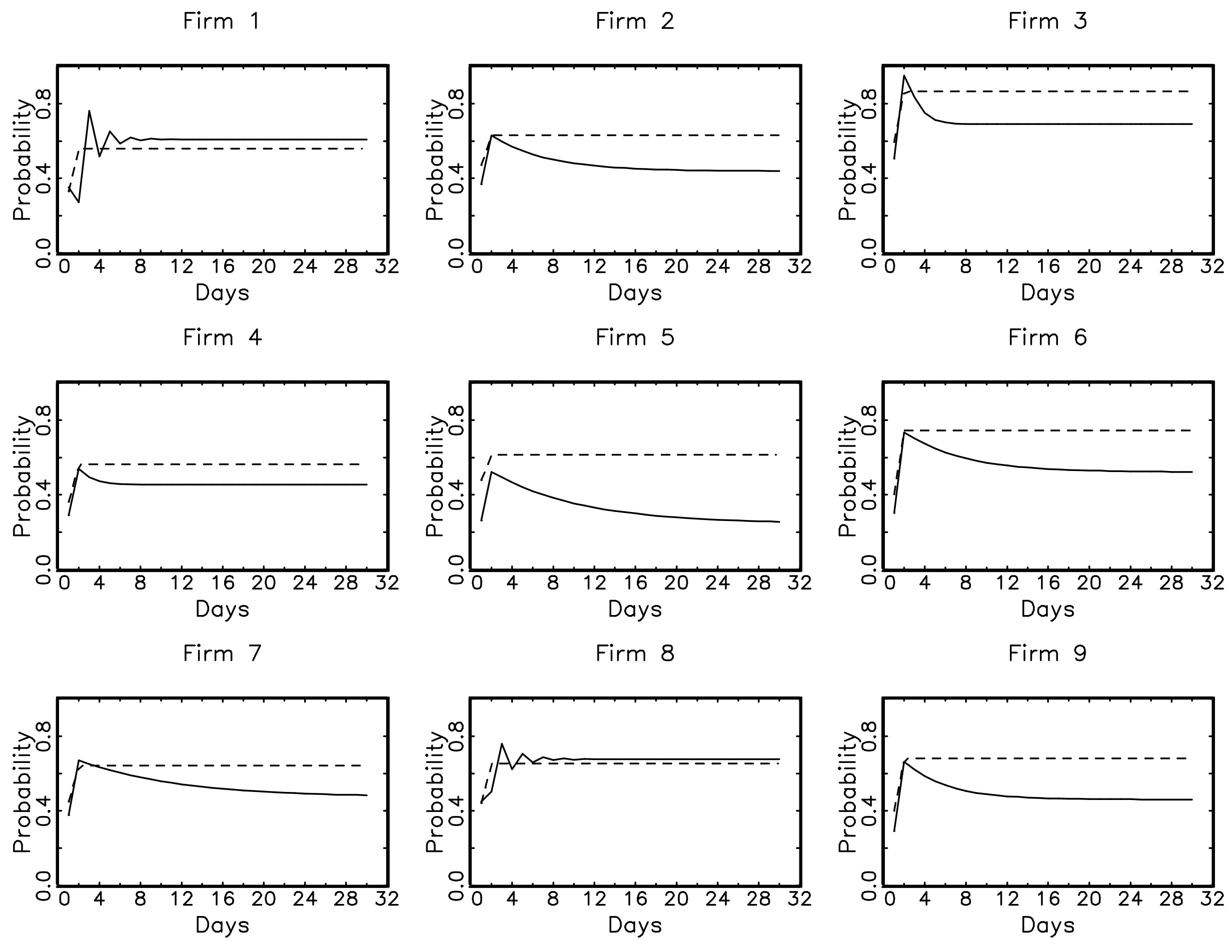
Dashed Line: Logit; Solid Line: ACB

Figure 2: ACB Impulse Response for a 1.36¢ and 10¢ Shock, Assuming the Firm Changed Its Price



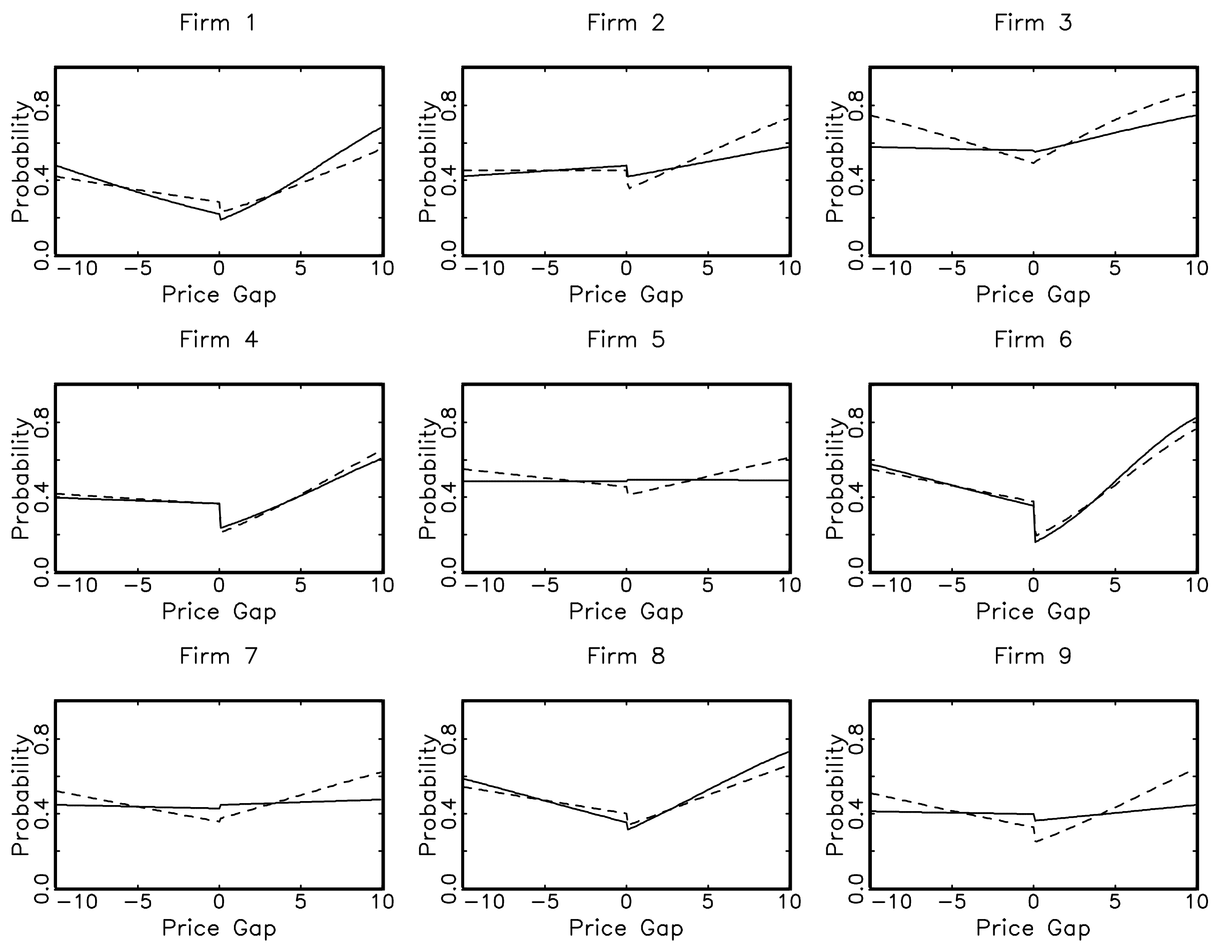
Dashed Line: 10¢ shock; Solid Line: 1.36¢ shock

Figure 3: ACB and Logit Impulse Responses Assuming the Firm Left Its Price Unchanged



Dashed Line: Logit; Solid Line: ACB

Figure 4: Asymmetric ACB and Logit Estimated Probabilities



Dashed Line: logit; Solid Line: ACB