Dynamic Pricing and Asymmetries in Retail Gasoline Markets: What Can They Tell Us About Price Stickiness?

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Abstract

Theoretical explanations for price stickiness used in businesses cycle models are diverse (e.g., information processing delays, rational inattention and fair pricing), with each theory resulting in a different implication for inflation dynamics. Using an autoregressive conditional binomial model and a data set consisting of daily observations of price and cost for 15 Philadelphia retail gasoline stations, we test which of these theories is most consistent with the observed pattern of price adjustment. Our findings of time dependence, asymmetry and the role of cost volatility are consistent with a combination of fairness considerations and rational inattention by producers.

JEL Codes: C22, D4, E3
Keywords: sticky prices, price adjustment, gasoline prices, discrete valued time series.

1 Introduction

Business cycle models often rely on the assumption that prices adjust infrequently –due to market frictions– in order to generate the short-run non-neutrality of money documented in the empirical macroeconomic literature (Sims, 1992).[1] While on the surface, the difference between alternative theories (e.g., information processing delays, rational inattention, fair pricing) might seem slight, each motivation has different implications for inflation dynamics (Reis, 2006). Understanding the nature and extent of price stickiness is important for conducting macroeconomic and monetary policy. Moreover, studying the prevalence and

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[1] Examples include: Rotemberg and Woodford (1997), Clarida, Galí and Gertler (1999), Chari, Kehoe and McGrattan (2000), Erceg, Henderson and Levin (2003), and Dotsey and King (2006).

form of time dependence in micro level data on price changes can aid in choosing among alternative models of price stickiness

In this study, we utilize daily retail gasoline prices from Philadelphia, PA to inquire whether the empirical implications of some price adjustment models are borne out by micro level data on price changes. In particular, is a firm more likely to change its price if it changed its price on the previous day? Does the history of prices matter for the probability of a price change only through changes in costs the firm faces? Are periods of higher than average cost volatility more likely to result in changes in retail gasoline prices? Answering these questions is key because each theory of price stickiness implies a different combination of three elements: (i) a specific form of time dynamics in the firm's price change decision, (ii) the presence or absence of asymmetry in the pattern of price adjustment, and (iii) significance of other explanatory variables such as changes in cost or cost volatility. Whereas the vast majority of the empirical gasoline literature investigates the speed of pass-through from wholesale costs to retail gasoline prices and the asymmetric nature of price adjustments,[2] we focus on the discrete nature of price changes.

We extend the work of Davis and Hamilton (2004), Douglas and Herrera (2010), and Davis (2007). The first two articles study stickiness in Philadelphia's wholesale prices, whereas the latter studies Newburgh's, NY, retail gasoline prices. Davis and Hamilton (2004) and Davis (2007) estimate an autoregressive conditional hazard (ACH) model. Instead we use an autoregressive conditional binomial (ACB) model, which enables us to test for richer patterns of time-dependence than the ACH model. The ACB has been used by Douglas and Herrera (2010) to examine wholesale gasoline prices, thus it appears natural to extend this framework to retail gasoline prices. Furthermore, our work departs from the above mentioned studies in two aspects: (i) we directly observe the change in the price of wholesale gasoline (i.e., the change in the station's marginal cost) instead of having to impute the price-cost gap; and (ii) we study the role of cost volatility in determining the probability of price changes.

Our results suggest that the dynamics of price adjustment in Philadelphia's retail gasoline market have three characteristics. First, stations are more likely to make retail price decreases compared to retail price increases in response to small cost changes; a result that is consistent with the idea of "fair pricing". Second, stations are more likely to make retail price increases than retail price decreases in response to larger cost changes. Last but not least, stations are somewhat more likely to drop their price when a cost decrease is associated with higher cost volatility. This behavior is supportive of "rational inattention."

[2] See, e.g., Borenstein, Cameron, and Gilbert (1997).

The paper is organized as follows. Section 2 describes the data. Section 3 presents the ACB model and the testable predictions. Section 4 expounds the results and Section 5 concludes.

2 Data

Daily retail and wholesale gasoline prices for 15 retail gasoline stations in Philadelphia, PA spanning January 1, 2002 to December 31, 2004 were obtained from the Oil Price Information Service. The retail price is recorded whenever a fleet card is used to purchase gasoline. The wholesale price is recorded as the posted price at the wholesale terminal closest to the retail station. Fleet cards pose an issue: if no fleet card transaction takes place, then the observation for that day is coded as missing. We follow Davis (2007) and impute the last value observed to each daily unobserved data point. Since the average length of the missing periods is 1.7 days, and 74% of the missing periods in the data set have the same price before and after, we do not believe the missing observations pose a problem.

This data set provides a good testing ground for various reasons. First, retail gasoline sold in Philadelphia is a chemically homogenous good,[3] which minimizes the influence of product heterogeneity on the pattern of price adjustments. Second, the price of wholesale gasoline accounts for about 85% of the retail price, with the remaining 15% coming from labor costs and transportation costs of delivering gasoline from the wholesale terminal to the retail outlet. Because Philadelphia has a wholesale terminal, differences in transportation costs should be minimal. Third, since retail gasoline is sold in standardized lots of one gallon, sellers cannot reduce quantity in lieu of raising price. Fourth, price stickiness is evident in that changes in retail gasoline prices take place only at particular points in time, and often remain unchanged in the face of observable cost changes. As seen in Table 1, the retail price of gasoline changed on less than 14% of the days, whereas the wholesale price (i.e., the main input cost) changed on approximately 40% of the days. Finally, changes in retail gasoline prices appear to have distinct dynamics with price movements being more likely followed by movements in the same direction.[4]

[3] The local regulation supplementary to the Clean Air Act Amendments of 1990 is the same for the whole city.
[4] For all firms, the percentage of price changes that followed a price change of the same sign exceeds 70%.

3 ACB Model and Testable Predictions

Let x_{t+1} be a binary variable that takes the value of unity if a price change is observed on day $t+1$ and $\mathbf{z}_t$ is a vector of exogenous variables known at time t. Define h_{t+1} as the probability that a station changes its price on day $t+1$ as:

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

Let $G(\cdot)$ be a strictly increasing, continuous c.d.f. such as the logistic c.d.f. Since $G(\cdot)$ is strictly increasing, $G^{-1}(h_{t+1})$ is a link function that is well-defined by $G^{-1}(h_{t+1}) = y_t \iff G(y_t) = h_{t+1}$, or $G^{-1}(\cdot)$ is a 1-1 mapping from h_{t+1} to $\mathbb{R}$. Then, the ACB model is given by

$$G^{-1}(h_{t+1}) = \omega + \sum_{j=1}^{q} \alpha_j \left(x_{t-j+1} - h_{t-j+1}\right) + \sum_{j=1}^{r} \beta_j G^{-1}\left(h_{t-j+1}\right) + \sum_{j=1}^{s} \delta_j x_{t-j+1} + \gamma \mathbf{z}_t \tag{2}$$

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 $\theta = \{\omega, \alpha_1, ..., \alpha_q, \beta_1, ..., \beta_r, \delta_1, ..., \delta_s, \gamma\}$ can be obtained by maximizing the likelihood function given by

$$\sum_{t=1}^{T} \left\{x_{t+1} \log h_{t+1} + (1 - x_{t+1}) \log(1 - h_{t+1})\right\} \tag{3}$$

Gasoline stations set the retail price based on the cost of replacing the gasoline the station currently has in stock (Borenstein and Shepard, 1996). Thus, in the $\mathbf{z}$-vector of equation (2), we include the absolute value of the change in the wholesale price of gasoline, $|\Delta c_t|$, as it reflects changes in a station's cost. Because the wholesale price of gasoline is defined as the last posted price at the wholesale terminal closest to the retail station, it represents the replacement cost of gasoline for the station. We split $|\Delta c_t|$ into positive and negative wholesale price changes ($\left|\Delta c_t^+\right|$ and $\left|\Delta c_t^-\right|$, respectively) to test for asymmetry. Comparing the coefficients on $\left|\Delta c_t^+\right|$ and $\left|\Delta c_t^-\right|$ (γ_1 and γ_2, respectively) allows us to test whether a station is more likely to increase its price in response to a cost increase compared to lowering its price in response to a cost decrease (asymmetry "in the large"). Additionally, let θ_t be a dummy variable equal to one if there is a positive cost change, and zero otherwise. Replacing the constant (ω) in equation (2) with a positive and negative component (θ_t and $1 - \theta_t$, respectively) allows us to test whether or not a station is more likely to increase its price in response to a small cost increase than decrease it in response to a small cost decrease (asymmetry "in the small"). Finally, we construct a measure of wholesale price volatility that is modeled after the excess volatility measure suggested by Baillie and Osterberg (1997). Let the daily volatility be defined as the conditional variance generated through a GARCH(1,1) process:

$$\sigma_t^2 = \eta + \zeta\varepsilon_{t-1}^2 + \xi\sigma_{t-1}^2 \tag{4}$$

where $\Delta c_t = \varepsilon_t \sim Normal\left(0, \sigma_t^2\right)$, and define the average volatility as the unconditional variance from the GARCH(1,1) process in equation (4), which is given by:

$$\sigma^2 = \frac{\eta}{1 - \zeta - \xi}.$$

Then, the excess volatility is computed as the difference between the daily and average volatility of wholesale price changes, $\left(\sigma_t^2 - \sigma^2\right)$, which measures how volatile the cost changes a station faces are. Column 4 of Table 1 reports the sample mean of the excess cost volatility for each station. Positive excess volatility means that on day t, the daily conditional wholesale price volatility is greater than the average wholesale price volatility faced by the station. Negative excess wholesale price volatility means that on day t, the daily conditional wholesale price volatility is less than the average wholesale price volatility faced by the station. As seen from the table, average excess volatility is approximately 0.15 standard deviations above average cost volatility, with the exception of station 13. Station 13 is the only unbranded station in the data set. Since the station does not sell a particular brand of gasoline, it is free to buy gasoline from whichever wholesaler it wants, which might allow the station to smooth out volatility in the incurred wholesale price because it can switch suppliers. Given these variables, we summarize the testable implications of different theories of price stickiness.

- *Sticky information* models put forward that firms react to information with a lag (Sims, 1998): $\beta < 0$, or periods where the probability of a price change is high will be followed by periods where the probability is low. In addition, the coefficient on lagged cost changes (e.g. $|\Delta c_{t-1}|$), should have predictive power for current retail price changes if stations are reacting more strongly to past rather than current information.

- *Rational inattention by producers* (Reis, 2006) suggests that it is costly to process information, so it is optimal for firms to be inattentive for a period of time. Thus, we would expect similar predictions as in sticky information. Yet, because firms are not aware of new information as it arrives, they cannot respond in an asymmetric manner ($\omega_1 = \omega_2$ and $\gamma_1 = \gamma_2$). In addition, the inattentive period should be shorter the more volatile cost is, since volatile cost would cause the loss resulting from being inattentive to rapidly accumulate. Hence, excess volatility should increase the probability that a station changes its price.

- *Rational inattention by consumers* (Levy et at., 2006) contends that when information is costly, consumers are insensitive to small price changes, as the benefit of acquiring information regarding such price changes is less than the cost. Producers have an incentive to take advantage of this inattention and make small price increases over small price decreases ($\theta_t > 1 - \theta_t$). Producers have no similar incentive with regards to large price increases ($\gamma_1 = \gamma_2$) as consumers are attentive to large price changes.

- *Partial adjustment* (Rotemberg, 1982) suggests that firms stretch large price changes over a successive string of smaller price changes to avoid upsetting consumers. This implies $\delta > 0$ and $\beta > 0$ for price decreases and increases as firms will make price changes on consecutive days. Since there is incomplete adjustment to cost changes, past cost changes ($|\Delta c_{t-1}|$) should contain predictive power for future price changes.

- *Fairness* in pricing indicates that consumers feel entitled to their "reference" (past) price and firms to their "reference" profit (Kahneman et al., 1986). Consumers deem it fair for a firm to raise its price in order to protect its profit but unfair if it results in excess profit. Thus, we would expect $\beta > 0$ as firms seeks to maintain the status quo. Cost changes would be immediately passed through to consumers rather than over successive smaller price changes, so $|\Delta c_{t-1}|$ should have no predictive power for future retail price changes. In addition, the use of "rules of thumb" in evaluating prices (Rotemberg, 2005) would imply no asymmetry in the small ($\theta_t = 1 - \theta_t$) as small price increases would yield little benefit to the station relative to the cost of consumers searching for a lower price. Firms' concerns regarding consumer reaction to large price increases (Rotemberg, 2005 and Kahneman et al., 1996) imply a firm might be more willing to make a large price *decrease* over a large price *increase* ($\gamma_1 < \gamma_2$).[5]

Other theories of price stickiness involving inventories, countercyclical mark-ups and menu costs have been proposed. These theories involve firms accumulating inventories in anticipation of future price changes (see Kryvstov and Midrigan, 2012) or spreading production cost changes over several periods, since it is

[5]For another sticky price macroeconomic model based on fair pricing, see Rotemberg (2006, 2011)

costly to adjust production (see Borenstein and Shepard, 2002). However, because it is not possible for retail gasoline stations to store inventories in anticipation of future price increases, we do not consider these models for retail gasoline price stickiness. The fact that the physical cost of changing the retail price is minimal renders menu costs theories less relevant than for other goods.

4 Estimation Results

Table 2 reports the estimated coefficients for the preferred ACB specification, the ACB(0,1,1). β is significant and negative for five of the fifteen stations, which is in-line with sticky information. δ is only significant for one station, while the constant and the coefficient on $|\Delta c_t|$ are significant for all of the stations. The last three columns of Table 2 report the p-values from the likelihood ratio test that tests for the inclusion of $|\Delta c_{t-1}|$, $\left(\sigma_t^2 - \sigma^2\right)$, and the asymmetric variables, respectively, in the ACB(0,1,1) model compared to the restricted model that only includes $|\Delta c_t|$. As seen from the table, the coefficients on the first two variables are largely insignificant while the asymmetric specification is preferred for all stations.

We further investigate the issue of asymmetry by estimating an ACB model that includes lags of the positive and negative cost changes ($\left|\Delta c_{t-1}^{+}\right|$ and $\left|\Delta c_{t-1}^{-}\right|$) and the excess volatility associated positive and negative cost changes ($\left(\sigma_t^2 - \sigma^2\right)^{+}$ and $\left(\sigma_t^2 - \sigma^2\right)^{-}$ respectively) in addition to the previously described asymmetric variables. Three results emerge from Table 3. First, the constant for cost increases is smaller than for cost decreases, meaning a station is more likely to make small price decreases than small price increases. Second, positive changes in the wholesale cost $\left(\left|\Delta c_t^{+}\right|\right)$ are significant for all stations, yet negative changes in the wholesale cost $\left(\left|\Delta c_t^{-}\right|\right)$ are insignificant. That is, stations are more likely to increase the retail price in face of a large cost increase than to decrease the price when a large cost decrease occurs. Third, the volatility associated with negative cost changes is significant for six stations, whereas the volatility associated with positive cost changes, $\left(\sigma_t^2 - \sigma^2\right)^{+}$, is only significant for one station.[6] This suggests that stations are more likely to change the price if the cost drop is associated with higher excess volatility. These results are illustrated in Figure 1, which plots the probability of a price change for different combinations of cost change and excess volatility. As seen from the figure, asymmetry in the response of retail gasoline prices is reflected in two aspects: the probability of a price change increases when costs increase and when excess volatility increases. The reaction to cost increases is stronger than the reaction to excess volatility.

[6] Results available upon request show that the lagged positive and negative cost gap are only significant for one station.

To understand these results, it is important to keep in mind that, because retail margins are low, a cost increase can quickly turn margins negative prompting a station to increase its price.[7] Given that consumers are sensitive to gas prices, stations may prefer to make a price increase all at once, rather than a string of successive price increases so as not to irritate consumers (Rotemberg, 2005). This result is consistent with Douglas and Herrera (2010) and Davis and Hamilton (2004) who find support for the idea that fear of consumer reaction to price changes serves as a motivation for price stickiness in wholesale gasoline markets. In contrast, with a cost decrease, the information contained in the margin does not provide such a clear signal to change the price. Yet, we obtain a novel result: for a given cost decrease, the higher excess volatility is, the more likely the station is to change its price. This result is supportive of producer rational inattention (Reis, 2006).

5 Conclusion

We utilized a unique data set containing daily observations for 15 Philadelphia retail gasoline stations and a flexible methodology to test various empirical predictions of price stickiness. Using an ACB model, we found that the dynamics of price adjustment have two characteristics. First, stations price asymmetrically "in the large" but not "in the small," which is consistent with fair pricing. Second, cost decreases associated with lower cost volatility are more likely to result in lower retail prices. This behavior is consistent with producer rational inattention.

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Table 1: Summary Statistics

Station	Mean Price	Mean Wholesale	Mean Excess Volatility	Frequency of Price Change	Frequency of Wholesale Price Change
1	165.82	100.57	0.426	0.069	0.366
2	162.48	100.52	0.278	0.104	0.363
3	161.96	100.53	0.002	0.106	0.357
4	162.61	100.57	0.316	0.102	0.361
5	160.17	100.58	0.003	0.092	0.360
6	162.06	100.59	0.257	0.085	0.363
7	160.48	100.60	0.143	0.107	0.367
8	163.29	100.65	0.002	0.085	0.359
9	164.90	100.59	0.182	0.090	0.378
10	163.03	100.72	0.153	0.107	0.366
11	162.79	100.59	0.201	0.097	0.378
12	164.39	100.61	0.256	0.112	0.362
13	156.29	99.46	-0.002	0.136	0.401
14	158.60	100.69	0.002	0.124	0.364
15	161.60	100.63	0.138	0.106	0.348

Note: All prices are given in cents/gallon

Table 2: Estimation of the ACB(0,1,1)

Station	ω	β	δ	$\|\Delta c_t\|$	log lik	$\|\Delta c_{t-1}\|$	$(\sigma_t - \sigma)$	asymmetric
1	-3.368**	-0.100	-0.406	0.501**	-246.218	0.031*	0.026*	0.000**
	(0.552)	(0.183)	(0.630)	(0.068)				
2	-3.065**	-0.152	-0.404	0.602**	-315.116	0.207	0.917	0.000**
	(0.350)	(0.123)	(0.489)	(0.070)				
3	-3.459**	-0.295**	-0.802	0.645**	-309.731	0.610	1.00	0.000**
	(0.363)	(0.113)	(0.676)	(0.067)				
4	-2.947**	-0.082	-0.413	0.640***	-306.039	0.183	0.049*	0.000**
	(0.523)	(0.191)	(0.603)	(0.070)				
5	-3.371**	-0.229**	-1.658	0.521**	-290.002	0.106	1.00	0.000**
	(0.308)	(0.091)	(0.911)	(0.064)				
6	-3.251**	-0.148	-0.713	0.542**	-282.869	0.601	0.531	0.000**
	(0.526)	(0.177)	(0.830)	(0.070)				
7	-2.892**	-0.131	-0.198	0.533**	-335.465	0.649	0.112	0.000**
	(0.496)	(0.194)	(0.475)	(0.065)				
8	-3.578**	-0.235*	-0.052	0.575**	-277.741	0.301	1.00	0.000**
	(0.381)	(0.120)	(0.488)	(0.069)				
9	-3.686**	-0.338**	-0.034	0.518**	-296.134	0.360	0.153	0.000**
	(0.334)	(0.106)	(0.370)	(0.066)				
10	-3.173**	-0.252*	-0.516	0.508**	-330.422	0.586	0.763	0.000**
	(0.326)	(0.114)	(0.455)	(0.061)				
11	-3.412**	-0.287	0.070	0.491**	-315.911	0.641	0.530	0.000**
	(0.466)	(0.165)	(0.580)	(0.064)				
12	-2.542**	0.057	0.163	0.612**	-332.436	0.402	0.432	0.000**
	(0.321)	(0.123)	(0.347)	(0.066)				
13	-2.845**	-0.257*	-0.362	0.353**	-389.033	0.012*	0.459	0.000**
	(0.274)	(0.107)	(0.321)	(0.040)				
14	-2.869**	-0.183	-0.583	0.603**	-355.798	0.111	1.00	0.000**
	(0.302)	(0.114)	(0.403)	(0.064)				
15	-3.059**	-0.180	-1.020*	0.568**	-318.652	0.340	0.263	0.000**
	(0.316)	(0.107)	(0.547)	(0.065)				

Notes: standard errors in parenthesis; ** denotes statistically significant at the 1% level, * denotes statistically significant at the 5% level.

Table 3: Estimation of the Asymmetric ACB(0,1,1)

Station	θ_t	$1-\theta_t$	β	δ	$\lvert\Delta c_t^+\rvert$	$\lvert\Delta c_t^-\rvert$	$(\sigma_t-\sigma)^+$	$(\sigma_t-\sigma)^-$	log lik
1	-3.948**	-3.258**	-0.105	-0.603	0.690**	0.072	0.140*	0.152*	-229.396
	(0.476)	(0.482)	(0.130)	(0.650)	(0.104)	(0.103)	(0.059)	(0.077)	
2	-3.560**	-2.623**	-0.102	-0.093	0.938**	0.095	0.021	0.024	-289.048
	(0.348)	(0.349)	(0.101)	(0.501)	(0.104)	(0.083)	(0.090)	(0.076)	
3	-4.350**	-3.336**	-0.360**	-0.131	1.014**	0.089	0.000	0.100	-281.853
	(0.435)	(0.403)	(0.103)	(1.095)	(0.104)	(0.104)	(0.069)	(2.344)	
4	-3.428**	-2.520**	-0.104	-0.416	0.908**	0.122	0.102	0.218*	-286.583
	(0.405)	(0.405)	(0.120)	(0.572)	(0.103)	(0.091)	(0.082)	(0.096)	
5	-3.870**	-2.972**	-0.216**	-1.319	0.898**	0.009	0.003	0.099	-267.257
	(0.328)	(0.310)	(0.081)	(0.910)	(0.097)	(0.088)	(0.082)	(0.991)	
6	-3.813**	-3.017**	-0.215	-0.254	0.796**	0.001	0.060	0.175	-269.524
	(0.489)	(0.478)	(0.148)	(0.750)	(0.096)	(0.085)	(0.104)	(0.109)	
7	-3.453**	-2.725**	-0.159	-0.077	0.728**	-0.044	0.083	0.222*	-311.952
	(0.369)	(0.372)	(0.119)	(0.295)	(0.096)	(0.117)	(0.123)	(0.115)	
8	-4.107**	-3.269**	-0.247*	0.360	0.837**	0.111	0.000	0.000	-262.291
	(0.386)	(0.376)	(0.101)	(0.531)	(0.099)	(0.103)	(0.152)	(0.099)	
9	-4.248**	-3.456**	-0.321**	0.204	0.791**	-0.065	0.157	0.269*	-274.444
	(0.368)	(0.357)	(0.096)	(0.458)	(0.097)	(0.117)	(0.125)	(0.122)	
10	-3.651**	-2.893**	-0.248*	-0.295	0.758**	-0.087	-0.057	0.216	-307.611
	(0.346)	(0.336)	(0.102)	(0.470)	(0.087)	(0.114)	(0.131)	(0.115)	
11	-3.732**	-3.064**	-0.255*	0.228	0.668**	0.015	-0.082	0.047	-302.103
	(0.385)	(0.386)	(0.124)	(0.408)	(0.089)	(0.177)	(0.128)	(0.125)	
12	-3.091**	-2.135**	0.022	0.292	0.955**	-0.049	-0.048	0.304**	-301.414
	(0.291)	(0.283)	(0.085)	(0.366)	(0.099)	(0.108)	(0.075)	(0.091)	
13	-3.406**	-2.910**	-0.301**	-0.216	0.496**	0.029	0.891	0.898	-366.440
	(0.289)	(0.284)	(0.095)	(0.357)	(0.057)	(0.061)	(1.288)	(2.211)	
14	-3.103**	-2.062**	-0.111	-0.535	1.042**	0.019	0.000	0.000	-329.935
	(0.319)	(0.323)	(0.107)	(0.418)	(0.107)	(0.111)	(0.133)	(0.122)	
15	-3.709**	-2.870**	-0.244**	-0.850	0.838**	-0.102	-0.003	0.334*	-292.064
	(0.327)	(0.321)	(0.088)	(0.554)	(0.096)	(0.118)	(0.131)	(0.137)	

Notes: Standard errors in parenthesis. ** denotes statistically significance at the 1% level. * denotes statistically significant at 5% level.

Figure 1: ACB Estimated Probabilities of a Price Change